Left-Digit Bias in Household Inflation Expectations*

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Abstract: This paper theoretically defines and empirically tests left-digit bias in household inflation expectations. Using cross-country data and a regression discontinuity design, we find that inflation expectations jump discontinuously when inflation crosses round-number thresholds, especially when inflation is rising. Media sensationalism is the primary channel through which these effects operate, as confirmed by instrumental variable estimates and a randomized controlled experiment. Embedding left-digit-biased expectations into a New Keynesian model reveals important macroeconomic and policy implications: weaker initial responses to shocks, prolonged inflationary periods, and the need for more persistent monetary policy.

Keywords: expectations formation; media; monetary policy; New Keynesian model; round-number thresholds; sensationalism.

JEL classification: C83; D83; D84; E31; L82.

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1. Introduction

Inflation expectations play a crucial role in households' economic decisions and are highly relevant for monetary policy. How households form inflation expectations and what the precise determinants are, however, is still an ongoing question.[1] Several studies show that one such determinant is the current and past inflation rate (see, e.g., Carrillo and Shahe Emran, 2012; Coibion *et al.*, 2023). Whether households are subject to left-digit bias when processing information about the inflation rate and how this bias affects inflation expectations has not been studied, though. In this paper, we fill this gap by theoretically and empirically studying left-digit bias in household inflation expectations.

Left-digit bias arises when people process numerical values as round numbers, especially when cognitive efforts are low (Rosch, 1975). People pay less attention to the significance of numerical values beyond the leftmost digits, which affects information processing and downstream decisions. In the context of inflation, left-digit bias can induce discontinuities at round numbers in the relationship between current inflation and inflation expectations. To test for left-digit bias in inflation expectations, we examine how changes in current inflation influence household inflation expectations when inflation thresholds are crossed. These thresholds are cognitively salient values, such as integers or multiples of 5. For example, we investigate whether an increase in the inflation rate by 0.1 percentage point from 4.8 to 4.9 percent results in a similar change in inflation expectations as an increase from 4.9 to 5.0 percent, where an inflation threshold is crossed.

We present several results and contributions. First, we theoretically define left-digit bias in inflation expectations, providing a precise definition, examples, and intuition. We then demonstrate how left-digit bias induces discontinuities around inflation thresholds. Intuitively, households pay less attention to the rightmost digits of the inflation rate, leading to a jump in expectations once the inflation rate crosses a round-number threshold. Second, we use cross-country data and a regression discontinuity design to test for the theoretically motivated discontinuities between inflation thresholds and expectations.

Third, if household inflation expectations react discontinuously around round-number thresholds, the question arises as to why that is the case. We test and discuss one candidate explanation: sensationalism in news coverage of the inflation rate. Most households obtain their knowledge about the aggregate inflation rate from the media. Sensationalism accentuates a story's extraordinary or emotionally captivating aspects in the context of inflation-related news. For example, consider the headline "*Eurostat: Inflation on the rise*", which states a basic

[1] See Weber *et al.* (2022a) for a recent survey on the measurement and different determinants of household inflation expectations. We discuss the literature below.

fact in a non-sensational manner. A sensational version of the headline may read ”*Eurostat: Soaring inflation breaks all records*”, which uses stronger language and frames the fact as a historical anomaly. We study how sensationalism in news coverage mediates the effect of inflation threshold events on inflation expectations with cross-country data. We conduct a randomized controlled survey experiment on sensational inflation news and inflation expectations to validate our findings further and obtain more causal insights at the individual level. Lastly, we embed left-digit-biased inflation expectations into a standard New Keynesian model to study the macroeconomic and monetary policy implications.

We compile a dataset consisting of inflation rates, survey-based household inflation expectations, and inflation-related media coverage for 30 European economies at a monthly frequency over the period 2017–2023. Our media data include 281,206 inflation-related stories from each country's most important news sites. We instruct human coders to annotate a subsample of the headlines as sensational or not. We then use these annotations as training data for deep-learning classifiers based on large language models, such as Bidirectional Encoder Representations from Transformers (BERT; see Devlin *et al.* 2018). Using the resulting machine predictions, we compute the mean probability of sensational headlines by country and month.

Following the theoretical insights obtained, we use a regression discontinuity design to study how inflation affects inflation expectations when it passes round-number thresholds. The idea is to compare situations where a country's inflation rate crosses a round number, such as 10% or 20%, to situations that exhibit similar economic conditions but where no threshold is crossed. The identifying assumption is that round-number inflation threshold events occur as if randomly assigned after accounting for continuous changes in inflation. To study how inflation-related news coverage mediates the effect of round-number thresholds, we run an instrumental variable (IV) regression. The first stage of this regression captures the impact of threshold events on sensationalism, while the second stage models the effect of sensationalism on household inflation expectations. Lastly, we conduct a randomized controlled survey experiment to study how sensational phrasings of inflation-related news affect inflation expectation formation at the individual level. Specifically, we run a survey experiment showing headlines on several topics to survey participants, including sensational and non-sensational headlines related to inflation.

Our results show that an increasing-inflation threshold, defined as a situation when a country's inflation rate climbs above a round-number threshold, induces significantly more individuals to expect rising prices in the future, with mean and median inflation expectations jumping by 0.6 and 1.1 percentage points, respectively. We find the discontinuities to be most pronounced at multiples of five: 5, 10, 15, 20, and 25 percent. Decreasing-inflation thresholds, defined as a situation when the inflation rate falls below a round number, have no significant effect on inflation expectations.

The change in mean inflation expectations can be decomposed into an extensive margin—for example, when households previously expecting zero inflation now expect strictly positive inflation rates—and an intensive margin—for example, when households previously expecting strictly positive inflation now expect even higher inflation. We find that households predominantly react along the extensive margin rather than the intensive margin. More precisely, round-number threshold events induce individuals who previously expected zero or negative inflation to expect strictly positive and accelerating inflation.

After showing that increasing-inflation threshold events affect inflation expectations, we propose an explanation based on sensational news coverage. Information about new inflation data must travel from statistical agencies to individuals, and most people obtain this information not directly from the agencies' websites but through the media. According to our IV estimates, the mean probability of sensational headlines more than doubles when a country's inflation rate surpasses a round-number threshold. In turn, the increase in sensationalism induces more households to expect increasing inflation. We discuss and test alternative transmission channels but conclude that media sensationalism is the primary channel through which threshold events affect inflation expectations.

The results are robust to a battery of robustness checks, and we further analyze the following extensions. First, we test for alternative inflation thresholds, such as full integers instead of multiples of five or randomly drawn real numbers. We find that multiples of five are the only significant thresholds, while full integers or randomly drawn real numbers are not. Second, our results are not driven by the number of inflation news articles but by the share of sensational inflation news relative to non-sensational ones. Additionally, using the volume of Google searches, we do not find that inflation threshold events induce households to search more for information on inflation. Third, we show that inflation threshold events also exert real effects by studying the impact on households' *readiness to spend on durables* (Bachmann *et al.*, 2015). The readiness to spend on durables increases significantly in response to an increasing-inflation threshold event, which aligns with what the Euler equation in a standard New Keynesian model predicts.

To support our results based on aggregate cross-country data, we run a randomized controlled survey experiment. Respondents treated with a sensational inflation headline are likelier to expect higher inflation than participants exposed to a non-sensational headline. This effect is particularly pronounced for headlines that do not include any numerical information about the inflation rate. In other words, including the inflation rate value mitigates the effects of sensationalism, even if this value is provided as a round number.

Lastly, we embed left-digit-biased inflation expectations into a standard New Keynesian model to study the macroeconomic and monetary policy implications. We analyze the economy's reaction to a demand shock, comparing different degrees of left-digit bias. The more pronounced the left-digit bias in inflation expectations, the weaker the response of inflation and inflation expectations to a demand shock. The intuition is that households update their expectations less when subject to left-digit bias. Furthermore, when we incorporate the asymmetry in increasing- and decreasing-inflation threshold events uncovered in our empirical estimates, both expected and actual inflation remain higher for longer after a demand shock than in a scenario without left-digit bias. From a monetary policy perspective, it is therefore advisable to account for discontinuous jumps in household inflation expectations and maintain interest rates at elevated levels for extended periods when inflation is high. This finding also implies that contractionary monetary policy takes longer to reduce inflation and inflation expectations, and hence, no further interest rate hikes are necessary if inflation is not declining rapidly.

Related literature. Our paper unifies three strands of the literature. First, we build on a large body of work that studies household inflation expectations (see Weber *et al.*, 2022a, for a recent survey). One central question is how households form inflation expectations and what factors determine them. Previously studied determinants are observed prices of single goods (Andrade *et al.*, 2023; Cavallo *et al.*, 2017; Coibion and Gorodnichenko, 2015; D'Acunto *et al.*, 2021b; Weber *et al.*, 2022b), central bank announcements (Coibion *et al.*, 2022; Dräger *et al.*, 2016; Lamla and Vinogradov, 2019; Picault *et al.*, 2022), demographic characteristics (Carrillo and Shahe Emran, 2012; D'Acunto *et al.*, 2021c), and past experiences (Goldfayn-Frank and Wohlfart, 2020; Malmendier and Nagel, 2015). Our work is more closely connected to other determinants, as we will discuss now.

Past realized inflation has been shown to affect households' expectations of future inflation. Coibion *et al.* (2023) find that Dutch households who receive information about recent inflation adjust their expectations accordingly. This finding is consistent with numerous other studies that demonstrate the impact of current inflation on household inflation expectations (Bracha and Tang, 2023; Carrillo and Shahe Emran, 2012; Chen *et al.*, 2022; Coibion *et al.*, 2022; Dräger, 2015; Dräger *et al.*, 2016; Pfajfar and Santoro, 2013; Pfäuti, 2023; Weber *et al.*, 2023). Our paper contributes to this literature by examining how household inflation expectations respond differently to current inflation when it crosses a round-number threshold.

Another determinant of inflation expectations is cognitive ability. Studying the male Finnish population, D'Acunto *et al.* (2022) find that only high-IQ men behave mostly like rational-expectations agents, having small forecast errors, consistent inflation expectations, and behaving according to the Euler equation (see also Cavallo *et al.*, 2017; D'Acunto *et al.*, 2019). We show that left-digit bias, a cognitive factor, affects inflation expectations.

We also contribute to the literature on rational inattention to inflation (see, for example, Cavallo *et al.*, 2017; Weber *et al.*, 2023; Sims, 2003). Two recent studies by Pfäuti (2023) and Korenok *et al.* (2022) estimate a threshold for inflation above which attention becomes elevated. Left-digit bias in inflation expectations could be due to rational inattention, as it is cognitively costly to store entire numbers in memory (Gabaix, 2019). However, we are agnostic about the underlying, potentially non-rational, cognitive processes that lead to left-digit bias. In contrast to what Pfäuti (2023) and Korenok *et al.* (2022) find, the resulting thresholds from left-digit bias are multiples of round numbers.

We also share our focus with studies that consider the media as a determinant of household inflation expectations. Theoretical work by Carroll (2003) suggests that individuals update their expectations irregularly from the media. Empirical studies find that the frequency and tone of inflation-related news articles affect household inflation expectations (for example, Badarinza and Buchmann, 2009; Dräger *et al.*, 2016; Lamla and Maag, 2012; Larsen *et al.*, 2021). In particular, Lamla and Lein (2014) and Dräger (2015) differentiate between "bad" and "good" news on inflation and show that "bad" news on rising inflation increases household inflation expectations. Similarly, Kmetz *et al.* (2022) find that the increased volume and negativity of inflation news explains a significant portion of the gap between household and professional forecasters' inflation expectations in the US between June 2021 and June 2022. Our measure of sensationalism is related to the tone of inflation news but goes beyond the "good"/"bad" dichotomy. While negativity is often an important element of sensationalism, media outlets sometimes sensationalize "good" news too. We show that sensationalism in news coverage of inflation is a crucial determinant of household inflation expectations and that the likelihood of sensational news increases when inflation surpasses a round-number threshold.

Second, our paper contributes to the literature studying left-digit bias. Left-digit bias is most well-known and studied in the context of 99-cent pricing (Thomas and Morwitz, 2005; Sokolova *et al.*, 2020; Strulov-Shlain, 2023). Some studies demonstrate that left-digit bias leads to stock and currency price clustering as traders use round numbers as reference points (Sonnemans, 2006; Bhattacharya *et al.*, 2012; Urquhart, 2017). Agarwal *et al.* (2022) find that threshold events in stock market indices—such as 1,000-point round numbers—affect households' mortgage demand. Other areas where left-digit bias and round-number effects can be observed are sales prices of used cars and their mileage (Lacetera *et al.*, 2012); race times and athletes' willingness to take risks (Foellmi *et al.*, 2016); asking prices of online marketplace listings and negotiations (Backus *et al.*, 2019); students' scores in entrance exams and college enrollment (Goodman *et al.*, 2020); apartment purchases (Repetto and Solís, 2019); and ride-sharing services (List *et al.*, 2023). In addition, Garz (2018) and Garz and Martin (2021) show that round-number events in the unemployment rate have discontinuous effects on household perceptions of the state of the economy and voting for incumbent politicians, respectively. We contribute to this research by studying left-digit bias in inflation expectations for the first time, theoretically and empirically, and by analyzing the transmission via sensational news coverage and the monetary policy implications in a New Keynesian model.

Third, our work also speaks to the broader literature on the effects of media on economic outcomes (for surveys, see DellaVigna and Gentzkow, 2010; DellaVigna and La Ferrara, 2015; Prat and Strömberg, 2013). Particularly relevant is research investigating how media transmit macroeconomic information to the population and how that affects individual perceptions and actions, such as unemployment expectations (e.g., Garz, 2013; Sorić *et al.*, 2019), consumer sentiment (e.g., Nguyen and Claus, 2013; Garmaise *et al.*, 2020; Eggers *et al.*, 2021), and macroeconomic forecasting (e.g., Rambaccussing and Kwiatkowski, 2020; Aprigliano *et al.*, 2023). More closely related, Coibion *et al.* (2022) find that news articles from USA Today on FOMC postmeeting statements have smaller effects on inflation expectations than current inflation numbers or the FED's inflation target, suggesting that households may not trust these sources. However, their focus differs from ours, as we study news on actual inflation numbers, which are easier to understand than central bank announcements. Andre *et al.* (2023) analyze news articles to understand households' narratives about high inflation in 2021 and 2022. While most media-related literature examines the volume or tone of coverage, our approach differs by documenting the effects of sensationalism in news headlines about inflation. Sensationalism, well-studied in communications and journalism research for its ability to capture attention and evoke emotions (Grabe *et al.*, 2001; Uribe and Gunter, 2007; Vettehen *et al.*, 2008), has largely been neglected in economics. Our paper addresses this gap by exploring the implications of sensationalism for information transmission and expectation formation.

Layout. The rest of the paper is organized as follows. In section 2, we theoretically define left-digit bias for expectation formation. We describe the data in section 3 before explaining our estimation strategy in section 4. We present our results in section 5. Section 6 describes our survey experiment and its results. In section 7, we study the implications of left-digit-biased inflation expectations in a New Keynesian model before concluding in section 8.

2. Theoretical foundations of left-digit bias in inflation expectations

2.1. General formulation

We use a very general model of inflation expectations to define left-digit bias in inflation expectations. A household observes the current and previous periods' inflation rates π_t and π_{t-1}, respectively, and forms subjective inflation expectations $\mathbb{E}_t^b(\pi_{t+1})$ as follows:

$$\mathbb{E}_t^b(\pi_{t+1}) = f(\pi_t, \pi_{t-1}, \mathbf{X}_t), \tag{1}$$

where the superscript b denotes *behavioral* expectations that need not coincide with rational expectations. The matrix $\mathbf{X}_t$ is a stand-in for all other variables that potentially affect household inflation expectations; see our discussion of determinants of inflation expectations in the literature review in the previous section. If $\mathbf{X}_t$ contains all available information at t, then equation (1) can be a rational expectations model, depending on the functional form of f.

We now define inflation thresholds with the general inflation expectations function (1).

Definition 2.1 (Inflation threshold event)**.** The parameter τ is an *inflation threshold* if the inflation expectation function f has a jump discontinuity at $\pi_t = \tau$. An *increasing-inflation threshold event* is defined by $\pi_{t-1} < \tau$ and $\pi_t \geq \tau$ for some inflation threshold τ, and a *decreasing-inflation threshold event* is defined by $\pi_{t-1} > \tau$ and $\pi_t \leq \tau$ for some inflation threshold τ. A jump discontinuity is defined as follows. For

$$\bar{l}^{+} \equiv \lim_{\pi_t \searrow \tau} f(\pi_t, \pi_{t-1} < \tau, \mathbf{X}_t) \qquad \bar{l}^{-} \equiv \lim_{\pi_t \searrow \tau} f(\pi_t, \pi_{t-1} > \tau, \mathbf{X}_t)$$

$$\underline{l}^{+} \equiv \lim_{\pi_t \nearrow \tau} f(\pi_t, \pi_{t-1} < \tau, \mathbf{X}_t) \qquad \underline{l}^{-} \equiv \lim_{\pi_t \nearrow \tau} f(\pi_t, \pi_{t-1} > \tau, \mathbf{X}_t),$$

a jump discontinuity at an increasing-inflation threshold τ exists if $\bar{l}^{+} \neq \underline{l}^{+}$ and similarly, a jump discontinuity at a decreasing-inflation threshold τ exists if $\bar{l}^{-} \neq \underline{l}^{-}$.

This definition separates situations where inflation surpasses an inflation threshold from below from situations where inflation falls below an inflation threshold from above. Intuitively, households might pay more attention to negative events, like inflation surpassing a threshold from below, than to positive events, like inflation falling below a threshold from above. We will test for increasing- and decreasing-inflation thresholds in our empirical analysis, where our regression discontinuity approach explained in section 4 exploits the discontinuity underlying definition 2.1.

According to the above definition, an inflation threshold could take any value, like 5.123456789%. However, these thresholds are round numbers if households form inflation expectations subject to left-digit bias.

Definition 2.2 (Left-digit bias in inflation expectations)**.** Household inflation expectations are subject to *left-digit bias* if inflation thresholds exist at round numbers, where round numbers are defined as multiples of a strictly positive integer.

For example, if the integer is 1, then inflation thresholds are at 1%, 2%, 3%, ..., while if the integer is 5, then inflation thresholds are at 5%, 10%, 15%, and so on. We will test for left-digit bias in inflation expectations by testing different inflation thresholds, including integer and non-integer values.

Our definition of left-digit bias excludes thresholds at round numbers beyond the decimal place of the inflation rate, like multiples of 50 basis points that would result in thresholds at 0.5%, 1.0%, 1.5%, and so on. The reasons for this exclusion are twofold: first, statistical agencies typically provide inflation numbers up to one digit after the decimal point; second, considering multiples of arbitrarily small values would eventually include the entire set of real numbers.

2.2. Left-digit bias and perceived inflation

What might be the reason for left-digit bias in inflation expectations as just defined? We now provide an interpretation by considering one possible specification for equation (1). However, we do not restrict the empirical analysis to this specification.

A representative household[2] perceives inflation with a left-digit bias. Perceived inflation is described by

$$\begin{aligned}\overbrace{\pi_t^p}^{\text{Perception}} = \overbrace{\pi_{t-1}^p}^{\text{Perception } t-1} + \overbrace{d(\pi_t, \pi_{t-1})}^{\text{Discontinuous updating}} &+ \overbrace{(1-\theta)[\Delta\pi_t - d(\pi_t, \pi_{t-1})]}^{\text{Attention to inflation changes}} \\ &+ \underbrace{(1-\lambda)\left[\pi_{t-1} - \pi_{t-1}^p\right]}_{\text{Attention to inflation level}}, \end{aligned} \tag{2}$$

with $d(\pi_t, \pi_{t-1})$ capturing discontinuous updating, $\theta \in [0,1]$ inattention to changes in inflation, $\lambda \in [0,1]$ inattention to the level of inflation, and $\Delta\pi_t \equiv \pi_t - \pi_{t-1}$ the change in the actual inflation rate.[3] Households update their perceived inflation only discontinuously according to

$$d(\pi_t, \pi_{t-1}) = \left(\left\lfloor \frac{\pi_t}{\tau} \right\rfloor - \left\lfloor \frac{\pi_{t-1}}{\tau} \right\rfloor\right) \times \begin{cases} \tau & \text{if } \left\lfloor \frac{\pi_t}{\tau} \right\rfloor \geq \left\lfloor \frac{\pi_{t-1}}{\tau} \right\rfloor \\ \tau^- & \text{if } \left\lfloor \frac{\pi_t}{\tau} \right\rfloor < \left\lfloor \frac{\pi_{t-1}}{\tau} \right\rfloor. \end{cases} \tag{3}$$

The expression $\lfloor\rfloor$ is the floor function, which returns the greatest integer less than or equal to the argument. The inflation thresholds are given by multiples of $\tau > 0$. For example, with $\tau = 5$, inflation thresholds are given by 5%, 10%, 15%, and so on. We will test for different values of τ in the empirical analysis.

[2]One could also model two groups of households, one attentive and one inattentive, and aggregate their expectations, resulting in the same aggregate expectation formation process described here, except that the inattention parameter would reflect the group sizes. This approach would also be closer to the changes along the extensive margin at inflation threshold events in the empirical section. We keep the model simple and assume a representative household for illustrative purposes.

[3]We use the term *inattention* when referring to left-digit bias, but left-digit bias might also be the result of imperfect price recall, a tendency to choose round numbers to represent reference-prices, or price categorization (Strulov-Shlain, 2023).

It is cognitively costly to process and store an entire number in memory, and individuals might only pay attention to the leftmost digits. Therefore, households do not fully update their perceived inflation if inflation does not cross a threshold between two periods. However, if inflation crosses one threshold, then τ or τ^- is added to the perceived inflation rate, depending on whether inflation increases or decreases. For example, assume thresholds that are multiples of five, $\tau = \tau^- = 5$, and fully inattentive households, $\theta = \lambda = 1$. If inflation moves from $\pi_{t-1} = 4.8$ to $\pi_t = 4.9$, the floor function returns 0 for both, and the household does not update its perceived inflation, $d(\pi_t, \pi_{t-1}) = 0$. However, if inflation moves from $\pi_{t-1} = 4.9$ to $\pi_t = 5.0$, the floor function returns 0 for π_{t-1} and 1 for π_t. The household updates its perceived inflation by $\tau = 5$ percentage points, $d(\pi_t, \pi_{t-1}) = 5$ because the household pays attention to the leftmost digit, and the inflation rate crosses a threshold.

Why do we differentiate between increasing- and decreasing-inflation threshold events by considering τ^-, potentially different from τ? If $\tau^- = \tau$ and $\lambda = 1$, then equation (2) can be written more simply as

$$\pi_t^p = \tau \left\lfloor \frac{\pi_t}{\tau} \right\rfloor + (1-\theta)\left(\pi_t - \tau \left\lfloor \frac{\pi_t}{\tau} \right\rfloor\right).$$

This formulation follows the literature on 99-cent pricing, see, for example, List *et al.* (2023); Strulov-Shlain (2023), except that we apply it to inflation perceptions, and the 99-cent pricing literature considers $\tau = 1$.[4] For example, if inflation thresholds are multiples of five, $\tau = 5$, inattention θ is 0.5, and the actual inflation rate is 7.6%, the perceived inflation rate is 6.3%. This formulation of left-digit bias in inflation perceptions is more static, while equation (2) is more dynamic as it also has previous periods' inflation rates as arguments. This more static inflation perception is symmetric in that perceived inflation jumps upwards when an inflation threshold is surpassed from below. However, it also jumps downwards by the same magnitude when an inflation threshold is crossed from above.

The more general, dynamic formulation in equation (2) allows for the asymmetry between exceeding thresholds and falling below thresholds, captured by $\tau \neq \tau^-$. For example, if $\tau = 5$ and $\tau^- = 0$, perceived inflation jumps upwards by 5 percentage points when inflation crosses a threshold from below, but it does not jump downwards when inflation falls below a threshold. For perceived inflation also adjusting downwards over time, however, and converging to a long-run value π^*, the household has to pay some attention to the level of actual inflation, that is, $\lambda < 1$. If $\tau^- \neq \tau$ and $\lambda = 1$, perceived inflation would behave like a step-wise random walk without converging eventually to actual inflation. We, therefore, include the last term

[4] We followed the literature on 99-cent pricing (Strulov-Shlain, 2023; List *et al.*, 2023) and assumed that households exogenously pay only attention to the leftmost digit of inflation rates. This could potentially be endogenized by assuming that left-digit bias is due to cognitive costs of attention, following Gabaix (2019), and households endogenously choose the level of attention $\theta \in (0, 1)$ to pay to inflation rates.

in equation (2). In the empirical analysis, we will test whether i) $\tau = 0$ and $\tau^- = 0$, and ii) $\tau = \tau^-$.

Based on their perception of inflation, households form inflation expectations. The representative household assumes that inflation π_t evolves according to an AR(1) process

$$\pi_{t+1} = \rho\pi_t + (1-\rho)\pi^* + \epsilon_{t+1}, \tag{4}$$

where $\rho \in (0,1)$ is the perceived inflation persistence, π^* is the perceived long-run inflation rate, and ϵ_{t+1} is a white noise shock. Inflation might evolve differently, but the household believes it follows this process. Households then form inflation expectations based on perceived inflation and the AR(1) process:

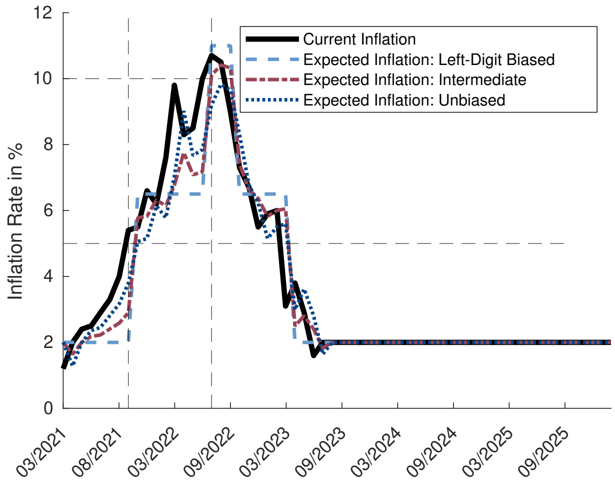
$$\mathbb{E}_t^b(\pi_{t+1}) = \rho\pi_t^p + (1-\rho)\pi^*. \tag{5}$$

Jump discontinuities in perceived inflation, as described in equation (2), directly translate into jump discontinuities in inflation expectations.

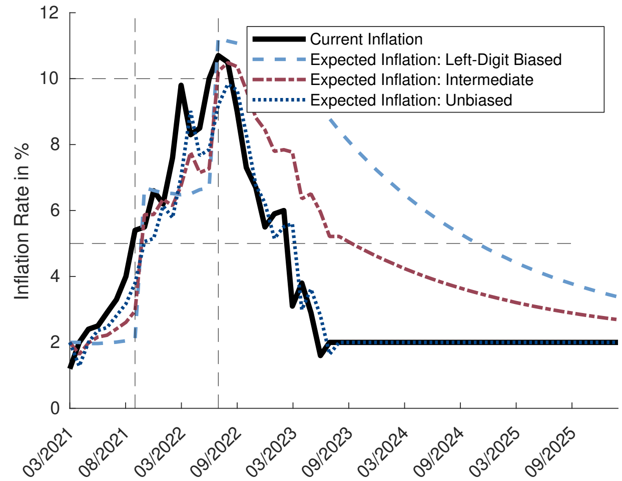
Figure 1 illustrates the example of inflation expectations just explained. For actual inflation, we use the HICP inflation in Spain from March 2021 until June 2023 and assume it stays constant at 2% afterward. Expected inflation is then calculated with equations (2), (3) and (5). In all three sub-figures, we consider three cases of left-digit bias in inflation expectations: no left-digit bias, $\theta = 0$, and perceived inflation equals actual inflation, intermediate left-digit bias, $\theta = 0.5$, and full left-digit bias $\theta = 1$. We consider inflation thresholds at multiples of 5.

In Figure 1a, we assume symmetric thresholds $\tau = \tau^- = 5$ and full inattention to the level of inflation, $\lambda = 1$. Initial values for perceived inflation are chosen such that perceived inflation converges to steady state inflation of 2% in the long run.[5] Under full attention to current inflation, $\theta = 0$, expected inflation follows current inflation closely with a lag. The other extreme of full inattention to current inflation beyond multiples of five, $\theta = 1$, shows that expected inflation is only updated once an inflation threshold event occurs. The first increasing-inflation threshold event occurred in October 2021, when inflation increased from 4.0% to 5.4%, and the second in June 2022, when inflation increased from 8.5% to 10.0%. After the first event, inflation expectations jump from 2% to 7%, and after the second event, they jump from 7% to 12%. During the subsequent decreasing-inflation threshold events, expected inflation jumps down immediately. In the intermediate case, $\theta = 0.5$, expected inflation also adjusts between thresholds, but a considerable part of the adjustment takes place only when a threshold is crossed.

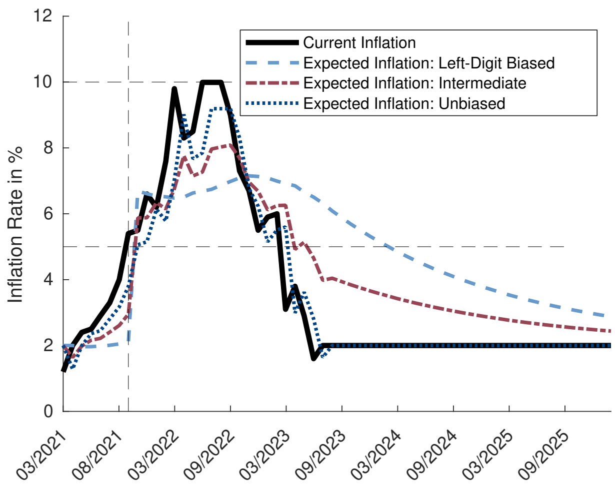
[5] To be precise, $\pi_0^p = \tau \lfloor \frac{\pi_0}{\tau} \rfloor + (1-\theta)\left[\pi_0 - \tau \lfloor \frac{\pi_0}{\tau} \rfloor\right] + \theta\left(\pi^* - \tau \lfloor \frac{\pi^*}{\tau} \rfloor\right)$, where π^* is steady state inflation which we set equal to 2%.



(a) Symmetric inflation threshold



(b) Asymmetric inflation threshold



(c) Asymmetric inflation threshold with inflation staying below 10%

Notes: Current inflation is the HICP for Spain from March 2021 to June 2023 from our main data described in section 3. Current inflation is assumed to remain at 2% afterward. Expected inflation is calculated with equations (2), (3) and (5), for $\theta = 0$ ('Unbiased'), $\theta = 0.5$ ('Intermediate'), and $\theta = 1$ ('Left-Digit Biased').

Figure 1: Example of inflation expectations with left-digit bias

Figure 1b shows the same example but with asymmetric thresholds, $\tau = 5$ and $\tau^- = 0$. For perceived and expected inflation to revert to low values and eventually coincide with actual inflation, λ has to be set to a value below 1. We set $\lambda = 0.95$, capturing some attention to the level of inflation. When inflation increases until July 2022, inflation expectations behave similarly to those in the symmetric case. However, when inflation falls below a threshold, expected inflation does not jump immediately but gradually converges to the actual inflation rate when households are inattentive, $\theta > 0$. This example shows that if households react more strongly to increasing-inflation threshold events than decreasing-inflation threshold events, inflation expectations are downward rigid, adjusting slowly to lower values once an increasing-inflation threshold has been surpassed. To make this point even more precise, Figure 1c shows the same example but with actual inflation staying counterfactually at 9.9% in June, July, and August 2022 instead of 10%, 10.7% and 10.5%, respectively. If inflation stood just below this threshold in June, July, and August 2022, inflation expectations would not increase drastically and remain lower.

3. Data

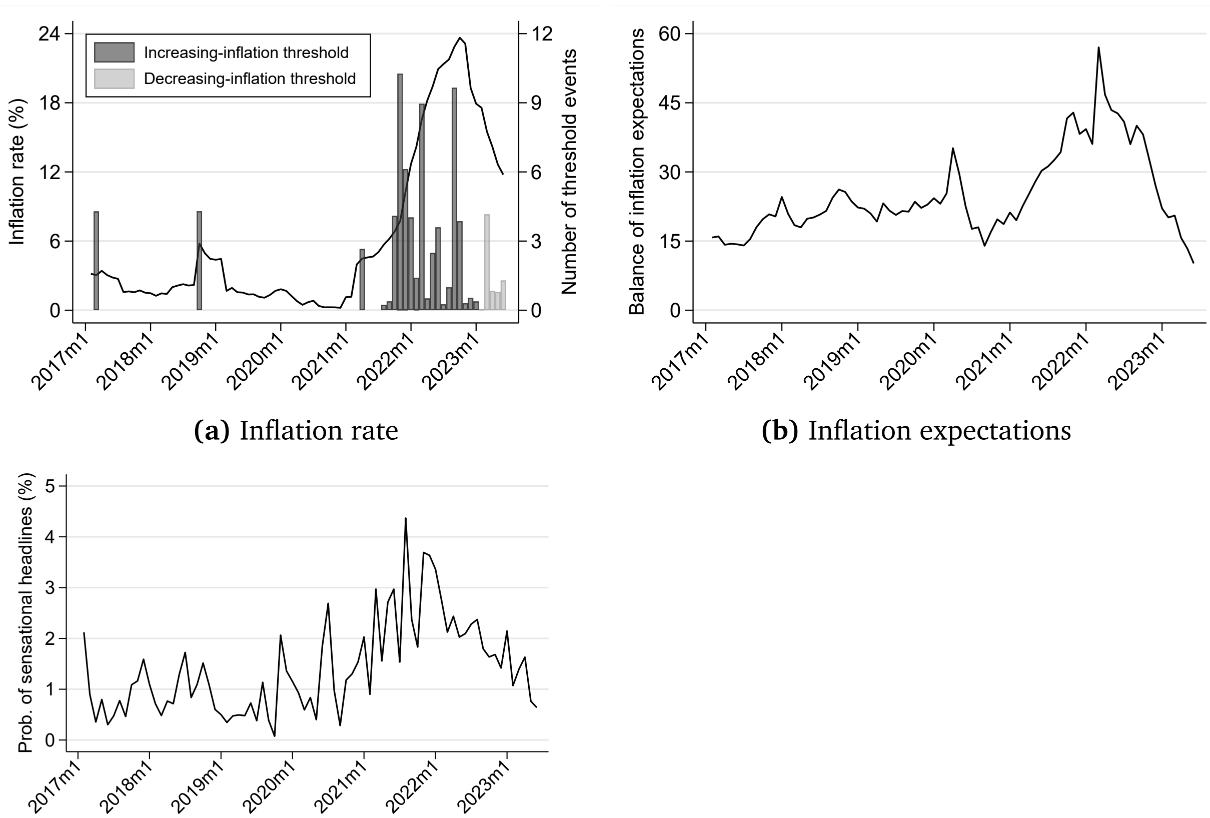
We compile an original dataset on consumer prices, household inflation expectations, and inflation-related media coverage in 30 European countries between 2017 and 2023. Our choice to focus on Europe is primarily motivated by the availability of comparable data at a monthly frequency for a large set of countries and over a long period. The set of included countries and the sample period are determined by those observations in which data on inflation expectations and the consumer price index—as first published—are available.

3.1. Consumer prices and inflation threshold events

We obtain the monthly year-on-year change in the Harmonized Index of Consumer Prices (HICP) of the countries in our sample from Eurostat. The data used to compile this index are provided to Eurostat by the countries' national statistical offices. The HICP is a central statistic when trends in inflation are communicated to the public. Eurostat and most national statistics offices regularly report the HICP in their monthly press releases and via announcements on their websites and social media accounts.[6] We use the initially published index and inflation rate before any later statistical revisions to analyze the figures available to the media at the time of publication. These data are available from January 2016 onward (Eurostat, 2018).

In our baseline estimations, we test whether inflation thresholds exist at multiples of 5: 5%, 10%, 15%, 20%, and 25%. We focus on this range because most observations in our sample fall between 0% and 25%. The value of 0% is not considered a threshold, as households

[6] In many countries, the national statistical office also reports the consumer price index (CPI), which slightly deviates from the HICP. We evaluate a random sample of 50 press releases from the statistical offices in France, Germany, Italy, Spain, and the Netherlands—countries with a high weight in our regressions due to their large population—and verify that the media rely on both indices when they issue reports about the inflation rate. Using the media data described in Section 3.3, we manually evaluate all inflation headlines that state the value of the inflation rate for the country in question in the days following the press release. This evaluation indicates that 46% of headlines refer to the HICP and 54% refer to the CPI, which supports the relevance of HICP; see Table A.4 for examples. While the national CPI is referenced by the media slightly more often, we use it only for robustness checks as CPI data are unavailable as initially published. The CPI data offered by Eurostat, the national statistical offices, or third parties like the OECD have been subject to statistical revisions, hence not reflecting the information available to the media at the time of publication.



(a) Inflation rate

(b) Inflation expectations

(c) Media coverage

Figure 2: Evolution of the main variables over time

and the media are likely less interested in price developments during low-inflation periods, and crossing this value has theoretically ambiguous implications. Other possible thresholds observed in the data, such as 30% and 35%, are rare and collinear with the fixed effects in the regression models. We run extensive tests on other potential inflation thresholds, as detailed in section 5.2, and show that inflation threshold events are most pronounced at multiples of 5.

Previous research shows that threshold events may not be salient if they occur too frequently and lack the historical element of newsworthiness (Garz and Martin, 2021). To address this issue, we mandate that the same threshold value must not have been crossed in the past 12 months, which helps to exclude crossings that likely do not draw much attention among households due to wear-out effects. We verify that our results hold when using other arbitrarily selected protection periods, such as 6 and 18 months.

Based on this definition, we identify 85 inflation threshold events, which we code as binary variables. In line with our theoretical discussion in section 2, we differentiate between increasing-inflation and decreasing-inflation threshold events. As Figure 2a illustrates, most threshold events in our sample occurred during the 2021–2023 inflation surge. We observe threshold events at 26 different month-year points and in 29 of the 30 countries in the sample.

3.2. Inflation expectations

Data on households' inflation expectations come from the European Business and Consumer Surveys, administered by the European Commission. These surveys are conducted by national institutes in the EU member states and candidate countries and have been previously used in several studies (for example, Andrade *et al.*, 2023; Badarinza and Buchmann, 2009; Bracha and Tang, 2023; Chen *et al.*, 2022; D'Acunto *et al.*, 2022, 2019, 2021a; Dräger, 2015; Duca-Radu *et al.*, 2021; Stanisławska *et al.*, 2021).

We primarily use two variables: a qualitative and a quantitative measure of households' inflation expectations for the next 12 months. The qualitative measure is based on the question: "By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months?" Survey respondents can choose one of the following answers: "increase more rapidly" (PP), "increase at the same rate" (P), "increase at a slower rate" (E), "stay about the same" (M), "fall" (MM), or "don't know" (N).

In our main specification, we use the balance of inflation expectations as provided by the European Commission:

$$(PP + 0.5P) - (0.5M + MM),$$

which ranges from -100 to +100. We also consider each single category in extensions. The balance is a weighted difference between households that expect weakly higher future inflation and those that expect zero or negative inflation. Simply put, a larger balance indicates that more households expect increasing inflation. As shown in Figure 2b, the average balance of inflation expectations increased during the 2021–2023 inflation surge. The aggregate balances within each country are representative of a country's population (European Commission, 2023).

The quantitative measure is based on the question, "By how many percent do you expect consumer prices will go up/down in the next 12 months?" and allows survey respondents to enter a number.

3.3. News coverage

3.3.1. Retrieval of inflation-related stories

Online media have become the primary source of news for households in Europe, outranking print news and offline newscasts (Newman *et al.*, 2023). We, therefore, measure inflation-related news coverage based on reports published by online news sites. The necessary data are obtained 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 over 88 million news reports annually and computationally analyzes the content by applying sophisticated natural language processing techniques (Saz-Carranza *et al.*, 2018; Consoli *et al.*, 2020). Its open-source repository allows researchers to access and analyze large-scale media data over long periods and across different countries (Hopp *et al.*, 2019). GDELT has been frequently used in economic research, for instance, to analyze 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."[7] Investigating the downloaded stories indicates that the platform's classification algorithm selects relevant content. Most headlines directly address inflation-related issues, such as overall price developments and trends in specific price categories—fuel, electricity, and food—its origins and effects, monetary policy, perspectives on different actors, and links between inflation and other macroeconomic developments. Some headlines discuss inflation jointly with other economic news, such as growth, trade, and unemployment, as the platform's classification algorithm assigns multiple themes to the same news report if applicable. Hence, inflation is not necessarily the only or primary topic addressed in the downloaded stories.

To obtain a proxy of inflation-related news coverage that reaches most households, we restrict the sources to a country's most influential mainstream media outlets. The reason is that it would be computationally challenging to analyze the universe of inflation-related stories archived in GDELT and potentially make for a poor proxy if we included the "long tail" of sources that do not attract much traffic. We, therefore, compile a list of the domains of each country's most important news sites based on the BBC's media country profiles[8], yielding a set of 179 outlets in total, or six news sites on average per country. See Table A.5 for the complete list. We downloaded all 281,206 inflation-related stories archived in GDELT during our sample period, corresponding to an average of 9,374 stories per country.

[7] The theme "econ_inflation" is one of approximately 60,000 themes in GDELT's taxonomy. We consider other GDELT themes as well, like "macroeconomic_performance," "econ_price," "price_controls," and "commodity_price_shock," but the sets of stories tagged in those categories are less relevant, wider, or narrower than those in the "econ_inflation" theme. The API also supports queries based on keywords, like "inflation" or "consumer price index," but we decide to rely on the platform's classification model to avoid omitting inflation-related stories that do not match those keywords. In the robustness section, we verify that our results remain the same when identifying inflation headlines based on the keywords "inflation" or "consumer price*" rather than GDELT's classification.

[8] 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 sites with the largest audiences and agenda-setting power.

3.3.2. Measuring sensationalism

According to most definitions, 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 is typically characterized by two elements: i) reference to round numbers and ii) historical rarities (Renton, 2000). Following our extensive screening of the downloaded headlines, we confirm that these elements are the primary means of sensationalizing inflation-related news. Sensational headlines state that inflation or prices have reached a milestone, broken some historical record, or surpassed some round-number threshold, such as 10% or 20%.[9] We focus on the headline because it is crucial in grabbing attention and is a key element in implementing sensationalism. In addition, readers often do not click on the article but absorb the information in the headline (Dor, 2003), which makes this content particularly relevant when studying media effects.

We first translate the headlines of the downloaded stories 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 in languages spoken among the co-authors indicate that the translations are reasonably accurate and reliable; see Tables A.2 and A.3 for examples.

As the next step, we instruct human coders to annotate a random subsample of 9,500 translated headlines. Specifically, we ask them to evaluate whether a headline sensationalizes the information. The coding procedure is described in full detail in online appendix A.1, including the exact coding instructions and verification of intercoder reliability. The annotations indicate that 1.5% of headlines classify as sensational.

We use the annotations as training data for deep-learning classifiers based on Bidirectional Encoder Representations from Transformers (BERT; see Devlin *et al.* 2018). By using word and position embeddings, the BERT framework accounts for differential meanings of words in

[9] 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. Similarly, words such as "milestone" and "threshold" do not have strong emotional associations in the general use of language, but they likely do in the context of inflation news.

different contexts, like "price index climbs past threshold" and "cat sits on threshold of a door." It recognizes semantic overlaps when similar issues are expressed differently, for example, "inflation is at record high" and "prices are at peak level." These features of transformer models make it possible to classify texts with outstanding accuracy.[10]

As described in detail in online appendix A.1, we use human annotations to fine-tune and compare the predictive performance of different transformer models. For our final classifier, we select RoBERTa, which was pretrained on 160 GB of text from books, news articles, and websites (Liu *et al.*, 2019). At the time of our study, the model was considered state-of-the-art for many natural language processing tasks, including text classification. Importantly, when comparing the model-based predictions with out-of-sample human annotations, the fine-tuned RoBERTa achieves the highest accuracy among a range of models (F_1 score = 0.909). After fine-tuning the model on the annotated subsample of 9,500 headlines, we obtain predictions for the headlines in the full sample of 281,206 inflation-related news stories. These predictions are expressed as the probability that a given headline is sensational.

Table A.2 shows examples of headlines with a probability larger than 0.5 of being sensational. Some headlines mention inflation generically, while others refer to specific price categories, such as oil, food, and energy prices. Many headlines include round numbers (e.g., inflation rates of 10% or 20%), talk about the number of digits of a figure (e.g., "one-digit," "double-digit"), make historical comparisons (e.g., "highest in 70 years", "first time since"), or explicitly mention that a record was broken. In contrast, headlines not classified as sensational may point out that an index is high or low, has risen or declined, or how much it has changed (Table A.3). Importantly, these headlines do not point out the historical uniqueness of a development or highlight any numerical peculiarity.

Based on these predictions, we compute the mean probability of sensational headlines by country and month. The sample-wide mean of that probability is 1.66%, similar to the share of sensational headlines tagged by human annotators. Sensational headlines are not limited to a set of countries but are produced by news sites across Europe. We observe the minimum average probability of sensational headlines in Cyprus, 0.53%, and the maximum in Serbia, 3.34%. Figure 2c plots the sample average of the probability over time, according to which sensational headlines tended to be more likely in times of high inflation, following a similar overall trend as average inflation and inflation expectations.

Note that our measure of sensationalism does not distinguish between increasing and decreasing inflation or good and bad news. The measure captures news sites' tendency to frame headlines using round-number thresholds and historical records. In addition, the measure is not mechanically determined by the occurrence of inflation threshold events. Sensationalist

[10]For details and applications of these models in economics, see Ash and Hansen (2023).

headlines may also appear when inflation-related indices or values do not cross any round-number threshold. However, those crossings arguably increase the probability of sensational headlines.

3.4. Data linking

Our analysis dataset is at the country-month level. Linking the data from the sources described above must be done considering the timing of the consumer surveys and the publication of information about the inflation rate. The consumer surveys are conducted in the first two to three weeks of each month (European Commission, 2023). Eurostat and the national statistical offices publish their initial consumer price index estimate between the end of the reference month and the beginning of the following month (Eurostat, 2018). Hence, when the interviews are conducted, households cannot know the inflation estimate for the current month—the most recent information refers to the previous month's price developments. We, therefore, link households' inflation expectations in the current month to the inflation rate and possible threshold events in the previous month, which also avoids potential reverse causality stemming from households' expectations affecting current inflation rates.

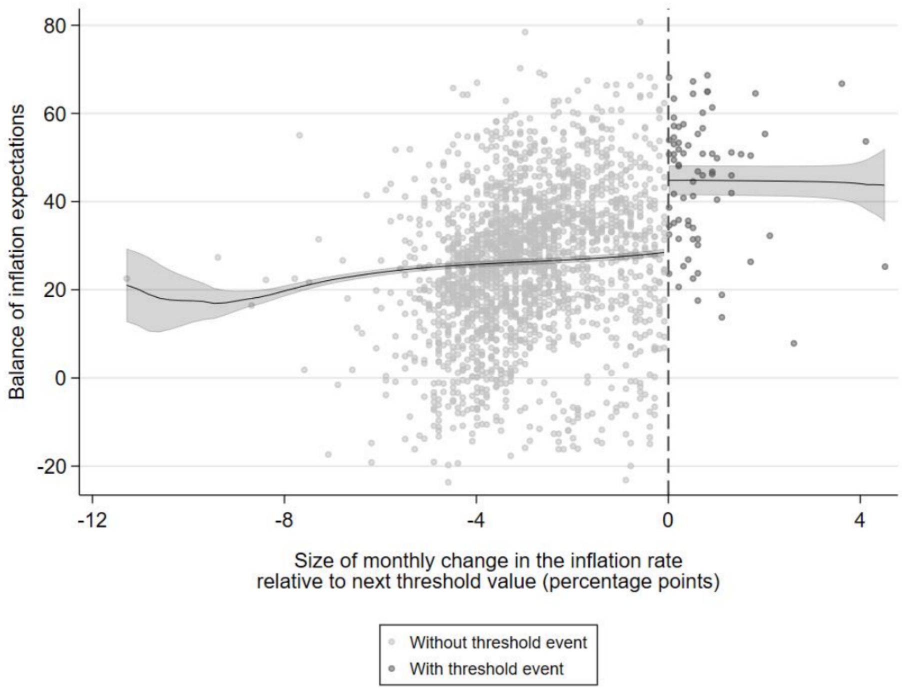
News value theory posits that the media covers new information typically as soon as it becomes available (Galtung and Ruge, 1965). Our spot checks confirm that the sampled news sites report on the inflation rate on the days following Eurostat and the national statistical offices' release of the inflation data. As mentioned above, these data are published at the end of the reference month or the beginning of the following month. We assign all reports published within the first seven days of a month to the previous month because these reports are most likely based on the inflation statistics from the previous month.[11] After making this adjustment, we merge households' survey responses from the current month with the news reports from the previous month.

4. Estimation strategy

4.1. Inflation threshold events

When inflation increases from, for example, 3.8% to 5.1%, two simultaneous effects on households' inflation expectations might occur. First, the substantial price increase leads to higher expected future inflation. Second, crossing the 5% threshold may impact expectations beyond the effect of the price increase itself. We employ a regression discontinuity-like design

[11]As discussed in section 5, the estimates are robust to other assignment rules.



Notes: The x-axis measures the difference between the size of the increase in a country's inflation rate from $t-2$ to $t-1$ and the distance of the rate in $t-2$ to the next upper round-number threshold (i.e., 5, 10, 15, 20, or 25%) using the following formula: $(rate_{t-1} - rate_{t-2}) - (threshold_{t-2} - rate_{t-2})$. By definition, values on the x-axis < 0 refer to situations without increasing-inflation threshold events, whereas values ≥ 0 imply an increase in a country's inflation rate large enough to offset the existing distance between the rate level and the next round-number threshold. The figure excludes threshold events where the same threshold was reached or exceeded in the past 12 months. The solid lines are local polynomial smooth plots with 95% confidence bands.

Figure 3: Increasing-inflation threshold events and inflation expectations

to disentangle these two effects on inflation expectations. This approach allows us to capture households' discontinuous responses to inflation changes when a threshold is crossed, as predicted by our theory in Section 2.

A conventional regression-discontinuity design (RDD) involves an assignment variable that determines which units receive treatment based on a specific cutoff value of the assignment variable. In our case, assignment into treatment and control observations depends on two variables: the level of and the monthly change in the inflation rate.[12]

While RDDs have been extended to accommodate multiple assignment variables (e.g., Cattaneo *et al.* 2020), we use a slightly different approach because our assignment variables do not have fixed cutoffs, but treatment status depends on the interplay of these variables. For exam-

[12]The following two studies have used an RDD to study left-digit bias. Repetto and Solís (2019) estimate discontinuous jumps in the final price as a function of the asking price for apartments, while Heraud and Page (2024) estimate discontinuities between the transaction price and the expected payoff of foreign exchange options. We study inflation and inflation expectations and consider a more dynamic setup as we consider both the level and the change in the inflation rate.

ple, if a country's inflation in the current month is 9.6%, an increase of 0.4 percentage points or more would be necessary to reach the 10% round-number threshold in the next month. The larger the initial distance between the inflation rate and the next threshold value, the larger the monthly change in the inflation rate necessary to cross the threshold. Hence, the treatment assignment is a function of the distance between the inflation rate and the next round-number threshold, as well as the size of the change in the rate between the current and next month.

We visualize the discontinuous response of households' inflation expectations to increasing-inflation threshold events in Figure 3. Accordingly, the difference between households expecting increasing and households expecting decreasing inflation is, on average, lower when the inflation rate does not cross a round-number threshold than in situations with a threshold event. To formally estimate the impact of round-number threshold events, we specify a two-way fixed effects model in which the balance of inflation expectations y in country i and month t is regressed on binary indicators $t_{i,t-1}^{increasing}$ and $t_{i,t-1}^{decreasing}$ of threshold events in the national inflation rate while controlling for actual price developments $X_{i,t-1}$:

$$y_{i,t} = \alpha_1 t_{i,t-1}^{increasing} + \alpha_2 t_{i,t-1}^{decreasing} + \alpha_3 X_{i,t-1} + \theta_i + \rho_t + \epsilon_{i,t} \tag{6}$$

The country fixed effects θ_i control for time-invariant differences in expectations between states, whereas the time fixed effects ρ_t account for overall trends in Europe. This specification is identical to the model proposed by Garz and Martin (2021), except that their assignment variables are the level and change of the unemployment rate. Apart from that, we specify the vector of controls $X_{i,t-1}$ in the same way: bin dummies for the level of the inflation rate as well as a polynomial of order 3 of the monthly change in a country's inflation rate.

The bin dummies account for real price effects and differences in the baseline probability of crossing a round-number threshold at different inflation rate levels. The closer the inflation rate is to the next round number, the more likely it is to cross this round number in the next month. While it would be possible to include the inflation rate level as a continuous variable, bin dummies have the advantage of accounting for possible nonlinear effects. Adjusting the bandwidth of the bin dummies is equivalent to selecting the bandwidth in standard regression discontinuity designs. Eurostat and its national counterparts measure the inflation rate with a precision of one decimal place. We include one bin dummy for each possible value, with a bandwidth of 0.1 percentage points. For example, we include separate bin dummies for inflation rates between 3.8% and 3.9%, and between 3.9% and 4.0%. This allows us to control for the rate level in the most fine-grained way possible. In Section 5.2, we verify that our results remain similar when we use other possible bandwidths, such as intervals of 0.2 and 0.5 percentage points.

The polynomial of the rate change controls for the mathematical fact that threshold events are more likely the greater the change in inflation from the previous to the next month. The results are generally not sensitive to the choice of the polynomial order, such as 2, 3, or 4, as we show in Section 5.2. The same applies when we substitute the rate change polynomial with rate change bin dummies and when we interact the rate change with the inflation level bin dummies.

Equation (6) yields causal estimates of α_1 and α_2, as long as the threshold events occur at random, conditional on continuous changes in inflation. The balance checks reported in Table A.6—that indicate that threshold events are not correlated with population size, GDP, government debt, interest rates, unemployment, and the balance of payments—support the notion of random assignment.

The surveys underlying our outcome variable are representative of a country's population. However, estimates that fail to account for the size of that population relative to the size of the other countries would be misleading. Therefore, we weight all regressions by the countries' population share in the sample. We compute standard errors robust to clustering by country and autocorrelation (Cameron and Miller, 2015). We report p-values based on these standard errors and p-values based on the wild cluster bootstrap method. The latter type of p-values support robust inference when the number of clusters is small (Cameron *et al.*, 2008). In our case, we have 30 countries.

4.2. Transmission via sensationalism

How are inflation threshold events transmitted to households? The information about current inflation rates must travel from statistical agencies to households, as households are unlikely to directly observe all prices included in the statistical agencies' consumption basket and then accurately calculate the consumption index to measure inflation. It is improbable that households receive this information directly from statistical agencies, as few regularly check such announcements. Some households might learn about inflation rates through social networks like friends, family, or colleagues. However, this information needs to originate from somewhere. This reasoning suggests that the media is the primary channel for disseminating information on inflation, leading us to examine sensational headlines on online news sites. Recent survey data from the ECB supports this conjecture. D'Acunto *et al.* (2024, Figure 6) show that Eurozone households predominantly rely on news media to obtain information on inflation. In contrast, official institutions, shopping experiences, family or friends, social media, and financial advisors are much less important.

We use $t_{i,t-1}^{increasing}$ as an instrument in a regression of inflation expectations on the degree of sensationalism in inflation-related news $s_{i,t-1}$. We do not use $t_{i,t-1}^{decreasing}$ as an instrument because sensationalism often relies on negative emotions. In contrast, threshold events induced by decreasing inflation should be considered "good news" by most households. In addition to this theoretical argument, the estimates in section 5 show that $t_{i,t-1}^{decreasing}$ neither correlates with $s_{i,t-1}$ nor with $y_{i,t}$, which disqualifies the variable as an instrument.

The first stage is analogous to the reduced form shown in equation (6), except that we model the impact of threshold events on the probability of sensational headlines $s_{i,t-1}$:

$$s_{i,t-1} = \beta_1 t_{i,t-1}^{increasing} + \beta_2 t_{i,t-1}^{decreasing} + \beta_3 X_{i,t-1} + \theta_i + \rho_t + \epsilon_{i,t} \tag{7}$$

The predicted values $\hat{s}_{i,t-1}$ from equation (7) are then used in the second stage:

$$y_{i,t} = \gamma_1 \hat{s}_{i,t-1} + \gamma_2 t_{i,t-1}^{decreasing} + \gamma_3 X_{i,t-1} + \theta_i + \rho_t + \nu_{i,t},$$

where γ_1 captures the IV effect of sensational headlines on inflation expectations.

A valid instrument mandates i) the absence of reverse causality, ii) the absence of confounding factors, iii) that the exclusion restriction holds, iv) instrument relevance, and v) monotonicity. It is plausible to assume that condition i) holds because households' expectations per se cannot induce threshold events in inflation statistics. Condition ii) is met, assuming threshold events are as good as randomly assigned. The exclusion restriction (condition iii) would be violated if threshold events affect households' expectations through mechanisms other than media sensationalism. For instance, it is conceivable that threshold events affect expectations because of volume effects, where news media do not change or sensationalize their coverage but report more about inflation when it crosses a round number. While we cannot completely rule out this possibility, complementary estimates in section 5 suggest that those volume effects do not occur. Alternatively, the exclusion restriction fails if threshold events impact households' expectations through unsampled sources of information that systematically deviate from the news site in our sample. For example, households may learn about macroeconomic price developments via broadcasts or social media. We argue that our measure of sensationalism is a reasonable proxy for the true extent to which households are exposed to sensationalism since it is based on a comprehensive sample of mainstream news sites in each country. The agenda-setting power of these media outlets implies that smaller, unsampled outlets with potentially fewer resources are likely to publish similar inflation-related content or copy it from mainstream sites. Hence, while the exclusion restriction may not hold exactly in our context, we are confident that there are no major violations. Condition iv) can be tested empirically. An instrument is relevant if it is a strong predictor of the endogenous regressor in the first-stage regression. Regarding condition v), there is no reason why increasing-inflation threshold events should lead to more sensationalism in some cases and less sensationalism in others. Hence, the monotonicity assumption is plausible.

We acknowledge that our instrument might not satisfy the exclusion restriction perfectly, so we emphasize the reduced-form estimates more when drawing conclusions. While we consider a possible causal path from sensationalist inflation headlines to households' expectations, we recognize that sensationalism may not be the only mechanism explaining the effects of threshold events.

5. Results

5.1. Baseline specification

The estimation results are summarized in Table 1. Column (1) presents the reduced-form results. Accordingly, increasing-inflation threshold events significantly increase the balance of inflation expectations. The point estimate suggests an increase of 5.8 percentage points, corresponding to approximately one-third of the standard deviation of the balance of expectations, as $5.764/17.071 = 0.338$. Hence, the effect of an increasing-inflation threshold event is sizable. The coefficient on the decreasing-inflation threshold dummy is estimated with much uncertainty and is not significant at conventional levels. Importantly, as discussed in section 2, we reject the null hypothesis that the effects of increasing- and decreasing-inflation threshold events are symmetric, i.e., that $\alpha_1 + \alpha_2 = 0$ in equation (6), with a p-value of 0.027.

The results of estimating the first stage are shown in Column (2). Increasing-inflation threshold events positively and significantly impact the probability of news sites sensationalizing inflation-related headlines. The relevant coefficient indicates an increase in this probability by 1.6 percentage points, which is more than twice the baseline probability of 1.4% and approximately half of the standard deviation of the measure of sensationalism $1.566/2.912 = 0.538$. The F statistic on excluding the increasing-inflation threshold event dummy confirms that the instrument is relevant. Both the Kleibergen-Paap version of this statistic and the Montiel-Pflueger version, which is robust to clustering, are reasonably large to rule out significant estimation bias due to a weak instrument, with $F = 24.211$ and 23.320, respectively. Given the size of the Montiel-Pflueger F statistic, the worst-case bias of the IV estimate is 5%. Note that decreasing-inflation threshold events, which are not used as an instrument but remain a covariate in the model, are not correlated with the probability of sensational headlines.[13]

Column (3) presents the IV estimate of the effect of sensationalism on inflation expectations, according to which an increase in the average probability of sensational headlines by

[13] This null result is compatible with negativity bias (Baumeister *et al.*, 2001) in news coverage, especially the argument that sensationalism focuses on negative rather than positive news (Tannenbaum and Lynch, 1960; Reinemann *et al.*, 2012).

	(1) Expectations (OLS reduced form)	(2) Sensational headlines (IV first stage)	(3) Expectations (IV second stage)
P(sensational headlines)			3.682***
			(1.145)
			[0.005]
Increasing-infl. threshold	5.764***	1.566***	
	(1.431)	(0.318)	
	[0.002]	[0.000]	
Decreasing-infl. threshold	4.909	-0.117	5.341
	(3.960)	(0.935)	(5.243)
	[0.278]	[0.935]	[0.423]
Mean of dependent variable	24.693	1.425	24.693
SD of dependent variable	17.071	2.912	17.071
Kleibergen-Paap F statistic		24.211	
Montiel-Pflueger F statistic		23.320	
Montiel-Pflueger % of worst case bias		5%	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country. Values in brackets are wild cluster bootstrap p-values.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 1: Inflation threshold events, sensational news, and inflation expectations

one percentage point raises the balance of inflation expectations by 3.7 percentage points. A one standard deviation increase in this probability shifts the balance by 0.6 standard deviations (i.e., $2.912 \times 3.682/17.071 = 0.628$). Thus, assuming that there are no major violations of the exclusion restriction, sensationalism in inflation-related headlines has a sizable impact on households' beliefs about future price developments.

5.2. Robustness and placebo tests

We now test for alternative inflation thresholds than multiples of 5. Table A.7 shows that we do not find a discontinuity when considering integers rather than multiples of five. Figure A.4 shows the results of the reduced-form regression when we replace the multiples-of-five treatment dummy with separate dummies for individual thresholds. Accordingly, we find significant positive effects for the 5% and 10% increasing-inflation thresholds. Threshold events at 15% and 20% are rare and yield relatively large standard errors. The 25%-threshold effect cannot be estimated individually because this dummy is perfectly collinear with the fixed effects, and we only observe four 25% threshold events in total. We also include a 2% threshold dummy in the regression. While this value is not a multiple of five, it could be psychologically relevant due to the European Central Bank's inflation target. However, as the figure shows, crossing this threshold does not induce a discontinuous change in inflation expectations.

Figure A.5 summarizes the results of estimating regressions with placebo thresholds based on randomly drawing 1,000 sets of non-integer values between 0.1 to 29.9% of the inflation rate. The distribution of coefficients from these placebo regressions is centered around zero, indicating null effects in both the reduced form and first stage.[14] A fraction of placebo regressions produce significant positive effects, i.e., 7.3% in the reduced form and 2.9% in the first stage, which is to be expected due to Type I error when testing for statistical significance. With 1,000 replications, approximately 50 regressions should yield a significant effect just by chance, even if the true effect of placebo thresholds is zero.

In the baseline specification, we do not consider it a threshold event if the inflation rate has already crossed the same threshold value in the past 12 months due to the lack of news value of repeated crossings. Table A.8 indicates that the results remain similar when using 6- and 18-month protection periods. However, the effect sizes tend to be somewhat larger when we exclude threshold events under the 18-month criterion. This is plausible as the news value of a crossing increases the more time has passed since the previous crossing of the relevant threshold.

According to Table A.9, our results are robust to specifying alternative bandwidths for the bin dummies that control for the level of the inflation rate. While the baseline model includes one bin for each possible step in the inflation rate, equal to 0.1 percentage points, the alternative specifications use bandwidths of 0.2 and 0.5 percentage points, respectively, which produces slightly smaller effect sizes but otherwise similar results. In Table A.10, we change the polynomial order of the change in the inflation rate from third to second and fourth order and find no noticeable differences. Another alternative for accounting for changes in the inflation rate is to include bin dummies rather than a polynomial. According to Table A.11, this modification does not affect the results either. We also estimate models with interaction terms between the absolute change in the inflation rate and the individual bin dummies of the rate level. This specification accounts for the possibility that households and news sites react differently to rate changes of equal magnitude if these changes occur at different inflation rate levels. As Table A.12 indicates, the results remain qualitatively similar, though.

We also verify that our results are not sensitive to changing the assignment of inflation-related headlines to the relevant reference month. As discussed in section 3, our preferred approach is to shift all reports published during the first seven days of a month to the pre-

[14] The second stage is not informative due to the estimation bias resulting from a weak/absent first stage.

vious month, given that the latest inflation statistics of the reference month are occasionally published a few days into the next month. As Table A.13 shows, the results do not substantially change when we refrain from shifting any reports (Columns 1 and 2) or shift all reports published within the first ten days of a month to the previous month; see Columns (3) and (4).

Throughout the paper, the regression results are obtained while accounting for differences in population size across countries. For example, the aggregated survey responses from Malta, a country with approximately 0.5 million inhabitants, should affect the estimates less than the responses from Italy, a country with approximately 60 million inhabitants. Table A.14 shows that we obtain qualitatively similar estimates when we omit the regression weights, which implies that the results are not exclusively driven by the population-heavy countries in the sample.

As discussed in Section 3, we use the HICP to measure inflation and define threshold events because this index is available for all countries in the sample as initially published. While a country's consumer price index (CPI) might be slightly more important when national statistical offices and news sites report about inflation, the CPI data are mostly only available in revised form. Hence, we cannot accurately evaluate the impact of CPI-based threshold events on inflation news coverage and expectations. Still, the results shown in Table A.15 confirm our baseline findings when using the CPI to measure inflation and threshold events. However, the coefficients are estimated less precisely—likely because the data revisions of the CPI introduce measurement error in the occurrence of threshold events.

Our measure of sensationalism is based on headlines that GDELT's classification algorithm considers to relate to the theme "econ_inflation." Table A.16 shows that we obtain very similar results when we identify inflation-related headlines manually, i.e., headlines including the keywords "inflation" or "consumer price*." The resulting estimates show that our findings are robust to alternative definitions of inflation news and help us rule out that our sensationalism classifier introduces unintended quantity effects. That is, as Tables A.2 and A.3 suggest, headlines classified as sensational are more likely to include the terms "inflation" and "consumer price*" than headlines classified as non-sensational. However, the results in Table A.16 imply that the effects of round-number events on households' inflation expectations are not simply driven by an increase in headlines that include these keywords but that sensationalist framing matters.

While our estimation strategy exploits discontinuous responses of households and news sites to changes in inflation, we do not use a conventional RDD because we have two assignment variables—monthly *changes* in and *level* of the rate of inflation—that do not have fixed cutoffs for assignment into treatment. It is possible to create a combined assignment variable by using the formula $(rate_{t-1} - rate_{t-2}) - (threshold_{t-2} - rate_{t-2})$, which measures the change in the rate minus the initial distance between the inflation rate and the next round-number threshold. The combined assignment variable can be used to estimate a conventional RDD, which has the advantage of using a data-driven approach to select the optimal bandwidth. On the downside, obtaining IV estimates is more complicated with this approach, and it remains unclear what value the assignment variable should take in cases where a threshold event occurs multiple times within the 12-month protection period. In addition, as the RDD results in Table A.17 show, our baseline specification tends to produce more conservative estimates, which reduces the chances of overestimating the effects of threshold events. The RDD effect is somewhat smaller when we treat repeated crossings of the same round number within the 12 months as any other threshold event. In contrast, the effect is substantially larger when we relocate these events to just below the cutoff (i.e., the value of assignment variable $= -0.1$; see Column 2) or drop these observations from the sample (Column 3).

Table A.18 shows reduced-form results for inflation perceptions. While increasing-inflation threshold events do not significantly shift the aggregate balance of perceptions, we find theory-consistent shifts of households across answer options. A possible explanation for comparatively weak effects on inflation perceptions is that survey responses about perceived price changes are more path-dependent and less responsive to new information than survey responses about expected inflation (cp. the smoothness of the time series shown in Figure A.3).

5.3. Changes in average expected inflation: intensive versus extensive margin

All results discussed so far refer to respondents' qualitative expectations. We do not use quantitative inflation expectations for our baseline models because individuals sometimes struggle to provide a numerical estimate. This is reflected by a high share of missing values—approximately 20% of respondents provide a qualitative but no quantitative expectation—as well as unrealistically high or low values. See, for example, D'Acunto *et al.* (2022) for a discussion on the advantages of qualitative compared to quantitative survey-based measures of household inflation expectations.

Households' quantitative estimates, however, help evaluate our results' robustness further and obtain more quantitative insights on the effect on average expected inflation rates. Table 2 summarizes the results when we use households' quantitative inflation expectations, aggregated by taking the mean and the median of responses, respectively. According to Column (1), an increasing-inflation threshold event raises the mean inflation estimate by 61 basis points, corresponding to 0.16 standard deviations of this variable. The IV estimate in Column (3) of 0.364 implies that a one-standard-deviation increase in the probability of sensational headlines leads to a 0.29-standard-deviation rise in quantitative expectations, an effect size somewhat lower than in the case of households' qualitative expectations. As Column (4) shows, the median of expected future inflation increases by 1.076 percentage points, or 0.17 standard deviations, when an increasing-inflation threshold event occurs. According to the IV estimate of 0.647 in Column (6), a one standard deviation increase in the probability of sensational headlines induces the median of households' quantitative expectations to rise by 0.42 standard deviations.

To provide an example of the magnitude of the threshold effect, assume that the median expected inflation was initially at 4.00 percent, and now current inflation has increased from 4.99 to 5.00 percent, crossing the 5 percent threshold. The change in current inflation is quantitatively negligible at one basis point, falling within the typical range of measurement errors encountered by statistical agencies. However, households' median inflation expectations discontinuously jump from 4.00 to $4.00 + 1.076 = 5.076$ percent, a substantial change. Since we find that inflation thresholds occur at multiples of 5, the size of this effect implies that if current inflation increases by 5 percentage points over several months, crossing one threshold, more than one-fifth of the updating of median inflation expectations happens discontinuously at the threshold. Hence, the results in Table 2 show that inflation threshold events exert pronounced effects on mean and median inflation expectations, similar to the results based on individuals' qualitative expectations.

	Mean estimate			Median estimate		
	(1)	(2)	(3)	(4)	(5)	(6)
	Expectations (OLS reduced form)	Sensational headlines (IV first stage)	Expectations (IV second stage)	Expectations (OLS reduced form)	Sensational headlines (IV first stage)	Expectations (IV second stage)
P(sensational headlines)			0.364**			0.647**
			(0.150)			(0.314)
Increasing-infl. threshold	0.605**	1.663***		1.076**	1.663***	
	(0.228)	(0.381)		(0.523)	(0.381)	
Decreasing-infl. threshold	1.314	0.640	1.081	3.299	0.640	2.885
	(0.876)	(1.238)	(1.047)	(1.995)	(1.238)	(2.326)
Mean of dependent variable	6.396	1.451	6.396	5.337	1.451	5.337
SD of dependent variable	3.740	2.983	3.740	6.406	2.983	6.406
Kleibergen-Paap F statistic		19.082			19.082	

N = 1,855 (up to 28 countries and 75 months between 2017 and 2023). The outcome variables are calculated by the authors using data on households' quantitative inflation expectations ("By how many per cent do you expect consumer prices to go up/down change in the next 12 months?") and the survey weights provided by the European Commission's Harmonised Consumer Survey. The data exclude country-months with less than 800 interviews. Responses with estimates < -5% or > 30% are omitted when calculating the mean estimate in Column (1) to (3), following the truncation approach of Huber et al. (2023). All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.

** p<0.10, ** p<0.05, *** p<0.01*

Table 2: Inflation threshold events, sensational news, and quantitative inflation expectations

How are changes in the quantitative measure of inflation expectations related to changes in the qualitative measure? We study this by differentiating between changes in average expected inflation along the extensive margin—changes in the qualitative measure—and changes along the intensive margin—changes in the quantitative measure. With a slight abuse of notation, let $\bar{\mathbb{E}}_t^b(\pi_{t+1})$ denote the mean over households' behavioral inflation expectations. This mean can be decomposed into a sum of within-group mean inflation expectations weighted by group sizes:

$$\bar{\mathbb{E}}_t^b(\pi_{t+1}) = \sum_{i=1}^{I} \omega_i \times \bar{\mathbb{E}}_{t,i}^b(\pi_{t+1}),$$

where ω_i is the representative share of respondents in group i, such that $\sum_{i=1}^{I} \omega_i = 1$, and $\bar{\mathbb{E}}_{t,i}^b(\pi_{t+1})$ is the mean inflation expectation of group i for a total of I groups. We consider $I = 5$ different groups, which correspond to the five possible responses to the qualitative question on inflation expectations: "increase more rapidly," "increase at the same rate," "increase at a slower rate," "stay about the same," and "fall." [15] A change in average expected inflation can be decomposed into changes along the intensive and extensive margins as follows:

$$\underbrace{\Delta\bar{\mathbb{E}}_t^b(\pi_{t+1})}_{\text{total change}} = \underbrace{\sum_{i=1}^{I} \Delta\omega_i \times \bar{\mathbb{E}}_{t,i}^b(\pi_{t+1})}_{\text{extensive margin}} + \underbrace{\sum_{i=1}^{I} \omega_i \times \Delta\bar{\mathbb{E}}_{t,i}^b(\pi_{t+1})}_{\text{intensive margin}} + \underbrace{\sum_{i=1}^{I} \Delta\omega_i \times \Delta\bar{\mathbb{E}}_{t,i}^b(\pi_{t+1})}_{\text{interaction term}} \tag{8}$$

where $\Delta\bar{\mathbb{E}}_{t,i}^b(\pi_{t+1})$ is the change in the mean inflation expectation of group i, and $\Delta\omega_i$ is the change in the share of respondents in group i in response to a threshold event. The first term on the right-hand side of equation (8) captures changes in inflation along the extensive margin, the second term captures the intensive margin, and the third term is the interaction term.

While we can accurately estimate how an inflation threshold event changes the share of households that belong to certain inflation expectations groups, $\Delta\omega_i$, we can only provide an imprecise estimate of how the within-group average inflation expectation responds to an inflation threshold event, $\Delta\bar{\mathbb{E}}_{t,i}^b(\pi_{t+1})$. Our treatment, current inflation surpassing a round-number threshold, also affects individuals' group assignments. Ideally, we would like to observe respondents' qualitative inflation expectations in the period before the treatment, keeping the assignment of respondents into groups constant when the treatment occurs. This pre-treatment assignment is impossible since the European Business and Consumer Survey is a repeated cross-section. Therefore, we estimate the total change in average inflation expectations and the contribution from the extensive margin and calculate the sum of the intensive

[15] We ignore the share of respondents answering the qualitative question with "do not know" since they cannot be used to calculate the mean expectation. On average, across countries and months, 6% of respondents answered "do not know," with a standard deviation of 0.24.

margin and the interaction term residually from equation (8).

The total change in average expected inflation in response to a threshold event is estimated in Table 2, Column (1), and equals 61 basis points. To obtain the extensive margin, we estimate equation (6) for each of the five groups separately, with the share of households in a given group as the dependent variable. The regression results are shown in Table A.19. The share of households that expect inflation to increase more rapidly increases significantly by four percentage points in response to an increasing-inflation threshold event. Since this group's average size is 20.2 percent, the inflation threshold event enlarges it by 20 percent. The increase in the group expecting accelerating inflation is mainly due to respondents leaving the groups that expect zero or negative inflation.

To calculate how this change along the extensive margin affects average inflation expectations, following equation (8), we have to multiply the changes in the share of respondents in each group with the average within-group inflation expectations. The sum of these values yields the extensive margin defined in equation (8) and equals 48 basis points. Most of that change in the extensive margin comes from the increase in the group of households expecting more rapidly increasing inflation, which has a value of 46 basis points. With a total change in average expected inflation of 61 basis points, we get the sum of the intensive margin and the interaction term of 13 basis points residually. Hence, we find that the main driver of the change in average expected inflation of 61 basis points is the extensive margin with 48 basis points, mainly because respondents who expected inflation to be zero or negative now expect inflation to increase more rapidly at a strictly positive rate. The intensive margin and the interaction term explain only 13 of the 61 basis points. This result is supported by what we find when we estimate how within-group inflation expectations change in response to a threshold event, as shown in Table A.20 where coefficients are small and insignificant.

These results are related to Andrade *et al.* (2023), who find that most of the variation in inflation expectations between 2004 and 2018 in France is due to variations along the extensive margin. We show that the extensive margin changes to a large degree because of increasing-inflation threshold events.

5.4. Other mechanisms

The main mechanism discussed in the paper through which increasing-inflation threshold events affect households' expectations is the media's tendency to sensationalize inflation-related news. An alternative or complementary explanation could be that media outlets increase the salience of the topic by expanding the number of relevant reports. According to

Table A.21, we do not find evidence of a volume effect.[16] The absence of evidence is not evidence of absence, though. Media outlets may increase the salience of inflation-related news by placing these reports where households are more likely to encounter them. For instance, threshold events may induce news sites to feature a story on their landing page rather than the business section. Unfortunately, the data do not allow us to evaluate placement effects. Relatedly, as Table A.23 shows, we do not find evidence that households actively search for relevant information when threshold events occur, using the volume of Google searches for the search topics "inflation" and "consumer price index" as proxies of interest in the topic.[17]

5.5. Inflation threshold events and durable consumption

We have shown that inflation threshold events have a sizable impact on households' inflation expectations, but do these changes also result in real economic effects? To answer this question, we study how "readiness to spend on durables" (Bachmann *et al.*, 2015) changes in response to threshold events.

Two questions in the European Business and Consumer Survey refer to durable consumption. A sociotropic question asks *"In view of the general economic situation, do you think that now it is the right moment for people to make major purchases such as furniture, electrical/electronic devices, etc.?"* In our regressions, we use the difference between the share of respondents stating "*yes, it is the right moment now*" and the share of respondents stating "*no, it is not the right moment now*" as a dependent variable. The other question is more egocentric, asking "*Compared to the past 12 months, do you expect to spend more or less money on major purchases (furniture, electrical/electronic devices, etc.) over the next 12 months?*", and the corresponding variable is constructed similarly. We focus on the first question because the second question is theoretically less suited as it combines the present and the future, and it is not clear whether nominal expenditures might increase because of inflation or because of real expenditure changes.

The results in Table A.24 show that the readiness to spend on durables increases significantly in response to an increasing-inflation threshold event. According to Column (1), the difference between the share of households stating that it is the right time to purchase durables and the share stating that it is not the right time increases by 6.6 percentage points in response to an increasing-inflation threshold event.[18] The IV estimate in Column (3) indicates that sensational

[16] As Table A.22 shows, we also obtain null effects when we count the number of reports based on headlines that include the keywords "inflation" or "consumer price*."

[17] We use the language-independent "search topic" feature of Google Trends to obtain these data. This feature relies on Google algorithms that combine related search terms into pre-defined search topics and calculate the aggregate volume of searches about these topics. The search data are normalized by the total number of searches within a specific geography (e.g., country) and period (e.g., month) and, therefore, capture the relative interest in the topic of Google users.

[18] The literature has not reached a consensus on how inflation expectations affect durable consumption and

headlines may again play an important role in increasing households' readiness to spend on durables.

6. Complementary survey experiment

6.1. Design and participants

We conducted a randomized controlled survey experiment to corroborate the relevance of media sensationalism as a channel through which inflation threshold events affect household expectations. The experimental design and analysis plan, which were subjected to an ethics review and preregistered at the American Economic Association's registry for randomized controlled trials (Garz and Larin, 2023), can be accessed at https://doi.org/10.1257/rct.11958-1.0.

Participants were exposed to five fictional news headlines. Four of these headlines were unrelated to inflation. They address issues in culture, politics, society, and sports; see Table B.1. These headlines were the same for all participants and were formulated in a neutral/non-sensational manner. They did not refer to country-specific events or actors so that participants with different backgrounds could relate to the content. The fifth headline was randomly drawn from eight headlines mentioning high prices or increasing inflation.[19] Each inflation headline came in two versions, one using neutral/non-sensational phrasing and the other being framed sensationally (see Table B.2). For example, in the neutral version, a headline reads "Price developments: Inflation rate accelerates," whereas the sensational version states "RECORD HIGH: Inflation reaches double digits ".[20] Each participant was exposed to precisely one inflation headline, where the treatment status, sensational or non-sensational, and selection among the eight inflation-related headlines were randomized. We used eight pairs of inflation headlines to strengthen the generalizability of the results and avoid idiosyncratic effects from individual terms used in a headline. The order of presentation of the five headlines—four unrelated to

whether the Euler equation holds in this context. See D'Acunto and Weber (section V, A. 2024) for a comprehensive overview of the existing research, which highlights differences in methods, data, and conflicting findings.

[19] In line with the observational part of this study, where we do not find any impact of decreasing-inflation threshold events (cp. Section 5.1), and for the sake of simplicity, we restricted the experiment to increasing-inflation scenarios.

[20] It could be argued that headlines classified as sensational do not affect household expectations because of psychological effects (i.e., attention and emotional arousal) but because these headlines provide additional information. For instance, the sensational version of the headline "Oil prices highest since 1973" tells households that oil prices have not been that high in fifty years, a piece of information not included in the neutral version of the headline ("Economy: Higher oil prices in 2023"). Theoretically, this information should not affect expectations for reasons other than psychological ones, as the implied income effects are the same for both versions of the headline.

inflation and one random inflation headline—was also randomized.

Participants were asked to read the headlines and rate their interest in reading the story. We use this information to estimate whether the sensational version of an inflation headline attracts more reading interest than the non-sensational version. We list either type with headlines on other topics to simulate a choice environment that mirrors a typical news site.

In addition, participants were asked to complete a short quiz. It took place on a separate page after reading and rating the headlines, but participants were informed about this quiz before reading the headlines to incentivize them to pay attention. The quiz consisted of three multiple-choice and an open-ended question, all presented randomly (see Table B.3). Two of the multiple-choice questions are related to the non-inflation headlines. They have precisely one factually correct answer, based on which we assess participants' attentiveness. The third multiple-choice question mirrors the European Business and Consumer Survey item about participants' inflation expectations for the next 12 months in their country of residence. The fourth, open-ended question asks participants for their quantitative estimate of the inflation rate for the next 12 months. Analyzing the answers to the inflation-related questions allows us to determine whether the sensationalist version of an inflation headline increases the chances that participants expect higher inflation rates than when exposed to the non-sensational version. We embedded the questions about respondents' inflation expectations and the inflation-unrelated questions in the quiz to avoid experimenter demand effects (Haaland *et al.*, 2023).

We used Prolific to recruit survey participants. Prolific is a popular online platform among researchers in economics and the social sciences (e.g., Zmigrod *et al.*, 2018; Schild *et al.*, 2019; Oreffice and Quintana-Domeque, 2021). The platform offers many advantages over alternative providers of survey-related services, such as Amazon Mechanical Turk. For instance, Prolific's quality management system and diverse pool of survey takers allow researchers to obtain more honest and reliable responses (Peer *et al.*, 2017, 2022; Palan and Schitter, 2018). Importantly, Prolific supports our goal to recruit survey takers from nearly all EU member states, which other survey platforms do not facilitate or, in the case of market research companies like Nielsen or Ipsos, only at a multiple of the cost. Prolific operates in compliance with relevant privacy and data protection regulations, such as GDPR. In addition, the platform provides basic demographic information about participants, which is beneficial for response and attrition rates in a given survey as these data do not have to be collected again.

We restricted the participation to residents in EU member states who stated to be fluent in English. The English fluency requirement excludes a large fraction of survey takers and likely skews the sample towards younger and better-educated people. However, dealing with an unrepresentative sample is likely less problematic than the unknown bias resulting from translating the headlines into more than 30 languages spoken in Europe, especially the possibility that translation effects are correlated with the treatment. In addition, it would not be feasible to obtain a representative sample of households, to begin with, because Prolific does not conduct offline surveys and does not operate in EU candidate countries like North Macedonia, Serbia, and Turkey or some of the more recent EU members like Bulgaria, Cyprus, Lithuania, Malta, and Romania.

We ran the experiment between October 5 and 12, 2023. We informed potential participants about the nature of the research, the voluntary nature of participation, and their right to stop participating at any time. We explicitly asked respondents for their consent to participate in the study and stopped the survey otherwise. We paid each participant 0.70 EUR. Considering that it took them 149.8 seconds on average to complete the survey, the payment is equivalent to a mean hourly wage of 16.82 EUR, corresponding to approximately 17.68 USD, which is well above Prolific's recommended payment and often a multiple of minimum wage levels in Europe. Following power calculations, we collected responses from 2,000 participants. The attrition rate was relatively low, 7.3%, as only 145 participants started the survey without completing it.

6.2. Analysis and results

As per our pre-analysis plan, we excluded the top and bottom 1% of participants (36 in total) in terms of survey duration and 3 participants who provided wrong answers in both inflation-unrelated multiple-choice questions (i.e., questions #1 and #2 in Table B.3), resulting in an analysis sample of 1,816 respondents. Besides the missing countries mentioned above, the distribution of participants across states approximately mirrors their population shares in the EU (Figure B.1).

The data collected in the experiment are summarized in Table B.4. On average, respondents rated their interest in reading the inflation-related article with a score of 3.68 on a scale from 1, "not interested at all," to 5, "very interested;" see Figure B.2. Approximately 69% of respondents expected increasing inflation—that consumer prices in their country of residence would increase more rapidly during the next 12 months (cp. Figure B.3). The average quantitative estimate of the inflation rate—the change in consumer prices over the next 12 months—was 15.85%, and the median was 10.00%. Unsurprisingly, respondents' estimates are clustered at round numbers, especially 5% (310 respondents), 10% (359 respondents), 15% (111 respondents), and 20% (222 respondents). Considering the wide range of estimates from -35% to +540%, we construct a winsorized version of this variable, using cutoffs at -5% and +30%; see Figure B.4.

In Table B.5, we compare the means of the demographic variables provided by Prolific between treated and untreated respondents. The comparison does not indicate any significant

	(1) Reading interest	(2) Expecting increasing inflation	(3) Quantitative estimate	(4) Winsorized quantitative estimate
Sensational headline treatment	-0.031	0.025	4.003***	1.384***
	(0.053)	(0.022)	(1.289)	(0.410)
Mean of dependent variable	3.682	0.687	15.849	11.552
SD of dependent variable	1.130	0.464	27.364	8.717
Observations	1816	1816	1797	1797

Notes: All models include an intercept (output omitted). Robust standard errors in parentheses.
** $p<0.10$, ** $p<0.05$, *** $p<0.01$*

Table 3: Results of survey experiment

differences between the two groups, which supports the notion of a random treatment assignment.

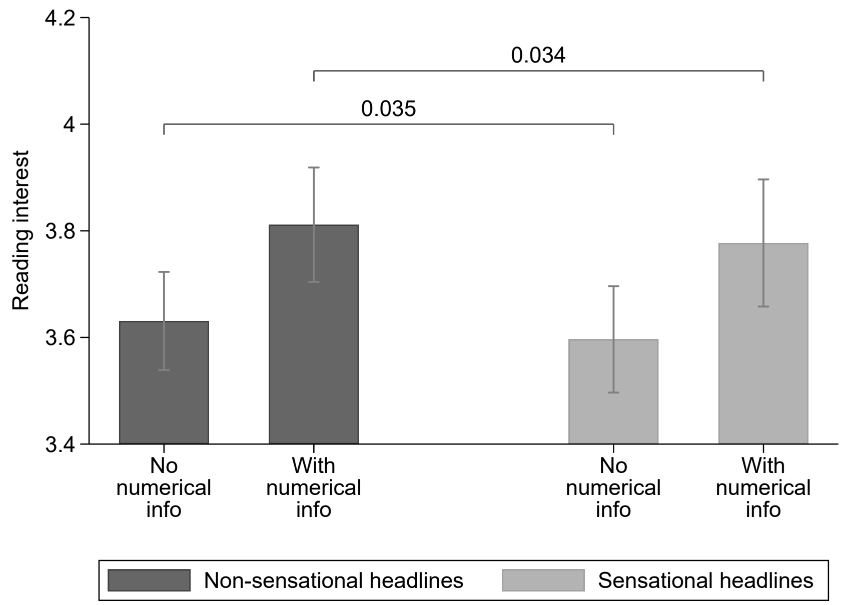
Following our pre-analysis plan, we regress the outcome variables on a binary treatment indicator T of whether headline pair h selected for participant i is sensational ($T = 1$) or not ($T = 0$):

$$y_{i,h} = \alpha_1 + \alpha_2 T_{i,h} + \alpha_3 X_{i,h} + \mu_h + \epsilon_{i,h},$$

where μ_h is an optional headline-pair fixed effect capturing potential effects due to variation in content between the eight pairs of inflation headlines, the optional vector X includes controls for sex, age, employment status, and country of residence, and the coefficient α_2 captures the average treatment effects.

Estimation results are presented in Table 3. As Column (1) shows, respondents' interest in reading the inflation article does not significantly differ between the neutral and sensational phrasing of the headline. According to Column (2), we do not find a significant treatment effect on the likelihood of expecting increasing inflation either. However, framing a headline sensationalistically increases the quantitative estimate of the future inflation rate significantly at the 1% level, both when using respondents' original figures (Column 3) and the winsorized values (Column 4). The effects sizes amount to $4.003/27.364 = 0.146$ and $1.384/8.717 = 0.159$ standard deviations, respectively, of respondents' inflation estimate. Table B.6 indicates that the coefficients remain virtually the same when we include headline fixed effects, country-of-residence fixed effects, and the full set of demographic controls.

Sensational inflation headlines may include numerical values about the inflation rate, for example, "Never seen before: Inflation exceeds 10% threshold", or they may not, for example, "Consumer prices skyrocket to unprecedented levels." In the pre-analysis plan, we hypothesized that the treatment effects are larger if a headline states a numerical value due to the



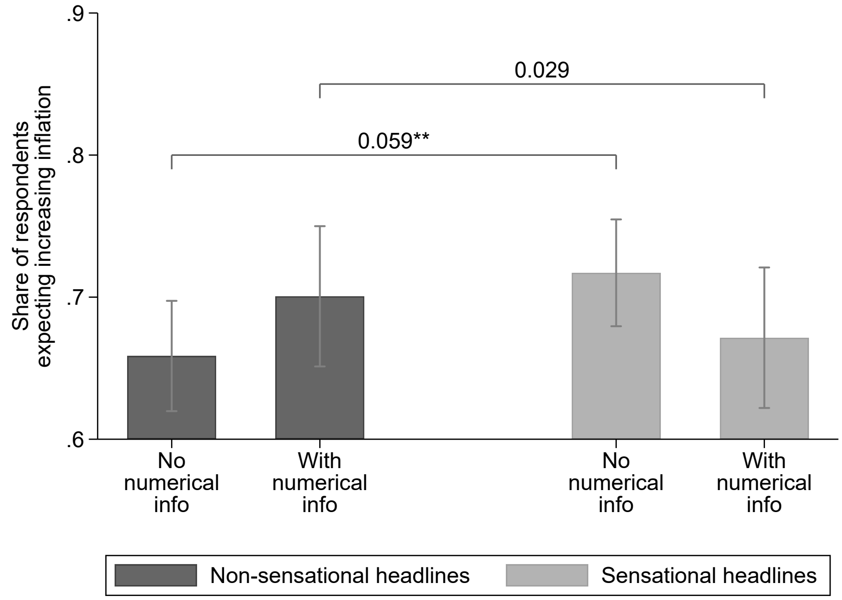
Notes: Based on randomly assigning 1,816 survey respondents on Prolific. The sample mean of the outcome is 3.68 (SD = 1.13). Headlines providing numerical information about the inflation rate are #3, #5, and #7 in Table B.2. The error bars denote 95% confidence intervals. Values above brackets denote absolute differences in means (p<0.10, ** p<0.05, *** p<0.01).*

Figure 4: Effects of sensational headline treatment on reading interest

psychological importance of round numbers in cognitive processes. An alternative hypothesis is that the treatment effects are smaller because numerical values help mitigate the impact of sensationalism, as the additional information allows respondents to form more accurate expectations. In the experiment, exposure to sensational headlines with (#3, #5, and #7 in Table B.2) and without numerical values (#1, #2, #4, #6, and #8) was randomized, which allows us to investigate the psychology versus information hypotheses.

We do not find significant differences regarding respondents' interest in reading the inflation headline (Figure 4). However, as Figure 5 shows, participants exposed to a sensational headline without numerical information were 5.9 percentage points more likely to state that they expect increasing inflation than respondents exposed to the non-sensational version of the headline, which corresponds to an effect size of $0.059/0.464 = 0.127$ standard deviations. In contrast, we do not find a significant treatment effect for headlines including numerical information.

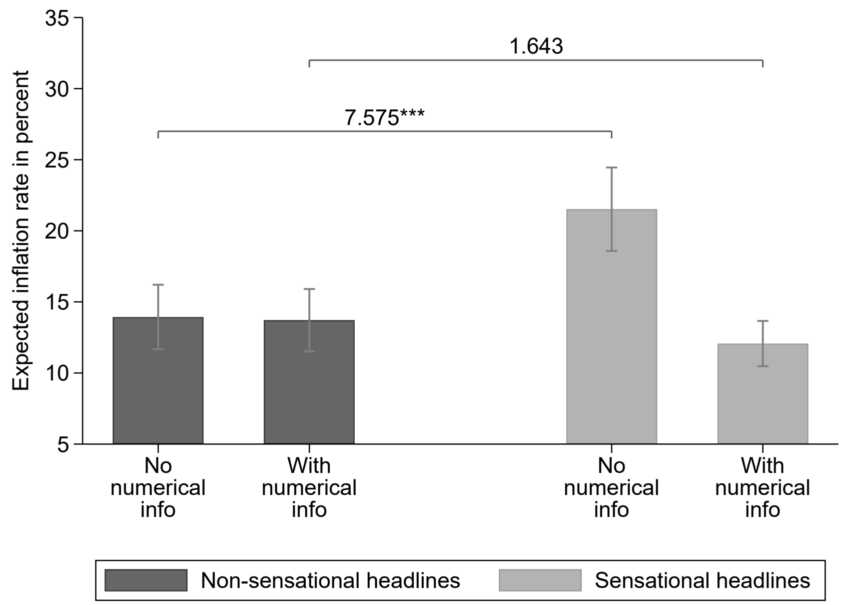
A similar pattern emerges when we look at respondents' quantitative estimate of the future inflation rate (Figure 6). While there are no effects of the sensationalism treatment when headlines include numerical values, participants' expected future inflation rate is on average 7.6 percentage points higher when exposed to a sensational headline without a numerical value, compared to the non-sensational version. The size of this effect equals $7.575/27.364 = 0.277$ standard deviations of participants' inflation estimate.



Notes: Based on randomly assigning 1,816 survey respondents on Prolific. The sample mean of the outcome is 0.69 (SD = 0.46). Headlines providing numerical information about the inflation rate are #3, #5, and #7 in Table B.2. The error bars denote 95% confidence intervals. Values above brackets denote absolute differences in means (p<0.10, ** p<0.05, *** p<0.01).*

Figure 5: Effects of sensational headline treatment on qualitative expectations

In conclusion, the survey experiment confirms the findings from the observational data. While respondents do not state any increased interest in reading an inflation-related news story when it is phrased sensationalistically, the data indicate that exposure to sensational headlines causes households to expect higher future inflation. The effects of sensational headlines are particularly pronounced when they do not include numerical information about the inflation rate. In contrast, stating a numerical value in a sensational headline appears to mitigate or cancel out the effects of sensationalism on household expectations, likely because numerical figures provide information that helps households better assess the macroeconomic situation.



Notes: Based on randomly assigning 1,797 survey respondents on Prolific. The sample mean of the outcome is 15.85 (SD = 27.36). Headlines providing numerical information about the inflation rate are #3, #5, and #7 in Table Table B.2. The error bars denote 95% confidence intervals. Values above brackets denote absolute differences in means (p<0.10, ** p<0.05, *** p<0.01).*

Figure 6: Effects of sensational headline treatment on quantitative expectations

7. A New Keynesian model with left-digit-biased inflation expectations

To study how left-digit-biased inflation expectations affect the dynamics of inflation and the output gap in general equilibrium and what the implications for monetary policy are, we now embed left-digit-biased inflation expectations as defined in section 2 in a simple New Keynesian model (Galí, 2015).

The following three equations summarize the model

$$\pi_t = \beta \mathbb{E}_t^b \pi_{t+1} + \kappa \tilde{y}_t \tag{9}$$

$$\tilde{y}_t = \mathbb{E}_t \tilde{y}_{t+1} - \frac{1}{\sigma}\left(\hat{i}_t - \mathbb{E}_t^b \pi_{t+1}\right) + \frac{1}{\sigma}(1-\rho_z) z_t \tag{10}$$

$$\hat{i}_t = \phi_\pi \pi_t + \phi_y \tilde{y}_t, \tag{11}$$

together with left-digit-biased inflation expectations as given by equations (2), (3) and (5) from section 2 and output-gap expectations

$$\mathbb{E}_t \tilde{y}_{t+1} = \rho_y \tilde{y}_t.$$

See online appendix C.1 for the derivation.

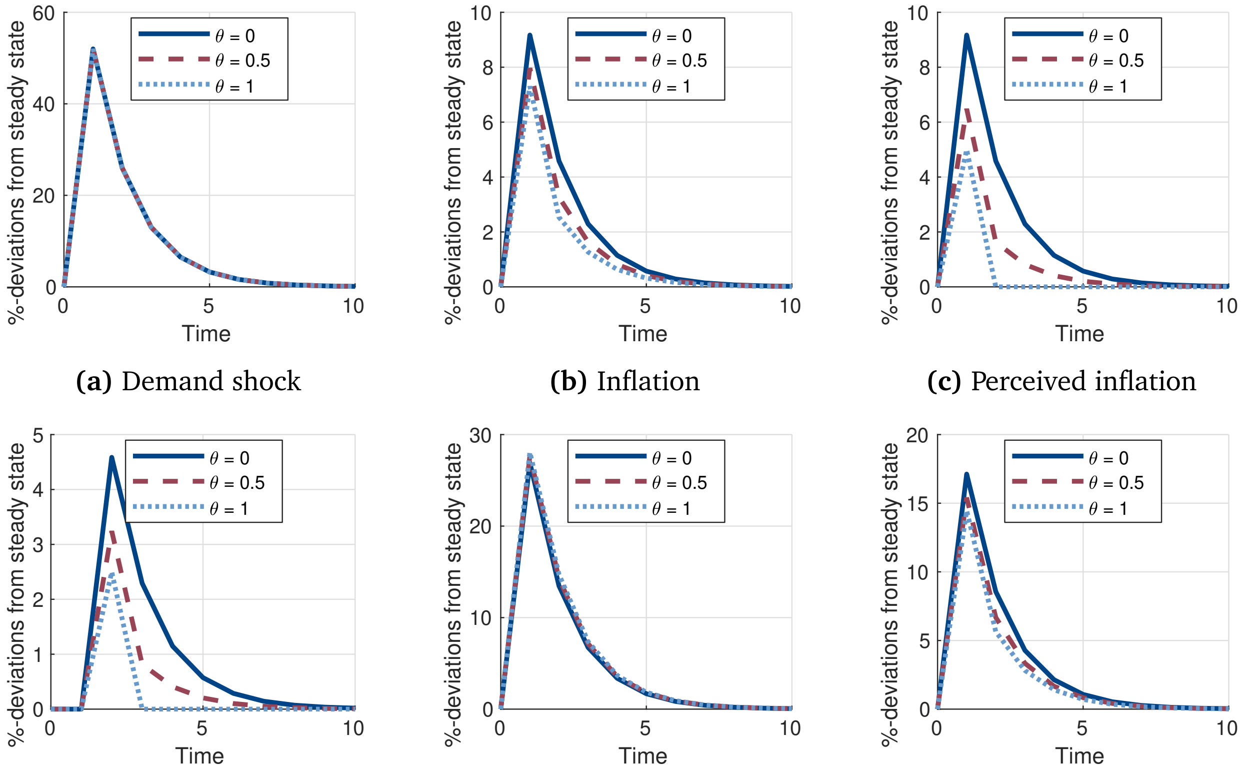
Equation (9) is the New Keynesian Phillips curve (NKPC) with π_t denoting the inflation rate, β the household's subjective discount factor, $\mathbb{E}_t^b \pi_{t+1}$ are *behavioral* inflation expectations, κ the slope of the Phillips curve, and $\widetilde{y}_t$ the output gap. It describes how firms set current prices and determine inflation based on their expectations of future inflation and the current output gap. Equation (10) is the aggregate Euler equation with $\frac{1}{\sigma}$ the intertemporal elasticity of substitution, $\hat{i}_t$ the difference of the nominal interest rate and its steady-state value, and z_t a demand shock following an AR(1) process with persistence ρ_z. It describes how households choose current relative to expected future consumption based on the next-period real interest rate. Finally, equation (11) is a simple Taylor rule with inflation coefficient ϕ_π and output gap coefficient ϕ_y. This monetary policy rule captures how the central bank sets the nominal interest rate based on inflation and the output gap.

This model differs from the standard New Keynesian model in two ways. First, households believe that consumption and inflation follow AR(1) processes, and firms have forecasters that are identical to households regarding forming expectations about inflation and the output gap. Second, households do not perfectly observe inflation but instead have left-digit-biased inflation perceptions and expectations as defined in section 2. Perceived inflation can differ from actual inflation, affecting a household's forecast of future inflation.

We now study how left-digit-biased inflation expectations affect the propagation of a demand shock. This system of equations can be solved by forward iteration, given initial values $\pi_0^p, \pi_0, \widetilde{y}_0, \hat{i}_0$ and an exogenous sequence $\{z_t\}$, solving a non-linear system of equations at each time step. The nonlinearity comes from the left-digit-biased inflation expectation formation.

We set the following parameters to standard values from the literature (Galí, 2015): β is set to 0.99, κ is set to 0.172, σ is set to 1, ϕ_π is set to 1.5, and ϕ_y is set to 0.125. We will study different values for the inattention to the right digits in inflation, θ. Following our findings from the empirical analysis, we study inflation thresholds that are multiples of five by setting $\tau = 5$. The parameters for the subjective persistence of inflation and consumption are set to $\rho_\pi = 0.5$ and $\rho_y = 0.5$. Lastly, we consider a demand shock that results in inflation surpassing the threshold of 5% on impact, $u_1 = 0.52$, then reverts to 0 with persistence $\rho_z = 0.5$. The results shown are not intended to be quantitatively accurate but to illustrate the qualitative effects of left-digit-biased inflation expectations on inflation dynamics and the output gap. We present three main sets of results.

First, the more pronounced the left-digit bias in inflation expectations, the more inflation expectations are anchored at lower values. This relation can be seen by taking the derivative of perceived inflation (2) with respect to actual inflation, assuming no threshold is crossed. This derivative is $-\theta$. The more pronounced the left-digit bias, the higher θ, and the smaller the effect of current inflation on perceived inflation. Once current inflation surpasses an inflation



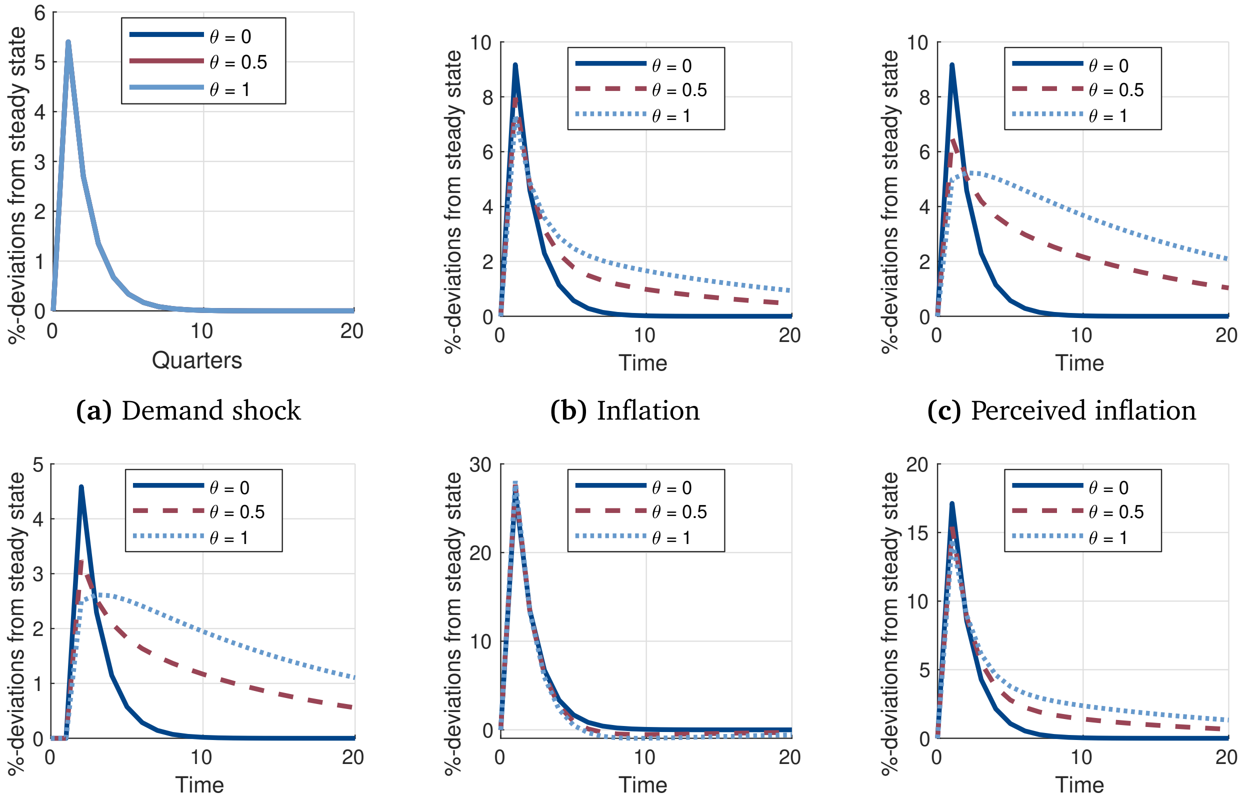
(a) Demand shock **(b)** Inflation **(c)** Perceived inflation

(d) Expected inflation **(e)** Output gap **(f)** Nominal interest rate

Figure 7: Impulse-response to a demand shock: Symmetric left-digit bias

threshold, perceived inflation jumps upwards, and this discontinuous increase is higher the higher θ. However, perceived inflation for a high θ never exceeds perceived inflation for a lower θ.

Figure 7 shows the impulse-response functions to a demand shock for $\theta \in \{0, 0.5, 1\}$. We first consider symmetric reactions of inflation perceptions to threshold events, i.e., $\tau^- = \tau$, and can, therefore, simplify by setting $\lambda = 1$. The demand shock is the same in all cases, but all other variables react differently depending on the degree of left-digit bias. Higher demand directly raises output through the Euler equation (10). Firms raise prices in response to higher demand, raising inflation through the NKPC (9). Higher output and inflation raise nominal interest rates through the Taylor rule (11), which dampens output and inflation. Expected inflation increases, thus amplifying the effect of the demand shock on inflation. The higher the left-digit bias (higher θ), the smaller the effect of the demand shock on inflation because this amplification through inflation expectations is weaker. This becomes clear when considering full inattention to the right digits, $\theta = 1$. In that case, inflation is above 5% only for one period, so perceived inflation jumps to 5% in period one and back to zero in period two. Expected inflation is only above the steady state in period one, implying minimal amplification



(a) Demand shock **(b)** Inflation **(c)** Perceived inflation

(d) Expected inflation **(e)** Output gap **(f)** Nominal interest rate

Figure 8: Impulse-response to a demand shock: Asymmetric left-digit bias

of the demand shock through inflation expectations. In the contrary case of no left-digit bias, $\theta = 0$, perceived inflation equals actual inflation, and inflation expectations are elevated for many periods, resulting in higher inflation for more periods. To summarize, left-digit biased inflation expectations with symmetric thresholds anchor inflation expectations more, resulting in weaker inflation responses and requiring less aggressive and less persistent monetary policy responses to demand shocks.

Our empirical results, however, reject the assumption that threshold effects are symmetric, implying $\tau^- \neq \tau$. We now more plausibly assume $\tau^- = 0$. For inflation perceptions to converge to the steady state inflation of 0%, we have to assume that households pay some attention to the current inflation level, $\lambda < 1$. We set $\lambda = 0.9$. Figure 8 shows the impulse response functions. As before, a higher left-digit bias implies a weaker initial response of inflation to the demand shock. The immediate response of output is dominated by the direct effect of the demand shock, implying little differences in the output gap depending on the degree of left-digit bias. However, inflation perceptions remain elevated for longer once they cross the 5% threshold under left-digit bias. This persistence implies that inflation expectations remain elevated for longer, and actual inflation remains high for longer. As a result, monetary policy has to keep interest rates high for much longer under left-digit-biased inflation expectations, $\theta = 1$, than without it, $\theta = 0$. This more persistent policy response results even in a mild recession along the transition path, as the output gap remains below zero for some periods under left-digit bias, $\theta \in \{0.5, 1\}$, while it is strictly positive if no left-digit bias is present, $\theta = 0$. Taken together, left-digit-biased inflation expectations with asymmetric reactions to threshold events imply that inflation takes more pronounced shocks to increase. However, it takes longer to get back to lower levels once at a higher level. More technically, the higher θ is, the less amplified but more persistent the effect of a demand shock on inflation. Hence, monetary policy does not have to react as aggressively to such a shock but much more persistently.

Lastly, we show how the nonlinearity underlying left-digit-biased inflation expectations affects inflation dynamics and the output gap. Figure C.1 in the online appendix, therefore, shows the impulse response functions to a demand shock of different sizes. Small changes in the size of the demand shock can have large effects on inflation, inflation perceptions, and expectations once the shock is large enough for inflation to cross a threshold. Put differently, two shocks of almost the same size can have very different effects on inflation under left-digit-biased inflation expectations.

8. Conclusion

This paper investigates left-digit bias in household inflation expectations. We theoretically define left-digit bias in inflation expectations and show how it leads to jump discontinuities between current and expected future inflation. Using data from 30 European countries between 2017 and 2023, we employ a regression-discontinuity design to estimate the impact of inflation threshold events.

Our main findings are as follows: First, inflation thresholds occur at multiples of 5 percent. Second, when inflation rises above these thresholds, mean and median inflation expectations jump by 0.6 and 1.1 percentage points, respectively. Third, we find an asymmetry in the effects of rising and falling inflation. When inflation falls below these thresholds, it does not significantly impact expectations. Fourth, the effect is primarily driven by households that previously expected zero or negative inflation. After inflation rises above these thresholds, these households now expect rising inflation.

Using an instrumental variable approach and a randomized controlled survey experiment, we show that sensationalist media coverage of inflation transmits the effects of increasing inflation threshold events to households' inflation expectations. The survey experiment confirms that exposure to sensationalist headlines leads to higher inflation expectations, especially when the headlines do not provide specific numerical values.

To study the macroeconomic implications, we embed left-digit-biased inflation expectations in a New Keynesian model. Demand shocks have a weaker initial effect on inflation and the real economy. However, their impact becomes more persistent once an inflation threshold is crossed, compared to a model without left-digit bias. This persistence arises because households' inflation expectations remain elevated longer after crossing a threshold. Consequently, monetary policy should react less aggressively but more persistently to such shocks.

Our findings have important policy implications. First, central banks should account for households' discontinuous reactions to round-number threshold events. Second, for households to form more accurate inflation expectations, statistical offices should include key numerical values in their headlines and avoid sensationalist framing. Third, our results raise questions about the adequacy of current self-regulation practices in the news industry and highlight the need for improved statistical and media literacy among the public.

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Online Appendix

A. Cross-country empirical analysis

A.1. Classification of news headlines

A.1.1. Tagging of sensational headlines by human coders

We used an online platform for freelance services to recruit a human coder to evaluate a random subsample of 9,500 translated headlines. We asked the coder to tag headlines expressing that inflation or prices have reached a milestone, broken some historical record, or surpassed some round-number threshold, such as 10% or 20%; in short, sensational headlines. The full coding instructions are shown in Figure B1. When selecting the coder, we imposed no requirements other than proficiency in English and understanding of the task. We did not require the coder to have sophisticated knowledge of macroeconomics to obtain evaluations of the headlines from a layperson's perspective mirroring the background that can be assumed for any ordinary consumer. To ensure that the coder would accurately and reliably tag the relevant headlines, we requested annotations for batches of 500 headlines, where a fully processed batch would be rewarded with 20.00 EUR. The coder was assured of receiving further batches with the same payment if the annotations passed a quality check by the co-authors (which was the case throughout). A second, independent coder was recruited and instructed analogously to annotate a subset of 1,055 headlines (11.1%) of the coding sample. Comparing the annotations between both coders yields a Cohen's kappa coefficient of 0.865 and an F_1 score of 0.867, which indicates "almost perfect" intercoder agreement when using the scale of Landis and Koch (1977).

A.1.2. Machine classification using large language models

We randomly split the coded sample of 9,500 headlines into training data (66.6%), validation data (22.2%), and test data (11.1%) to fine-tune a classifier based on pre-trained Bidirectional Encoder Representations from Transformers, including the seminal BERT (Devlin *et al.*, 2018) and the derivations ALBERT (Lan *et al.*, 2020), DistilBERT (Sanh *et al.*, 2019), and RoBERTa (Liu *et al.*, 2019). Based on large text corpora, these transformer models are pre-trained to predict randomly masked words in sentences, resulting in a learned understanding of the general use of the English language.

These models need to be fine-tuned for the task at hand, e.g., evaluating 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

Model	Precision	Recall	F 1 score
ALBERT	0.909	0.588	0.714
BERT	0.875	0.824	0.848
DistilBERT	1.000	0.765	0.867
RoBERTa	0.938	0.882	0.909

Table A.1: Evaluation of classifiers

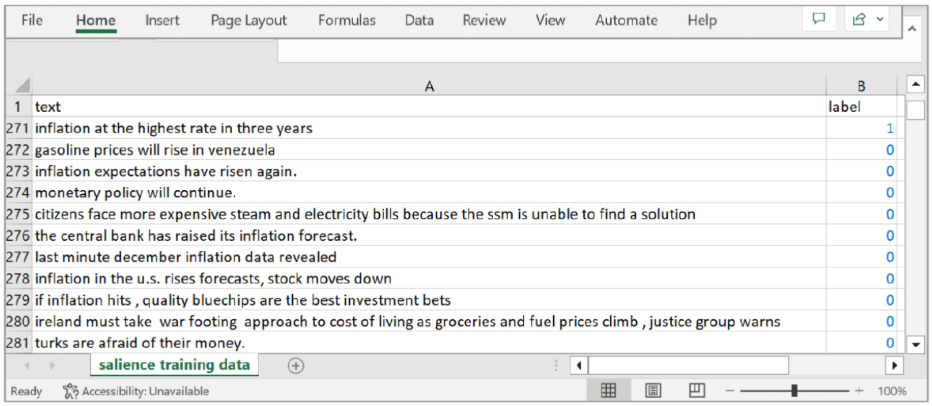
obtain vectors of word embeddings with position encodings by applying the weights of the respective model. The human annotations in the training data are then used to update the model weights and create the fine-tuned version of each model. The validation data are used to evaluate the progress of the fine-tuning process and the performance of the updated models. We conclude the fine-tuning once the loss metric stops to significantly improve, i.e., when further training steps would not improve the model's ability to correctly classify the headlines. To select the final model, we compare the human annotations in the test data with predictions of the fine-tuned models of whether or not a headline classifies as sensational.

Table A.1 summarizes the results of this exercise. The final model (RoBERTa) is selected based on the F_1 score, which accounts for class imbalance. Obtaining the best performance with this model is plausible because RoBERTa is considered the "larger" and more complex language model among the evaluated models. At the time of our analysis, the model achieves state-of-the-art results in many natural language processing tasks (Liu *et al.*, 2019). We use the fine-tuned RoBERTa to classify the headlines in the entire sample of 281,206 inflation-related news stories and compute the mean probability of sensational headlines by country and month.

Evaluation of news headlines about inflation

The attached Excel file includes 500 real, randomly selected headlines of news stories related to inflation, the development of consumer prices, and other macroeconomic price trends. The column “text” shows the content of the headlines, whereas the column “label” includes your evaluation results.

We would like to know whether or not the headline mentions that inflation or prices have reached a milestone, broken some historical record, or surpassed some round-number threshold, such as 10% or 20%. Please enter the value “1” in the column “label” if the headline include this kind of statement and “0” if not. (The “label” column is empty when receiving the Excel file and needs to be filled in.)



	A	B
1	text	label
271	inflation at the highest rate in three years	1
272	gasoline prices will rise in venezuela	0
273	inflation expectations have risen again.	0
274	monetary policy will continue.	0
275	citizens face more expensive steam and electricity bills because the ssm is unable to find a solution	0
276	the central bank has raised its inflation forecast.	0
277	last minute december inflation data revealed	0
278	inflation in the u.s. rises forecasts, stock moves down	0
279	if inflation hits , quality bluechips are the best investment bets	0
280	ireland must take war footing approach to cost of living as groceries and fuel prices climb , justice group warns	0
281	turks are afraid of their money.	0

To guide your evaluations, the following table includes examples of inflation headlines of type “0” and type “1”.

Label = 0 (not sensational)	**Label = 1 (sensational)**
Gasoline price rise contributed to accelerated inflation in November	The price of gasoline continues to drop and hits its historic record
House price inflation remains at 0.2% in October	House price inflation reaches double digits in 2022
German consumer prices increase as expected	German consumer prices jumped to 5.2% - highest since 1992
Inflation in Lithuania at 0.94% in November	Inflation in Lithuania fell to the 10% threshold for the first time since 2021
Food price index up	Food price growth breaks new record

As the table illustrates, a sensational headline of type 1 is a headline that highlights a significant achievement, milestone, or event. It emphasizes that a specific record has been broken or reached, indicating that the occurrence is remarkable, unprecedented, or historic in some way, often by mentioning some round-number threshold or a change in digits of a number or rate. A type 1 headline captures readers’ attention by sensationalizing the information. In contrast, an “ordinary” headline of type 0 describes an event or development in a plain way without framing it as a record, milestone, or special achievement.

A fully processed file is rewarded with 20.00 EUR. After returning the work, we carry out a quality control. If the quality is satisfactory, we offer further files to be worked on (with the same remuneration of 20.00 EUR per 500 headlines).

Figure A.1: Coding instructions

Headline	Translation	Outlet	Date	Country
Inflacija u prosincu 5,5 posto, najviša od listopada 2008. Rast cijena u svim kategorijama	Inflation in December 5.5 percent, the highest since October 2008. Price increases in all categories	novilist.hr	Jan 17, 2022	Croatia
Inflace v Česku je nejvyšší za 24 let. Nahoru ji vyhnaly drahé energie a paliva.	Inflation in the Czech Republic is the highest in 24 years. Expensive energy and fuel.	blesk.cz	Apr 11, 2022	Czechia
Le pétrole au plus haut depuis début janvier 2020	Oil prices highest since January 2020	lefigaro.fr	Feb 24, 2021	France
Höchste Rate seit 70 Jahren: Inflation steigt im September auf 10 Prozent	Highest rate in 70 years: Inflation rises to 10% in September	tagesspiegel.de	Sep 29, 2022	Germany
Ireland records second lowest Eurozone inflation in past year	Ireland records second lowest Eurozone inflation in past year	irishexaminer.com	Oct 17, 2017	Ireland
Inflazione e alimenti: a gennaio l'olio (non di oliva) cresce di quasi il 20%, a doppia cifra anche vegetali e burro	Inflation and food: in January (non-olive) oil grows by almost 20%, double-digit also vegetables and butter	corriere.it	Feb 05, 2022	Italy
Infliacija Lietuvoje birþelá smuko þemiau kritinës 10 % ribos pirmà kartà nuo 2021.	Inflation in Lithuania fell to the 10% threshold for the first time since 2021.	vz.lt	Jun 28, 2023	Lithuania
Инфлацијата почна да се намалува, очекувам да биде едноцифрена	Inflation begins to decline, I expect it to be one-digit	vecer.mk	Jan 31, 2023	North Macedonia
Rata anuală a inflației a urcat la 5,4%, record al ultimilor 5 ani	The annual inflation rate has risen to 5.4%, a record of the last 5 years	jurnalul.ro	Jun 12, 2018	Romania
Toto sme tu dlho nemali: Inflácia presiahla 10%, je najvyššia od roku 2000! Čo zdraželo najviac?	This has not been the case for a long time: Inflation has exceeded 10%, the highest since 2000! What costs the most?	cas.sk	Apr 19, 2022	Slovakia

Notes: Probability of sensational headline > 0.5.

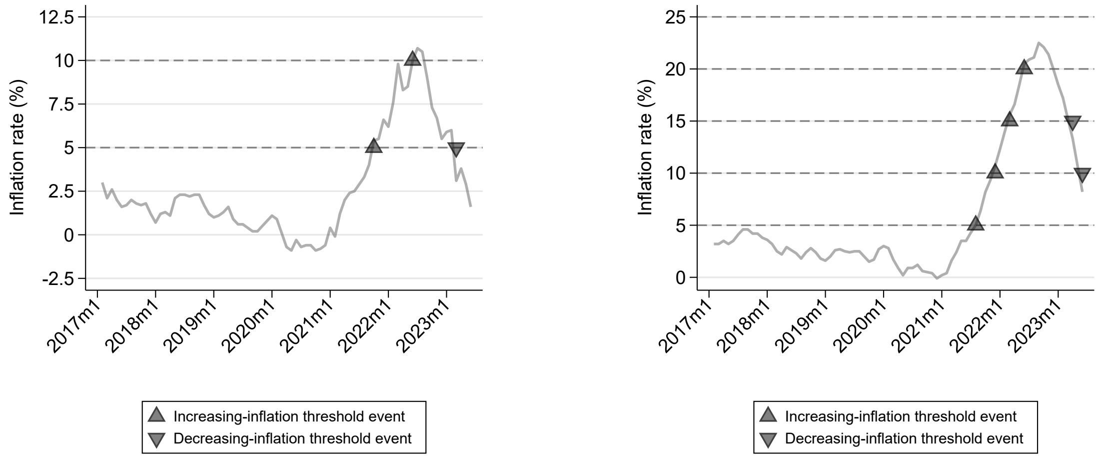
Table A.2: Examples of inflation-related stories with sensational headline

Headline	Translation	Outlet	Date	Country
Gastkommentar - Papiergeld oder Bitcoin?	Guest Commentary - Paper money or bitcoin	krone.at	Jun 06, 2021	Austria
Malgré linflation, les tour - opérateurs font le plein de réservations avant les vacances d'été	Despite inflation, tour operators make full reservations before the summer holidays	lemonde.fr	May 10, 2023	France
Ο Πούτιν εκβιάζει την Ευρώπη με τρόφιμα και λιπάσματα	Putin is blackmailing Europe with food and fertilizers	tanea.gr	Jul 15, 2022	Greece
Tonno in scatola, produzione giù dell 8% per i costi troppo alti	Thunfish in box, production down 8% for too high costs	ilsole24ore.com	May 29, 2023	Italy
Geldpolitische Hilfe immer noch nötig	Monetary policy support is still needed	tageblatt.lu	April 21, 2017	Luxembourg
Jak nie traciæ oszczêdności przy wysokiej inflacji	How not to lose savings with high inflation	rp.pl	Dec 13, 2017	Poland
El mercado de la vivienda ante la subida de tipos	The housing market in the face of rising rates	elapis.com	Jul 09, 2022	Spain
Inflacija raste, ali ostaje u okviru cilja	Inflation rises but remains within target	danas.rs	Aug 18, 2021	Serbia
C vill slopa skatten på ISK för småsparare	C wants to eliminate the tax on ISK for small savers	aftonbladet.se	Aug 11, 2022	Sweden
Yurt içi piyasalar yeni haftada Merkez Bankası na odaklandı.	Domestic markets focus on the central bank in the new week	milliyet.com.tr	Feb 17, 2020	Turkey

Notes: Probability of sensational headline ≤ 0.5.

Table A.3: Examples of inflation-related stories without sensational headline

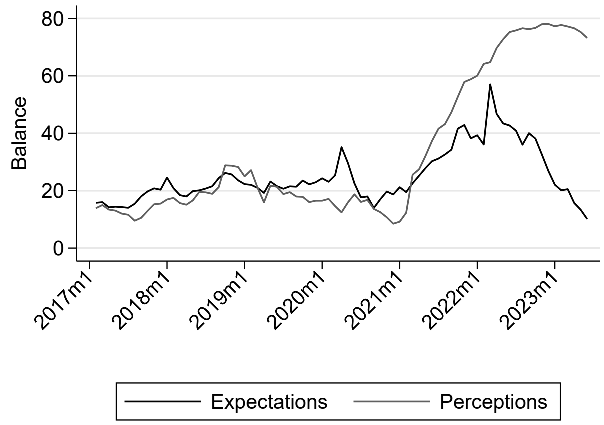
A.2. Additional figures and tables



(a) Spain **(b)** Lithuania

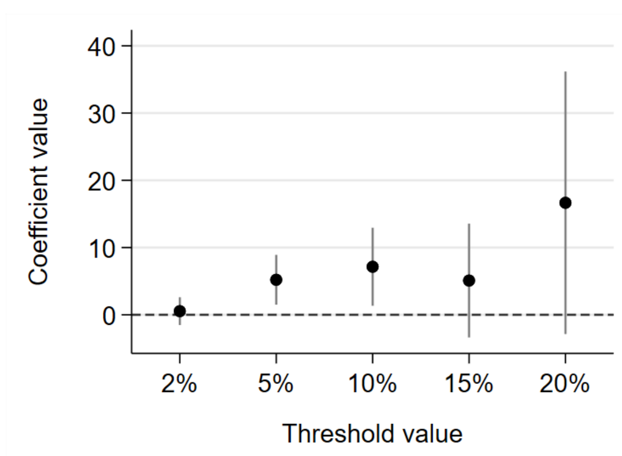
Notes: An increasing-inflation threshold event refers to a situation where a country's inflation rate reaches or exceeds a value of 5, 10, 15, 20, or 25%, compared to the previous month, while not reaching or exceeding that threshold in the past 12 months. A decreasing-inflation threshold event refers to a situation where a country's inflation rate falls below a value of 5, 10, 15, 20, or 25%, compared to the previous month, while not falling below that threshold in the past 12 months.

Figure A.2: Examples of round-number thresholds in the inflation rate



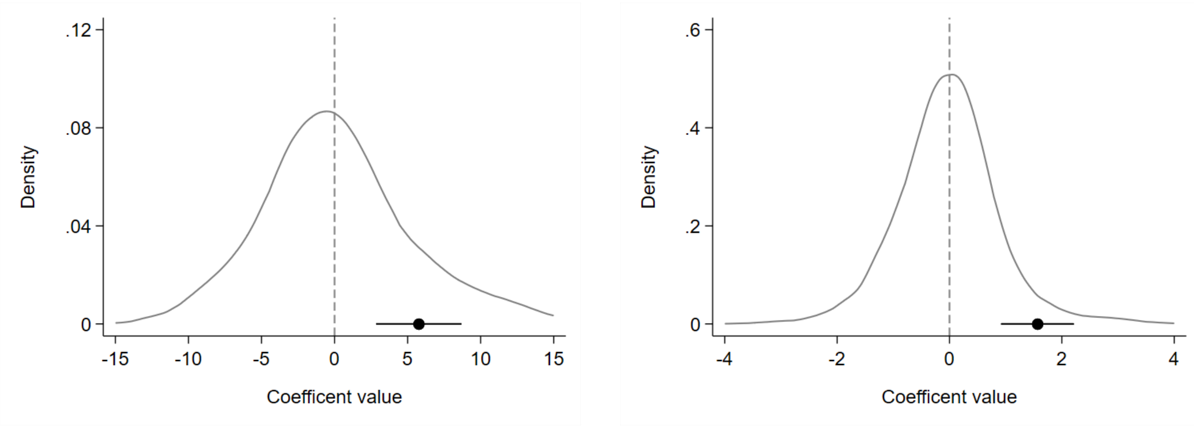
Notes: Based on data from the European Business and Consumer Surveys. Inflation expectations are based on the question, "By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months?" while inflation perceptions are based on the question, "How do you think that consumer prices have developed over the last 12 months?".

Figure A.3: Balance of inflation expectations vs. balance of inflation perceptions



Notes: The graph shows regression coefficients from estimating equation (6) with separate dummy variables for the increasing-inflation threshold values shown on the x-axis. The y-axis measures the reduced-form effect of the threshold events on qualitative inflation expectations (i.e., the ratio of households expecting increasing vs. decreasing inflation). The vertical bars denote the 90% confidence interval based on standard errors clustered by country.

Figure A.4: Individual inflation thresholds and inflation expectations



(a) Reduced form **(b)** First stage

Notes: The figure shows kernel density plots of the distribution of coefficients from re-estimating the baseline specification 1,000 times with increasing-inflation placebo thresholds. The dependent variables are qualitative inflation expectations on the left-hand side and the probability of sensational headlines on the right-hand side. Each set of placebo thresholds consists of five non-integer values randomly drawn from all possible values (with one decimal place) in the interval from 0.1 to 29.1%. We create a new threshold event dummy that replaces the multiples-of-five treatment dummy when re-estimating the baseline specification. Cases in which the inflation rate crosses an integer value are set to 0 to avoid contamination of the placebo regressions with actual threshold effects. The black circle denotes the coefficient of the multiples-of-five increasing-inflation threshold dummy from equations (6) and (7), along with the 95% confidence interval (based on standard errors clustered by country).

Figure A.5: Regression results with placebo thresholds

Country	Month	HICP	CPI	Example headline
France	Nov 2019	1.2%	**1.0%**	France: inflation rose again in November to 1% per year (*lefigaro.fr, Dec 12, 2019*)
Germany	Mar 2022	7.6%	**7.3%**	Federal Office Confirms Pricing Rate of 7.3 Percent (*tagesspiegel.de, Apr 12, 2022*)
Italy	Jun 2021	**1.3%**	**1.3%**	Italy, inflation June +0.1% month, +1,3% year (*ilmessaggero.it, Jun 30, 2021*)
Netherlands	Jul 2022	**11.6%**	10.3%	Inflation rises to 11.6% in July after previous decline (*telegraaf.nl, Jul 29, 2022*)
Spain	Jan 2023	**5.9%**	7.5%	Inflation rises by two-tenths, up to 5.9%, due to the withdrawal of fuel aid (*lavanguardia.com, Feb 15, 2023*)

Notes: The values of the harmonized index of consumer prices (HICP) and the consumer price index (CPI) are obtained from press releases issued by the countries' statistical offices at the time of publication of the data. The example headlines are English machine translations.

Table A.4: Examples of headlines stating the value of the inflation rate

Country	News sites	Number of stories
Austria	diepresse.com, krone.at, kleinezeitung.at, wienerzeitung.at, derstandard.at, kurier.at, news.at	8,964
Belgium	nieuwsblad.be, hln.be, lesoir.be, standaard.be, tijd.be, demorgen.be, lalibre.be, grenzecho.net	5,919
Bulgaria	dnevnik.bg, 24chasa.bg, telegraph.bg, trud.bg, standartnews.com, segabg.com, capital.bg	7,409
Croatia	vecernji.hr, jutarnji.hr, 24sata.hr, slobodnadalmacija.hr, novilist.hr, gla-sistre.hr, poslovni.hr	9,612
Cyprus	cyprus-mail.com, cyprusweekly.com.cy, philenews.com, politis.com.cy, sime-rini.sigmalive.com	606
Czechia	lidovky.cz, idnes.cz, pravo.cz, blesk.cz, hn.cz, respekt.cz	2,298
Denmark	jyllands-posten.dk, berlingske.dk, politiken.dk, ekstrabladet.dk, infor-mation.dk, bt.dk	1,120
Estonia	postimees.ee, ohtuleht.ee, epl.delfi.ee, aripaev.ee, maaleht.delfi.ee, ek-spress.delfi.ee	2,391
Finland	hs.fi, is.fi, iltalehti.fi, hbl.fi, kauppalehti.fi, helsinkitimes.fi	5,357
France	lemonde.fr, liberation.fr, lefigaro.fr, ouest-france.fr, lexpress.fr, lepoint.fr	22,168
Germany	faz.net, sueddeutsche.de, welt.de, handelsblatt.com, focus.de, spiegel.de, zeit.de, bild.de	30,597
Greece	tanea.gr, ethnos.gr, tovima.gr, kathimerini.gr, naftemporiki.gr	14,436
Hungary	magyarhirlap.hu, nepszava.hu, magyarnemzet.hu, blikk.hu, metropol.hu, hvg.hu	6,223
Ireland	irishtimes.com, independent.ie, irishexaminer.com, sundayworld.com, busi-nesspost.ie, thesun.ie, irishmirror.ie	10,099
Italy	corriere.it, repubblica.it, ilmessaggero.it, lastampa.it, ilsole24ore.com	16,271
Latvia	diena.lv, nra.lv, db.lv, la.lv, ves.lv, mklat.lv	1,934
Lithuania	lrytas.lt, kauno.diena.lt, vz.lt, veidas.lt	9,076
Luxembourg	journal.lu, wort.lu, tageblatt.lu	1,786
Malta	timesofmalta.com, independent.com.mt, maltatoday.com.mt	4,405
Netherlands	ad.nl, nrc.nl, telegraaf.nl, volkskrant.nl, trouw.nl, fd.nl, vn.nl, parool.nl	3,770
Macedonia	novamakedonija.com.mk, vecer.mk, koha.mk, slobodenpecat.mk	1,943
Poland	wyborcza.pl, rp.pl, fakt.pl, se.pl, dziennik.pl, polityka.pl, wprost.pl, newsweek.pl	10,521
Portugal	dn.pt, publico.pt, cmjornal.pt, jn.pt, expresso.pt	1,333
Romania	adevarul.ro, click.ro, libertatea.ro, evz.ro, jurnalul.ro, romanialibera.ro, capi-tal.ro	14,102
Serbia	politika.rs, blic.rs, danas.rs, glas-javnosti.rs, nin.co.rs, vreme.com, novosti.rs	9,341
Slovakia	dennikn.sk, pravda.sk, sme.sk, cas.sk, pluska.sk	4,130
Slovenia	dnevnik.si, delo.si, vecer.com, slovenskenovice.si, finance.si, dnevnik.si, mladina.si, primorske.svet24.si	4,998
Spain	elmundo.es, elpais.com, abc.es, larazon.es, lavanguardia.com, elperiodi-co.com/es	19,115
Sweden	aftonbladet.se, dn.se, expressen.se, svd.se, gp.se, sydsvenskan.se	8,019
Turkey	hurriyet.com.tr, sozcu.com.tr, milliyet.com.tr, cumhuriyet.com.tr	43,263
	Total	281,206

Table A.5: Sample of news sites and inflation-related stories

	(1) Population size	(2) GDP	(3) Government debt	(4) Interest rate	(5) Unemploy-ment rate	(6) Balance of payments
Increasing-infl. threshold	-2.37	-1.14	-23.24	0.14	0.10	-6.59
	(3.05)	(0.70)	(18.55)	(0.10)	(0.14)	(345.98)
Decreasing-infl. threshold	3.66	3.63	-93.61	0.10	-0.78	-394.49
	(7.77)	(3.36)	(56.04)	(0.16)	(0.53)	(435.26)
Country fixed effects	no	yes	yes	yes	yes	yes
Observations	2146	2077	1942	1977	2031	1745

Notes: Population size is based on yearly observations and refers to the number of inhabitants (in million) of a country on 1 January. GDP is based on quarterly observations and refers to chain-linked volumes. Government debt is based on quarterly observations and is measured in billion euros. Interest rate is based on monthly observations and refers to long-term government bond yield. The unemployment rate is based on monthly observations. The balance of payments (current account) is based on monthly observations and is measured in millions of euros. All specifications include time fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% 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 A.6: Balance checks

	(1) Expectations (OLS reduced form)	(2) Sensational headlines (IV first stage)	(3) Expectations (IV second stage)
P(sensational headlines)			-6.029
			(18.000)
Increasing-inflation threshold	1.047	-0.174	
	(0.944)	(0.527)	
Decreasing-inflation threshold	-0.017	0.279	1.666
	(1.169)	(0.266)	(5.136)
Mean of dependent variable	24.693	1.425	24.693
SD of dependent variable	17.071	2.912	17.071
Kleibergen-Paap F statistic		0.109	

Notes: $N = 2{,}146$ *(up to 30 countries and 77 months between 2017–2023). All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses any integer between 1 and 29 for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.*

* *p<0.10,* ** *p<0.05,* *** *p<0.01*

Table A.7: Inflation threshold events, sensational news, and inflation expectations (integers as thresholds)

	(1) Expectations (OLS reduced form)	(2) Sensational headlines (IV first stage)	(3) Expectations (IV second stage)	(4) Expectations (OLS reduced form)	(5) Sensational headlines (IV first stage)	(6) Expectations (IV second stage)
P(sensational headlines)			3.821***			4.419***
			(1.211)			(1.502)
6-month protection period						
- Increasing-infl. threshold	5.870***	1.536***				
	(1.442)	(0.332)				
- Decreasing-infl. threshold	1.346	0.554	-0.770			
	(3.965)	(0.618)	(5.473)			
18-month protection period						
- Increasing-infl. threshold				6.701***	1.516***	
				(1.728)	(0.389)	
- Decreasing-infl. threshold				NA	NA	NA
Mean of dependent variable	24.693	1.425	24.693	25.683	1.465	25.683
SD of dependent variable	17.071	2.912	17.071	17.331	3.040	17.331
Kleibergen-Paap F statistic		21.462			15.180	
Observations	2098	2098	2098	1903	1903	1903

Notes: All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 6 or 18 months. NA denotes that decreasing-inflation threshold events are not observed in the sample when using an 18-month protection period. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country. * *p<0.10,* ** *p<0.05,* *** *p<0.01*

Table A.8: Inflation threshold events, sensational news, and inflation expectations (alternative threshold protection periods)

	(1) Expectations (OLS reduced form)	(2) Sensational headlines (IV first stage)	(3) Expectations (IV second stage)	(4) Expectations (OLS reduced form)	(5) Sensational headlines (IV first stage)	(6) Expectations (IV second stage)
P(sensational headlines)			3.685**			2.206**
			(1.342)			(0.828)
Increasing-infl. threshold	4.684***	1.271***		2.794**	1.267***	
	(1.332)	(0.358)		(1.223)	(0.325)	
Decreasing-infl. threshold	4.150	0.271	3.152	2.503	-0.142	2.818
	(5.093)	(0.749)	(5.655)	(4.604)	(0.935)	(4.663)
Bandwidth of inflation rate bin dummies	0.2	0.2	0.2	0.5	0.5	0.5
Mean of dependent variable	24.740	1.419	24.740	24.858	1.427	24.858
SD of dependent variable	16.999	2.896	16.999	16.990	2.886	16.990
Kleibergen-Paap F statistic		12.642			15.242	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). All specifications include time and country fixed effects and a 3rd order polynomial of the change in inflation rate. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.
** p<0.10, ** p<0.05, *** p<0.01*

Table A.9: Inflation threshold events, sensational news, and inflation expectations (alternative bandwidths for inflation rate bin dummies)

	(1) Expectations (OLS reduced form)	(2) Sensational headlines (IV first stage)	(3) Expectations (IV second stage)	(4) Expectations (OLS reduced form)	(5) Sensational headlines (IV first stage)	(6) Expectations (IV second stage)
P(sensational headlines)			3.722***			3.802***
			(1.187)			(1.204)
Increasing-infl. threshold	5.824***	1.565***		5.964***	1.569***	
	(1.463)	(0.325)		(1.490)	(0.336)	
Decreasing-infl. threshold	4.319	-0.112	4.735	5.641	-0.106	6.046
	(3.707)	(0.918)	(5.050)	(3.877)	(0.987)	(5.414)
Change of inflation rate, order of polynomial	2	2	2	4	4	4
Mean of dependent variable	24.693	1.425	24.693	24.693	1.425	24.693
SD of dependent variable	17.071	2.912	17.071	17.071	2.912	17.071
Kleibergen-Paap F statistic		23.183			21.840	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). All specifications include time and country fixed effects and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.

* p<0.10, ** p<0.05, *** p<0.01

Table A.10: Inflation threshold events, sensational news, and inflation expectations (alternative polynomial orders for inflation rate change)

	(1)	(2)	(3)
	Expectations (OLS reduced form)	Sensational headlines (IV first stage)	Expectations (IV second stage)
P(sensational headlines)			3.314***
			(1.117)
Increasing-infl. threshold	5.336***	1.610***	
	(1.360)	(0.315)	
Decreasing-infl. threshold	5.021	-1.122	8.739
	(6.519)	(1.039)	(9.191)
Mean of dependent variable	24.646	1.426	24.646
SD of dependent variable	17.088	2.921	17.088
Kleibergen-Paap F statistic		26.040	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.11: Inflation threshold events, sensational news, and inflation expectations (bin dummies for inflation rate change)

	(1)	(2)	(3)
	Expectations (OLS reduced form)	Sensational headlines (IV first stage)	Expectations (IV second stage)
P(sensational headlines)			5.359**
			(2.395)
Increasing-infl. threshold	7.131***	1.331***	
	(2.322)	(0.406)	
Decreasing-infl. threshold	-4.134	-0.169	-3.228
	(4.479)	(0.599)	(5.681)
Inflation rate bin dummies (bandwidth = 0.1) × absolute change in the inflation rate	yes	yes	yes
Mean of dependent variable	24.693	1.425	24.693
SD of dependent variable	17.071	2.912	17.071
Kleibergen-Paap F statistic		10.729	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). All specifications include time and country fixed effects. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.12: Inflation threshold events, sensational news, and inflation expectations (interactive specification)

	(1) Sensational headlines, no shifting (IV first stage)	(2) Expectations (IV second stage)	(3) Sensational headlines, shifting 10 days (IV first stage)	(4) Expectations (IV second stage)
P(sensational headlines), no shifting		4.272**		
		(1.939)		
P(sensational headlines), shifting 10 days				4.061***
				(1.248)
Increasing-infl. threshold	1.349***		1.350***	
	(0.453)		(0.252)	
Decreasing-infl. threshold	-0.126	5.447	-0.389	6.501
	(0.783)	(4.792)	(0.724)	(4.753)
Mean of dependent variable	1.417	24.693	1.387	24.693
SD of dependent variable	2.854	17.071	2.605	17.071
Kleibergen-Paap F statistic	8.870		28.671	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). In the baseline specification, all reports published within the first 7 days of a month are shifted to the previous month. In Columns (1) and (2), no reports are shifted. In Columns (3) and (4), all reports published within the first 10 days of a month are shifted to the previous month. All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.13: Inflation threshold events, sensational news, and inflation expectations (alternative assignment rules for inflation headlines)

	(1) Expectations (OLS reduced form)	(2) Sensational headlines (IV first stage)	(3) Expectations (IV second stage)
P(sensational headlines)			3.100*
			(1.673)
Increasing-infl. threshold	3.631**	1.171***	
	(1.327)	(0.403)	
Decreasing-infl. threshold	2.374	-0.089	2.648
	(4.010)	(0.861)	(4.951)
Mean of dependent variable	26.563	1.663	26.563
SD of dependent variable	17.017	4.058	17.017
Kleibergen-Paap F statistic		8.456	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.14: Inflation threshold events, sensational news, and inflation expectations (without regression weights)

	(1) Expectations (OLS reduced form)	(2) Sensational headlines (IV first stage)	(3) Expectations (IV second stage)
P(sensational headlines)			3.957*
			(2.283)
Increasing-infl. threshold	3.679**	0.930**	
	(1.619)	(0.390)	
Decreasing-infl. threshold	6.126	-0.123	6.614
	(3.828)	(0.982)	(4.187)
Mean of dependent variable	24.618	1.419	24.618
SD of dependent variable	16.927	2.906	16.927
Kleibergen-Paap F statistic		5.693	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy.
** p<0.10, ** p<0.05, *** p<0.01*

Table A.15: Inflation threshold events, sensational news, and inflation expectations (CPI-based regressions)

	(1) Expectations (OLS reduced form)	(2) Sensational headlines (IV first stage)	(3) Expectations (IV second stage)
P(sensational headlines narrow)			5.558***
			(1.872)
Increasing-infl. threshold	5.764***	1.037***	
	(1.431)	(0.211)	
Decreasing-infl. threshold	4.909	-0.192	5.974
	(3.960)	(0.608)	(5.894)
Mean of dependent variable	24.693	0.764	24.693
SD of dependent variable	17.071	2.150	17.071
Kleibergen-Paap F statistic		24.261	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). The measure of sensationalism is based on headlines that include the terms "inflation" or "consumer price". All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy.*
** p<0.10, ** p<0.05, *** p<0.01*

Table A.16: Inflation threshold events, sensational news, and inflation expectations (narrow definition of inflation headlines)

	(1) Expectations	(2) Expectations	(3) Expectations
Increasing-infl. threshold	3.993***	12.254***	6.913***
	(0.812)	(2.033)	(0.581)
Value of assignment variable for threshold events occurring within 12 months after crossing the same threshold:	original	set to -0.1	set to missing
Original number of obs. left of the cutoff	2017	2072	2017
Original number of obs. right of the cutoff	129	74	74
Local number of obs. left of the cutoff	96	132	77
Local number of obs. right of the cutoff	75	32	28
Regression function: order of polynomial	1	1	1
Regression function: bandwidth	0.565	0.445	0.409
Bias function: order of polynomial	2	2	2
Bias function: bandwidth	1.741	0.722	0.625

Notes: The table shows robust bias-corrected regression discontinuity estimates based on mean squared error-optimal bandwidth selection, using the estimation implementation provided by Calonico et al. (2017). The assignment variable is defined as: $(rate_{t-1} - rate_{t-2}) - (threshold_{t-2} - rate_{t-2})$. All specifications include time fixed effects, country fixed effects, and a binary decreasing-inflation threshold event indicator. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% 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 A.17: Inflation threshold events and inflation expectations (regression discontinuity estimates)

	Share of households thinking prices have...					
	(1)	(2)	(3)	(4)	(5)	(6)
	Balance of perceptions	...risen a lot	...risen moderately	...risen slightly	...stayed about same	...fallen
Increasing-infl. threshold	-1.678	-0.646	0.317	2.333*	-1.711*	-0.294**
	(1.214)	(2.139)	(2.167)	(1.295)	(0.993)	(0.139)
Decreasing-infl. threshold	0.605	8.730	-2.482	-11.965	5.194	0.523
	(4.096)	(7.095)	(10.754)	(7.249)	(3.863)	(0.451)
Mean of dependent variable	31.679	26.275	27.774	27.880	17.167	0.905
SD of dependent variable	27.712	22.375	8.483	13.575	12.821	1.039

N = 2,146 (Column 1) and N = 1,855 (Columns 2 to 6). The table shows OLS reduced-form estimates. The outcome variables in Columns (2) to (6) are calculated by the authors using microdata on households' inflation expectations and the survey weights provided by the European Commission's Harmonised Consumer Survey. The data exclude country-month pairs with less than 800 interviews. All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.18: Inflation threshold events and inflation perceptions

	Share of households expecting prices to...				
	(1)	(2)	(3)	(4)	(5)
	...increase more rapidly	...increase at same rate	...increase at slower rate	...stay about same	...fall
Increasing-infl. threshold	3.956**	1.022	-1.441	-2.749**	-0.788**
	(1.442)	(1.006)	(1.039)	(1.040)	(0.372)
Decreasing-infl. threshold	6.639	-2.816	-7.615*	2.603	1.189*
	(4.688)	(2.740)	(3.877)	(3.775)	(0.616)
Mean of dependent variable	20.191	38.955	14.759	24.194	1.901
SD of dependent variable	10.595	11.775	7.178	14.612	2.070

N = 1,855 (up to 28 countries and 75 months between 2017–2023). The table shows OLS reduced-form estimates. The outcome variables are calculated by the authors using microdata on households' inflation expectations and the survey weights provided by the European Commission's Harmonised Consumer Survey. The data exclude country-months with less than 800 interviews. All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.

** $p<0.10$, ** $p<0.05$, *** $p<0.01$*

Table A.19: Inflation threshold events and qualitative inflation expectations (decomposed by answer options)

	Mean inflation estimate of households expecting prices to...			
	(1)	(2)	(3)	(4)
	...increase more rapidly	...increase at the same rate	...increase at a slower rate	...fall
Increasing-infl. threshold	0.112	-0.203	0.005	0.226
	(0.292)	(0.274)	(0.155)	(0.256)
Decreasing-infl. threshold	-0.764	0.813	-0.158	-1.119***
	(1.050)	(0.755)	(0.752)	(0.401)
Mean of dependent variable	11.724	9.358	6.916	-3.183
SD of dependent variable	4.871	4.221	3.061	1.064
Observations	1854	1854	1854	1683

The table shows OLS reduced-form estimates. The outcome variables are calculated by the authors using data on households' quantitative inflation expectations ("By how many per cent do you expect consumer prices to go up/down change in the next 12 months?") and the survey weights provided by the European Commission's Harmonised Consumer Survey. The data exclude country-months with less than 800 interviews. Responses with estimates < -5% or > 30% are omitted when calculating the mean inflation estimate, following the truncation approach of Huber et al. (2023). All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.20: Inflation threshold events and quantitative inflation expectations (decomposed by answer options)

	(1) Number of inflation reports (IV first stage)	(2) Expectations (IV second stage)	(3) Number of inflation reports (IV first stage)	(4) Expectations (IV second stage)
Number of inflation reports		-22.154		-26.672
		(16.718)		(26.300)
Increasing-infl. threshold	-0.260		-0.206	
	(0.216)		(0.219)	
Decreasing-infl. threshold	0.811	22.887	0.809	26.508
	(0.669)	(22.062)	(0.674)	(30.972)
Total number of reports			-0.000*	-0.000
			(0.000)	(0.001)
Mean of dependent variable	2.191	24.693	2.191	24.693
SD of dependent variable	2.062	17.071	2.062	17.071
Kleibergen-Paap F statistic	1.457		0.882	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.
* *p<0.10,* ** *p<0.05,* *** *p<0.01*

Table A.21: Inflation threshold events, number of inflation headlines, and inflation expectations

	(1) Number of inflation reports (IV first stage)	(2) Expectations (IV second stage)	(3) Number of inflation reports (IV first stage)	(4) Expectations (IV second stage)
Increasing-infl. threshold	-0.034		0.004	
	(0.037)		(0.037)	
Decreasing-infl. threshold	0.110	23.729	0.109	-153.165
	(0.143)	(25.825)	(0.148)	(1591.083)
Number of inflation reports		-170.892		1454.383
(narrow definition)		(168.621)		(14346.929)
Total number of reports			-0.000***	0.016
			(0.000)	(0.162)
Mean of dependent variable	0.313	24.693	0.313	24.693
SD of dependent variable	0.386	17.071	0.386	17.071
Kleibergen-Paap F statistic	0.833		0.011	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). Counts of inflation reports are based on headlines that include the terms "inflation" or "consumer price". All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.*
* *p<0.10,* ** *p<0.05,* *** *p<0.01*

Table A.22: Inflation threshold events, number of inflation headlines, and inflation expectations (narrow definition of inflation headlines)

	(1) Google searches for inflation (IV first stage)	(2) Expectations (IV second stage)	(3) Google searches for CPI (IV first stage)	(4) Expectations (IV second stage)
Google searches for inflation		1.494		
		(1.918)		
Google searches for CPI				1.506
				(2.086)
Increasing-infl. threshold	3.858		3.639	
	(4.988)		(5.240)	
Decreasing-infl. threshold	-8.969	18.309	-11.272	21.900
	(7.743)	(15.558)	(7.231)	(24.046)
Mean of dependent variable	24.626	24.693	29.586	24.693
SD of dependent variable	24.290	17.071	23.807	17.071
Kleibergen-Paap F statistic	0.598		0.482	

Notes: $N = 2{,}146$ (up to 30 countries and 77 months between 2017–2023). All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. "Google searches for inflation" measures the monthly volume of searches for the search topic inflation, whereas "Google searches for CPI" measures the monthly volume of searches for the search topic consumer price index, based on data from Google Trends. The search volume is measured in relative terms and ranges from 0 (least amount) to 100 (most amount). A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.23: Inflation threshold events, Google searches, and inflation expectations

	Sociotropic question			Egocentric question		
	(1)	(2)	(3)	(4)	(5)	(6)
	Attitudes (OLS reduced form)	Sensational headlines (IV first stage)	Attitudes (IV second stage)	Attitudes (OLS reduced form)	Sensational headlines (IV first stage)	Attitudes (IV second stage)
P(sensational headlines)			4.186***			1.346**
			(1.489)			(0.593)
Increasing-infl. threshold	6.553***	1.566***		2.108**	1.566***	
	(1.976)	(0.318)		(0.812)	(0.318)	
Decreasing-infl. threshold	4.071	-0.117	4.562	2.185	-0.117	2.343
	(4.657)	(0.935)	(6.663)	(5.123)	(0.935)	(6.060)
Mean of dependent variable	-17.851	1.425	-17.851	-13.689	1.425	-13.689
SD of dependent variable	22.037	2.912	22.037	12.290	2.912	12.290
Kleibergen-Paap F statistic		24.211			24.211	

N = 2,146 (up to 30 countries and 77 months between 2017–2023). Data on households' readiness to spend on durables come from the European Business and Consumer Surveys. The sociotropic question asks: In view of the general economic situation, do you think that now it is the right moment for people to make major purchases such as furniture, electrical/electronic devices, etc.? The corresponding variable is the balance of the number of respondents stating "yes, it is the right moment now" minus the number of respondents stating "no, it is not the right moment now". The egocentric question asks: Compared to the past 12 months, do you expect to spend more or less money on major purchases (furniture, electrical/electronic devices, etc.) over the next 12 months? The corresponding variable is the balance of the number respondents stating to spend more minus the number of respondents stating to spend less. All specifications include time and country fixed effects, a 3rd order polynomial of the change in inflation rate, and inflation rate bin dummies with a bandwidth of 0.1. The regressions are weighted by countries' population share in the sample. A threshold event refers to a situation where a country's inflation rate crosses a value of 5, 10, 15, 20, or 25% for the first time in the past 12 months. The excluded instrument is the increasing-inflation threshold event dummy. Standard errors (in parentheses) are clustered by country.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table A.24: Inflation threshold events, sensational news, and readiness to spend on durables

B. Survey experiment

B.1. Survey screenshots

This survey is part of a research project at Jönköping University (JU), Sweden. The project investigates the impact of news coverage on public opinion.

The survey takes about 3 minutes and consists of two steps:

1) You will see the headlines of five fictional articles from various news sites, such as New York Times and BBC. You will be asked to rate your interest in reading each of the articles.

2) We will ask about your opinion about issues mentioned in the headlines. This part also includes an attention check in the form of a simple quiz. You can use the back button to re-read the headlines if necessary.

Participation does not entail any personal risks, is voluntary, and can be stopped anytime. Your information is confidential and does not include sensitive personal data. The data will be stored on an encrypted, GDPR-compliant drive provided by JU's IT department and analyzed using statistical methods. The anonymous data may be made available to other academic researchers (via Harvard Dataverse) only to replicate the results. Results will be disseminated in standard academic outlets and via mainstream media outlets. You will not be identifiable in any report or publication.

Responsible researcher: Marcel Garz, Jönköping University, P.O. Box 1026, SE-55111 Jönköping; email: marcel.garz@ju.se

I have read and understand the above information and consent to participating in the study.

I do not consent to participating in the study.

→

What is your Prolific ID?
Please note that this response should auto-fill with the correct ID

→

Joaquin Phoenix wins best actor Oscar for role in "Joker"

Please rate how interested you would be to read this article:

1 Not interested at all

2

3

4

5 Very interested

←

→

Narendra Modi elected as Prime Minister of India

Please rate how interested you would be to read this article:

1 Not interested at all

2

3

4

5 Very interested

←

→

Elon Musk announces that Twitter will be rebranded to X

Please rate how interested you would be to read this article:

1 Not interested at all

2

3

4

5 Very interested

←

→

Co-host New Zealand exits Women's World Cup after goalless draw

Please rate how interested you would be to read this article:

1 Not interested at all

2

3

4

5 Very interested

←

→

Economy: Higher oil prices in 2023

Please rate how interested you would be to read this article:

- 1 Not interested at all
- 2
- 3
- 4
- 5 Very interested

← →

Thank you! Now the second part of the survey starts, which consists of questions about facts included in the headlines you just read, as well as questions about your personal opinion about various issues. You can use the back button to re-read the headlines if necessary.

← →

What will Twitter be rebranded as?

- X
- Twitter-X
- xTwitter

← →

Who won the Oscar for his role in "Joker"?

- Joaquin Phoenix
- Anthony Hopkins
- Christian Bale

← →

How will consumer prices develop in the next 12 months in your country of residence? Prices will ...

- ... increase more rapidly
- ... increase at the same rate
- ... increase at a slower rate
- ... stay about the same
- ... fall

← →

By how many percent do you expect consumer prices to go up in the next 12 months in your country of residence?

Enter a value in percent

← →

Thank you for taking part in the study. Please return to Prolific and enter the following completion code to register your submission:

CUTI53S4

B.2. Additional figures and tables

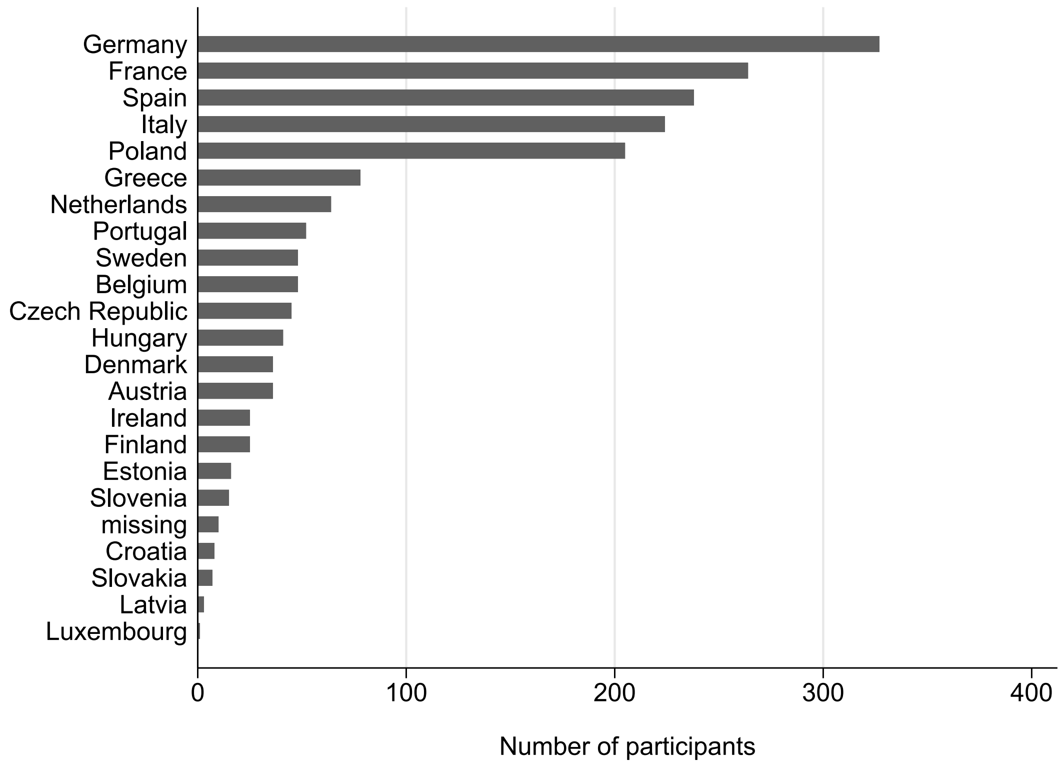


Figure B.1: Distribution of survey participants by country

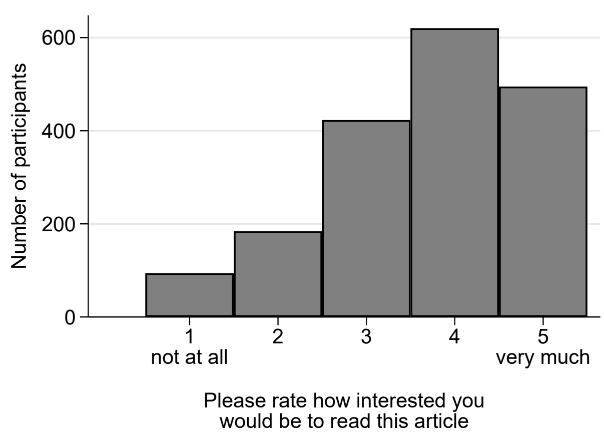


Figure B.2: Interest in the reading the inflation story – distribution of responses

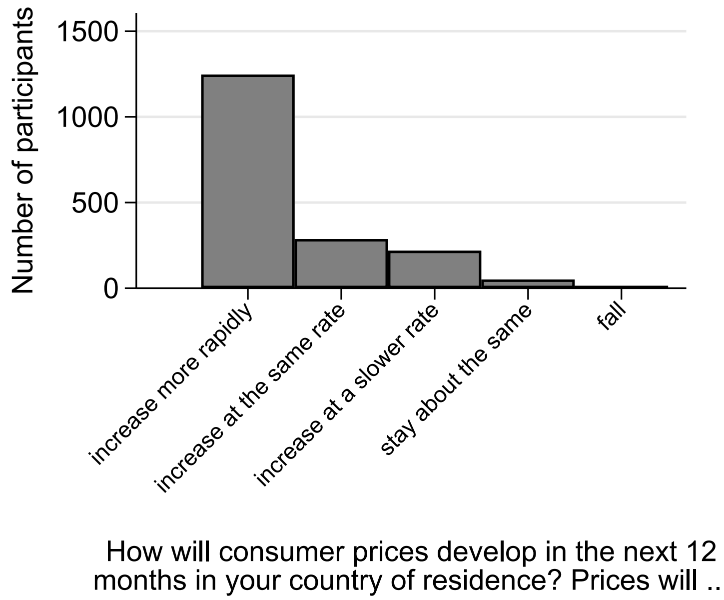
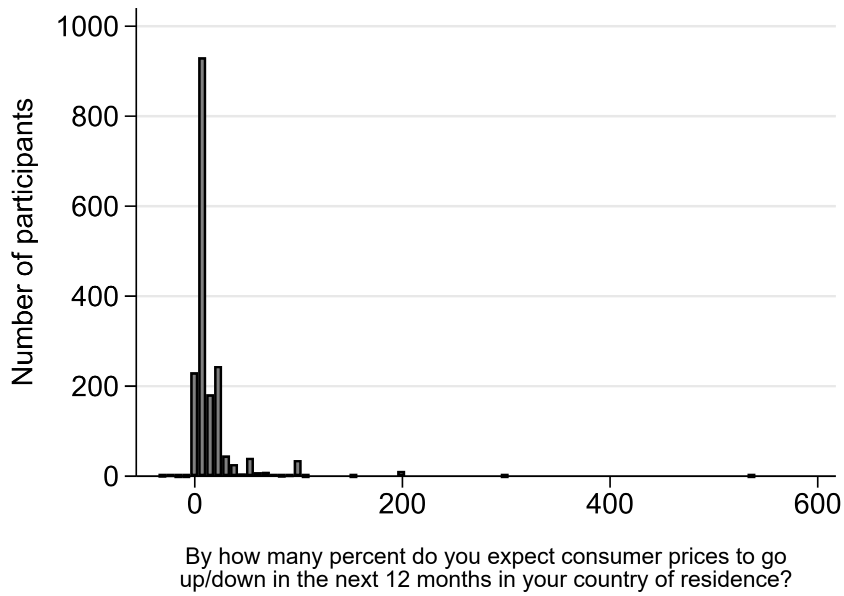
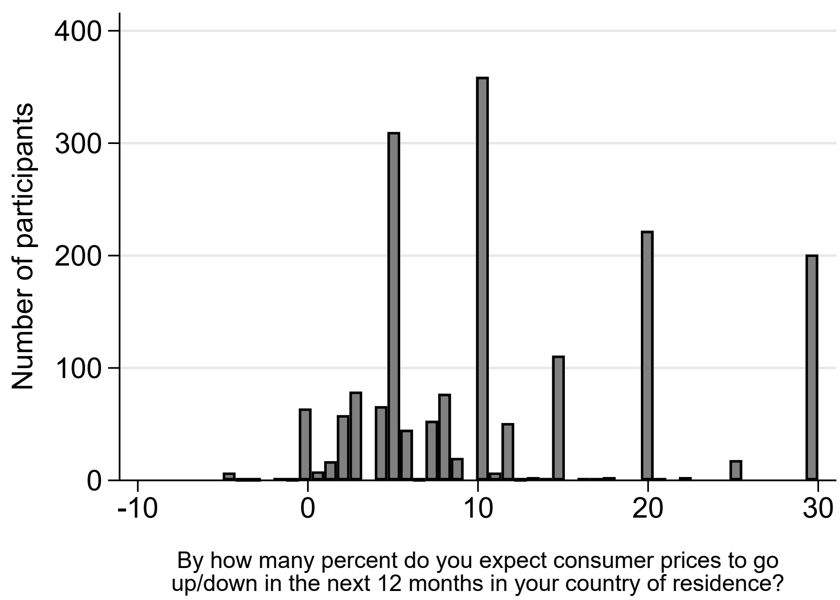


Figure B.3: Qualitative inflation expectations – distribution of responses



(a) Original responses



(b) Winsorized responses

Figure B.4: Quantitative inflation expectations – distribution of responses

Category	Headline
Culture	Joaquin Phoenix wins best actor Oscar for role in "Joker"
Politics	Narendra Modi elected as Prime Minister of India
Society	Elon Musk announces that Twitter will be rebranded to X
Sports	Co-host New Zealand exits Women's World Cup after goalless draw

Table B.1: Inflation-unrelated headlines

#	Non-sensational phrasing	Sensational phrasing
1	Consumer price index increases in 2022	Consumer price index reaches historic double-digit threshold in 2022
2	Consumer prices have climbed to higher level	Consumer prices skyrocket to unprecedented levels
3	New inflation estimate: Higher rate of price change	Never seen before: Inflation exceeds 10% threshold
4	Eurostat: Inflation on the rise	Eurostat: Soaring inflation breaks all records
5	Food price growth accelerates	Food price growth reaches 5% milestone!
6	Price developments: Inflation rate accelerates	RECORD HIGH: Inflation reaches double digits
7	Inflation rate on rise, according to Statistical Office	Inflation rate hits 20% barrier for the first time ever
8	Economy: Higher oil prices in 2023	Oil prices highest since 1973

Table B.2: Inflation-related headlines

#	Question	Answer options
1	Who won the Oscar for his role in "Joker"?	a) Joaquin Phoenix (correct) b) Anthony Hopkins c) Christian Bale
2	What will Twitter be rebranded as?	a) X (correct) b) Twitter-X c) xTwitter
3	How will consumer prices develop in the next 12 months? Prices will ...	a) ... increase more rapidly b) ... increase at the same rate c) ... increase at a slower rate d) ... stay about the same e) ... fall
	If 3 is answered with a), b), or c), proceed to 4a, if 3 is answered with d), end, and if 3 is answered with e), proceed to 4b.	
4a 4a	By how many percent do you expect consumer prices to go up in the next 12 months?	Consumer prices will increase by [—.-]%.
4b 4b	By how many percent do you expect consumer prices to go down in the next 12 months?	Consumer prices will decrease by [—.-]%.

Table B.3: Content of the Quiz

	Mean	SD	Min.	Max.
Headline number:				
- 1	0.12	0.33	0.00	1.00
- 2	0.12	0.33	0.00	1.00
- 3	0.13	0.34	0.00	1.00
- 4	0.13	0.34	0.00	1.00
- 5	0.11	0.32	0.00	1.00
- 6	0.12	0.33	0.00	1.00
- 7	0.13	0.34	0.00	1.00
- 8	0.13	0.33	0.00	1.00
Treated (yes/no)	0.50	0.50	0.00	1.00
Headline includes numerical value (binary)	0.38	0.48	0.00	1.00
Interested to read (scale 1: not at all to 5: very)	3.68	1.13	1.00	5.00
Expecting increasing inflation (binary)	0.69	0.46	0.00	1.00
Quantitative estimate (percent)	15.85	27.36	-35.00	540.00
Winsorized quantitative estimate (percent)	11.55	8.72	-5.00	30.00
Male (binary)	0.51	0.50	0.00	1.00
Age category:				
- missing	0.01	0.09	0.00	1.00
- 18 to 25	0.27	0.44	0.00	1.00
- 26 to 30	0.25	0.44	0.00	1.00
- 31 to 38	0.23	0.42	0.00	1.00
- 39 to 74	0.23	0.42	0.00	1.00
Employment status:				
- other	0.25	0.43	0.00	1.00
- full-time	0.54	0.50	0.00	1.00
- part-time	0.12	0.33	0.00	1.00
- unemployed	0.09	0.28	0.00	1.00

Notes: $N = 1{,}816$ respondents.

Table B.4: Summary of data from survey experiment

	Mean treated	Mean untreated	Difference (p-value)
Male (binary)	0.51	0.51	0.961
Age category:			
- missing	0.01	0.01	0.606
- 18 to 25	0.27	0.27	0.974
- 26 to 30	0.25	0.26	0.725
- 31 to 38	0.24	0.23	0.358
- 39 to 74	0.23	0.24	0.681
Employment status:			
- other	0.24	0.25	0.463
- full-time	0.55	0.53	0.431
- part-time	0.12	0.13	0.326
- unemployed	0.09	0.08	0.385
Number of participants	911	905	

Notes: The p-values refer to t tests on the equality of means between treated and untreated participants.

Table B.5: Balance table of demographic variables

	(1) Reading interest	(2) Expecting increasing inflation	(3) Quantitative estimate	(4) Winsorized quantitative estimate
Sensational headline treatment	-0.034	0.023	4.063***	1.349***
	(0.052)	(0.021)	(1.288)	(0.405)
Mean of dependent variable	3.682	0.687	15.849	11.552
SD of dependent variable	1.130	0.464	27.364	8.717
Observations	1816	1816	1797	1797

Notes: All models include an intercept, headline fixed effects, country fixed effects, and controls for age (categories), sex, and employment status (output omitted). Robust standard errors in parentheses.
** $p<0.10$, ** $p<0.05$, *** $p<0.01$*

Table B.6: Results of survey experiment (with control variables)

C. Model derivations and additional results

C.1. New Keynesian model with left-digit-biased inflation expectations

We use a standard New Keynesian model (see, e.g., Galí, 2015). Instead of assuming full rational expectations, we assume households have left-digit-biased inflation expectations to align with our results. We further abstract from long-run growth and consider only one exogenous shock, a demand shock, to illustrate the implications of left-digit-biased inflation expectations. The model environment is described next, with derivations identical to those in Galí (2015, ch. 3) omitted for brevity.

C.1.1. Households

A representative infinitely-lived household seeks to maximize intertemporal utility

$$\mathbb{E}_t^b \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\varphi}}{1+\varphi} \right) Z_t, \tag{C.1}$$

where C is a consumption index, N denotes hours worked, Z_t is an exogenous preference shifter following an AR(1) process in logs with zero mean and $\rho_z \in [0,1)$ persistence, $\beta \in (0,1)$ is the discount factor, and $\sigma \geq 0$ and $\varphi \geq 0$ determine the intertemporal elasticity of substitution and the Frisch elasticity of labor supply, respectively. The expectation operator $\mathbb{E}_t^b$ denotes *behavioral* expectations, which do not need to coincide with rational expectations. The consumption index is given by

$$C_t = \left(\int_0^1 C_t(i)^{1-\frac{1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}},$$

where $\epsilon > 1$ is the elasticity of substitution between goods and $C_t(i)$ denotes the consumption of variety i. The period budget constraint reads

$$\int_0^1 P_t(i) C_t(i) di + Q_t B_t \leq W_t N_t + B_{t-1} + D_t, \tag{C.2}$$

where $P_t(i)$ is the price of good i, Q_t is the nominal price of a risk-free bond, B_t is the stock of nominal bonds, W_t is the nominal wage, and D_t is dividends.

Household inflation expectations are explained in detail in section 2.2: A household perceives inflation, π_t^p, with a left-digit bias as specified in equations (2) and (3), believes that inflation follows an AR(1) process, equation (4), with steady-state inflation $\pi^* = 0$ and hence forms inflation expectations based on perceived inflation, equation (5).

The household chooses consumption/savings and labor supply to maximize intertemporal utility (C.1) subject to the budget constraint (C.2) and an optimal allocation of consumption expenditures among different goods. The resulting first-order conditions are

$$\begin{aligned}
C_t(i) &= \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} C_t \\
P_t &\equiv \left(\int_0^1 P_t(i)^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}} \\
P_t C_t + Q_t B_t &\leq W_t N_t + B_{t-1} + D_t \\
C_t^{\sigma} N_t^{\varphi} &= \frac{W_t}{P_t} \\
Q_t &= \beta \mathbb{E}_t^b \left(\frac{C_t^{\sigma}}{C_{t+1}^{\sigma}} \frac{P_t}{P_{t+1}} \frac{Z_{t+1}}{Z_t}\right) \qquad \text{(C.3)}
\end{aligned}$$

The first equation is the demand for good i, the second defines the ideal price index, the third denotes total consumption expenditures, the fourth is the re-written budget constraint, the fifth is the labor supply equation, and the last is the Euler equation.

C.1.2. Firms

Risk-neutral firms indexed by $i \in [0,1]$ produce a differentiated good $Y_t(i)$ according to

$$Y_t(i) = N_t(i),$$

where $N_t(i)$ is labor demand. Marginal costs are then equal to the real wage $mc_t = W_t/P_t$. Each firm has two managers, one setting prices and one making forecasts (see, e.g., Pfäuti, 2023). We assume that the forecasters form expectations as households do. When setting prices, firms face quadratic price-adjustment cost (Rotemberg, 1982) such that per-period real profits are given by

$$\frac{P_t(i)}{P_t} Y_t(i) - mc_t N_t(i) - \frac{\delta}{2}\left(\frac{P_t(i)}{P_{t-1}(i)} - 1\right)^2 C_t - T_t,$$

where $\delta > 0$ and T_t is a lump-sum tax. Using the production function and the demand for good i with $Y_t(i) = C_t(i)$ in equilibrium, the price-setter chooses the price $P_t(i)$ to maximize

$$\Pi_t(i) = \mathbb{E}_t^b \sum_{j=0}^{\infty} \beta^j \left[\frac{P_{t+j}(i)}{P_{t+j}} \left(\frac{P_{t+j}(i)}{P_{t+j}} \right)^{-\epsilon} C_{t+j} - mc_{t+j} \left(\frac{P_{t+j}(i)}{P_{t+j}} \right)^{-\epsilon} C_{t+j} \right.$$
$$\left. - \frac{\delta}{2} \left(\frac{P_{t+j}(i)}{P_{t+j-1}(i)} - 1 \right)^2 C_{t+j} + T_{t+j} \right].$$

The FOC reads

$$(\epsilon - 1) \left(\frac{P_t(i)}{P_t} \right)^{-\epsilon} \frac{C_t}{P_t} = \epsilon mc_t \left(\frac{P_t(i)}{P_t} \right)^{-\epsilon-1} \frac{C_t}{P_t} - \delta \left(\frac{P_t(i)}{P_{t-1}(i)} - 1 \right) \frac{C_t}{P_{t-1}(i)}$$
$$+ \beta \delta \mathbb{E}_t^b \left[\left(\frac{P_{t+1}(i)}{P_t(i)} - 1 \right) \frac{P_{t+1}(i)}{P_t(i)} \frac{C_{t+1}}{P_t(i)} \right].$$

Since all firms face the same profit-maximization problem, a symmetric equilibrium exists, implying $Y_t(i) = C_i(t) = C_t = Y_t$ and $P_t(i) = P_t$. The FOC then simplifies to

$$(\epsilon - 1) Y_t = \epsilon mc_t Y_t - \delta \pi_t (1 + \pi_t) Y_t + \beta \delta \mathbb{E}_t^b [\pi_{t+1} (1 + \pi_{t+1}) Y_{t+1}] \tag{C.4}$$

where $\pi_t \equiv \frac{P_t}{P_{t-1}} - 1$ is the inflation rate.

C.1.3. Government and monetary policy

The government follows a balanced budget rule such that

$$T_t = \frac{D_t}{P_t} = \left[\frac{P_t(i)^*}{P_t} - mc_t \right] Y_t(i)^* - \frac{\delta}{2} \left(\frac{P_t(i)^*}{P_{t-1}(i)^*} - 1 \right)^2 C_t,$$

where a star denotes the optimal price and quantity. Under the balanced budget rule, the government sets taxes (T_t) so that after-tax firm profits are zero, meaning that the government redistributes all profits to households. In equilibrium, bonds are in zero supply, $B_t = 0$, and hence do not appear in the government budget.

Monetary policy is conducted by a central bank that sets the nominal interest rate according to a Taylor rule

$$i_t = \rho + \phi_\pi \pi_t + \phi_y \hat{y}_t, \tag{C.5}$$

where $\hat{y}_t \equiv y_t - y$ is the deviation of log-output from its steady state.

C.1.4. Three-equation New Keynesian model

A log-linear approximation of the Euler equation C.3 around the zero-inflation, zero-growth steady state yields

$$c_t = \mathbb{E}_t^b c_{t+1} - \frac{1}{\sigma}\left[i_t - \mathbb{E}_t^b \pi_{t+1} - \rho - (1-\rho_z)z_t\right] \tag{C.6}$$

where lower-case variables are the logarithm of the uppercase variables and $i_t \equiv -\log Q_t$ and $\rho \equiv -\log \beta$ denote the nominal interest and discount rate, respectively.[21]

Log-linearizing the firm's FOC (C.4) around the steady state yields

$$\pi_t = \beta \mathbb{E}_t^b \pi_{t+1} + \frac{\epsilon - 1}{\delta}(\sigma + \varphi - 1)\,\hat{y}_t, \tag{C.7}$$

where a hatted variable denotes the log deviation of the respective variable from its steady state value.

Next, we must express the NKPC in terms of the output gap $\tilde{y}_t \equiv y_t - y_t^n$, where y_t^n is the natural output level. We calculate output under flexible prices with $\delta = 0$ to obtain it. The optimal price is then a constant mark-up over marginal cost, $\frac{P_t(i)}{P_t} = \frac{\epsilon}{\epsilon-1} mc_t$, and natural output in logs is given by $y_t^n = \frac{1}{\sigma+\varphi}\log\left(\frac{\epsilon-1}{\epsilon}\right)$, which is constant (no technology shocks) and hence equal to steady-state output (no adjustment cost in steady state) such that $y_t^n = y$. Replacing $\hat{y}_t$ in equation (C.7) accordingly yields the NKPC, equation (9) in the main text:

$$\pi_t = \beta \mathbb{E}_t^b \pi_{t+1} + \kappa \tilde{y}_t,$$

where $\kappa \equiv \frac{\epsilon-1}{\delta}(\sigma + \varphi - 1)$.

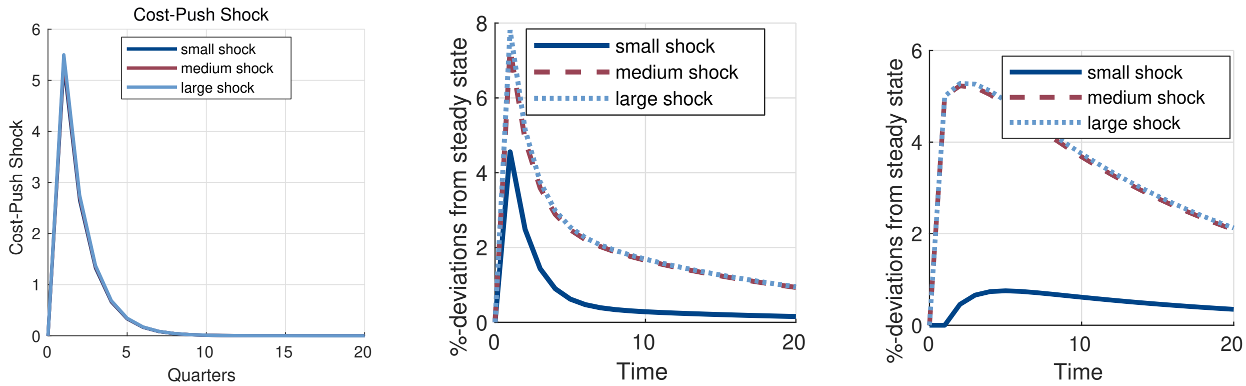
Given $\hat{y}_t = \tilde{y}_t$ and defining $\hat{i}_t = i_t - \rho$, the Euler equation (C.6) and the Taylor rule (C.5) and can be rewritten to

$$\begin{aligned}
\tilde{y}_t &= \mathbb{E}_t^b \tilde{y}_{t+1} - \frac{1}{\sigma}\left[\hat{i}_t - \mathbb{E}_t^b \pi_{t+1} - (1-\rho_z)z_t\right] \\
\hat{i}_t &= \phi_\pi \pi_t + \phi_y \tilde{y}_t,
\end{aligned}$$

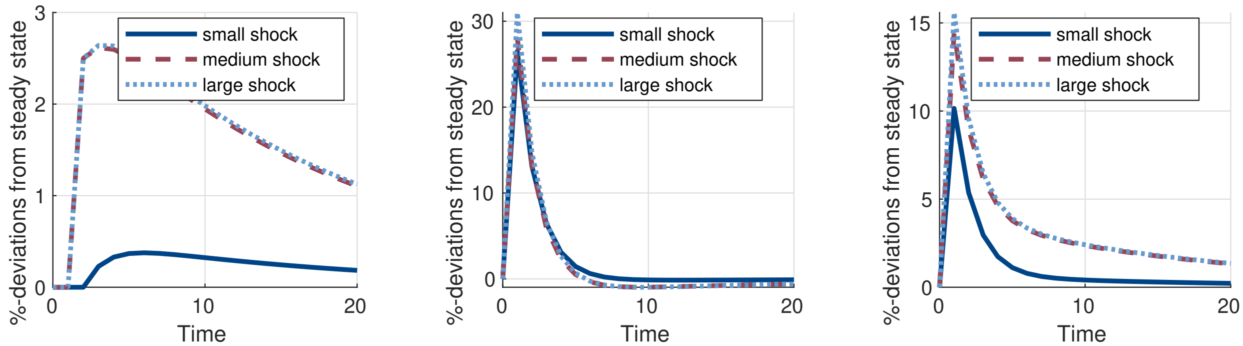
which are equations (10) and (11) in the main text.

[21] To keep the differences between our model and the textbook model (Galí, 2015) minimal, we have assumed that households have *rational* expectations towards the demand shock Z_t.

C.2. Non-linearities in the New Keynesian model



(a) Demand shock **(b)** Inflation **(c)** Perceived inflation



(d) Expected inflation **(e)** Output gap **(f)** Nominal interest rate

Figure C.1: Impulse-response to a demand shock: Non-linearity in shock size

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