

# Pressing on Prices: The Media's Influence on Attention to Inflation \*

Yiyang Chen

Harvard University

November 20, 2024

[[Link to latest version](#)]

## Abstract

This paper examines the influence of media coverage on public attention to inflation, drawing on a dataset of over 8 million news articles from 1966–2024 and a transformer-based topic classification model to identify inflation-related coverage. I developed a rational inattention model in which the cost of acquiring information depends on the precision of signals. Empirically, I use natural disaster coverage as an instrument for inflation-related news coverage, exploiting the crowding-out effect whereby significant disasters displace other topics in the news. The results show that an 1 percentage point increase in the share of total news coverage focused on inflation leads to a 2.7% decrease in inattentive individuals. These findings highlight the role of the media in reducing informational costs and shaping economic expectations, with important implications for monetary policy during inflationary periods.

**Keywords:** *Inflation; Rational inattention; News media.*

**JEL Classification:** *E31; D80; C38; C55.*

---

\*Writing sample prepared for PhD application to xx University. All errors (if any) are mine. As a side note, I wish I could present some preliminary results on my other project “dam displacement and economic growth” (as outlined in my Statement of Purpose), but I’m still in the data collection phase. I have a writeup with more details available [here](#).

# 1 Introduction

Attention is scarce. People don't pay attention to everything. It is an explicit choice made by individuals to absorb and process the most valuable information available to them, and thus shaping their set of information used to make economic decisions. Rational inattention theory, proposed by the seminal work of Sims (2003), provides a framework to study economic decisions made by inattentive agents, whose preferences give rise to endogenous deviations from outcomes in a complete information and fully rational environment. Given obtaining and processing information is costly, the theory builds on the intuitive observation that individuals pay attention to more important things and only when the benefit outweighs the cost.

Prices are the most common economic signals. (In)attention to prices influences expectation and subsequently future consumption-saving behaviors. Federal Reserve Chair Jerome Powell reminded the audience in his 2022 speech at Jackson Hole: "When inflation is persistently high, households and businesses must pay close attention and incorporate inflation into their economic decisions. When inflation is low and stable, they are freer to focus their attention elsewhere." (Powell, 2022)

While individuals may experience price changes in their daily lives, they do not always attribute them to inflation. For instance, if groceries cost 5% more this week than last, a consumer might assume this reflects heavier produce, additional purchases, or other benign explanations. Unit prices are often hard to recall. News media, on the other hand, fill in this gap, allowing individuals recognize inflationary pressures and adjust their expectations accordingly.

In this work, I look at how consumers' inattention interact with inflation dynamics. In particular, I examine if news media serves as a possible channel to reduce costs to obtaining and processing information and thus reduce inattention.

Empirically, this paper documents the relationship between inflation, news coverage, and public attention. Using a novel dataset of over 8 million news articles from sources such as the *New York Times* and *Washington Post*, I find that a 1 percentage point increase in the share of news coverage dedicated to inflation reduces the share of inattentive individuals by 2.7% in my baseline specification. These results highlight the media's role in reducing informational costs and shaping public attention during inflationary periods.

This paper builds on an extensive body of literature exploring attention to economic signals. Research such as Woodford (2003), Andrade and Le Bihan (2013), and Coibion and Gorodnichenko (2015) highlights the role of prior uncertainty in shaping attention to inflation, while Pfäuti (2024) and Baker, McElroy, and Sheng (2020) confirm that attention increases with the level of inflation. Mackowiak and Wiederholt (2009) and Nakamura and Steinsson (2008) further connect these insights to the literature on price setting, exploring how firms adjust prices in response to inflation. The media’s role as a conduit for information dissemination is equally critical, such as highlighted by Soroka (2012), who emphasizes its ability to shape public perceptions and attention. This paper extends these strands of literature by focusing on the interplay between news coverage and public attention to inflation.

Of particular relevance is the recent work by Bracha and Tang (2024), who propose the Attention–Inflation Hypothesis. Using a unique inattention index derived from the Michigan Survey of Consumers, they show that attention to inflation increases with inflation levels. As an additional exercise, they also show that higher inflation correlates with increased supply and consumption of inflation-related news. While their findings suggest a complementarity between inflation and news reporting (and mostly “individuals may consume more of [inflation] news when inflation is high”), I explore a different mechanism: the role of news media in reducing the cost of acquiring inflation-related information, thereby mitigating public inattention to inflation.

The empirical approach follows the methodology of Carroll (2003), who linked macroeconomic expectations of households to professional forecasters using media channels like the *New York Times* and *Washington Post*. I apply a similar strategy, combining large-scale text analysis with a *transformer*-based (deep learning) topic classifier to systematically identify inflation-related content. Again, the relationship between news coverage and attention to inflation can be bidirectional: attention to inflation increases news coverage on inflation, while inflation-related news prompts greater public attention. This reverse causality necessitates the use of an instrument. I use natural disaster coverage as an instrument, exploiting the crowding-out effect where disasters displace other topics from media coverage, providing exogenous variation in the supply of inflation-related news.

Theoretically, I follow Sims (2003), Gabaix (2019) and Bracha and Tang (2024) to de-

velop a simple rational inattention model in which agents decide how much costly information to acquire about inflation. The model incorporates the cost of acquiring information as a function of signal precision, capturing the trade-off between more accurate signals and the higher costs they entail.

This paper contributes to the understanding of how public attention to inflation evolves and the role of media in shaping economic perceptions. The analysis may provide valuable insights for policymakers aiming to manage public expectations in inflationary contexts.

The paper proceeds as follows. Section 2 develops a simple theoretical framework of rational inattention, incorporating costs of information acquisition based on signal precision. Section 3 describes the process to construct the data. Section 4 outlines the empirical methodology. Section 5 presents the main results and their interpretations. Section 6 discusses of the broader implications of these findings and some next steps. Section 7 concludes.

## 2 Rational inattention

In this section, I'll mostly follow Gabaix (2019) and Bracha and Tang (2024) to develop a simple theoretical framework of rational inattention to inflation, where agents decide how much costly information to acquire about the inflation rate before taking an action. Following the rational inattention literature pioneered by Sims (2003), I model attention as a parameter that agents can adjust, balancing the benefits of more accurate information against the costs of acquiring it. Importantly, I incorporate the notion that acquiring more accurate signals entails higher marginal costs, reflecting real-world observations that low-quality signals are easier and less costly to obtain than high-quality ones.

### Agent's Problem

Suppose that at time  $t$ , the true but unobserved inflation rate is  $\pi_t$ . The agent receives a signal about inflation given by:

$$s_t = \pi_t + \varepsilon_t, \tag{1}$$

where  $\varepsilon_t \sim \mathcal{N}(0, \sigma_{\varepsilon,t}^2)$  is Gaussian noise representing the uncertainty or error in the signal. The variance  $\sigma_{\varepsilon,t}^2$  is a choice variable for the agent, reflecting the precision of the signal they

decide to acquire.

The agent aims to choose an action  $a_t$  that minimizes the expected loss associated with the deviation from the true inflation rate. The agent's utility function is given by:

$$u(a_t, \pi_t) = -\frac{1}{2}(a_t - \pi_t)^2. \quad (2)$$

Acquiring information about  $\pi_t$  (through  $s_t$ ) is costly, and the cost depends on the precision (inverse of variance) of the signal. I model the cost of acquiring a signal with variance  $\sigma_{\varepsilon,t}^2$  (or precision  $\tau_t = 1/\sigma_{\varepsilon,t}^2$ ) as an increasing function of the precision:

$$C(\tau_t) = \lambda_t \cdot \tau_t^\alpha, \quad (3)$$

where  $\lambda_t > 0$  is a scaling parameter representing the marginal cost of information, and  $\alpha > 0$  determines how rapidly costs increase with precision.  $\lambda_t$  is the marginal cost when the cost function is linear.

### Information Acquisition and Attention

The agent has a prior belief about  $\pi_t$ , modeled as  $\pi_t \sim \mathcal{N}(\tilde{\pi}, \sigma_\pi^2)$ , where  $\tilde{\pi}$  is the prior mean and  $\sigma_\pi^2$  is the prior variance.

Upon acquiring the signal  $s_t$ , the agent updates their belief about  $\pi_t$  using Bayes' rule. The posterior distribution of  $\pi_t$  is normal with mean:

$$E[\pi_t | s_t] = (1 - m_t) \tilde{\pi} + m_t s_t, \quad (4)$$

where  $m_t$  is the weight placed on the signal, given by:

$$m_t = \frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_{\varepsilon,t}^2} = \frac{\tau_t}{\tau_\pi + \tau_t}, \quad (5)$$

with  $\tau_\pi = 1/\sigma_\pi^2$  being the precision of the prior.

The posterior variance is:

$$\sigma_{\pi|s,t}^2 = (1 - m_t) \sigma_\pi^2 = \frac{1}{\tau_\pi + \tau_t}. \quad (6)$$

Higher precision in either agent's prior or new signal reduces the variance.

## Optimization Problem

The agent chooses the signal precision  $\tau_t$  to maximize expected utility net of information costs:

$$\max_{\tau_t \geq 0} \left\{ -\frac{\gamma_t}{2} \mathbb{E} \left[ (a_t - \pi_t)^2 \right] - C(\tau_t) \right\}, \quad (7)$$

where:

- $\gamma_t$  is the marginal value of more accurate beliefs.
- $C(\tau_t) = \lambda_t \cdot \tau_t^\alpha$  is the cost of acquiring information with precision  $\tau_t$ .

Given that the agent's action  $a_t$  minimizes the expected squared error, it is optimal for the agent to set  $a_t = E[\pi_t \mid s_t]$ . Therefore, the expected loss simplifies to the posterior variance:

$$\mathbb{E} \left[ (a_t - \pi_t)^2 \right] = \sigma_{\pi|s,t}^2 = \frac{1}{\tau_\pi + \tau_t}. \quad (8)$$

Substituting back into the optimization problem:

$$\max_{\tau_t \geq 0} \left\{ -\frac{\gamma_t}{2} \left( \frac{1}{\tau_\pi + \tau_t} \right) - \lambda_t \tau_t^\alpha \right\}. \quad (9)$$

## First-Order Condition

To find the optimal  $\tau_t$ , I take the derivative of the objective function with respect to  $\tau_t$  and set it to zero:

$$\frac{\partial}{\partial \tau_t} \left( -\frac{\gamma_t}{2} \left( \frac{1}{\tau_\pi + \tau_t} \right) - \lambda_t \tau_t^\alpha \right) = 0. \quad (10)$$

Computing the derivative:

$$\frac{\gamma_t}{2} \left( \frac{1}{(\tau_\pi + \tau_t)^2} \right) - \lambda_t \alpha \tau_t^{\alpha-1} = 0. \quad (11)$$

Rewriting:

$$\frac{\gamma_t}{2 (\tau_\pi + \tau_t)^2} = \lambda_t \alpha \tau_t^{\alpha-1}. \quad (12)$$

## Solving for Optimal Precision

The optimal  $\tau_t$  depends on the values of  $\gamma_t$ ,  $\lambda_t$ ,  $\alpha$ , and  $\tau_\pi$ . While a closed-form solution is not available for arbitrary  $\alpha$ <sup>1</sup> and for simplicity, I will analyze the case where the cost function is linear.

When  $\alpha = 1$ , the cost function is linear in precision:

$$C(\tau_t) = \lambda_t \tau_t. \quad (13)$$

The first-order condition simplifies to:

$$\frac{\gamma_t}{2(\tau_\pi + \tau_t)^2} = \lambda_t. \quad (14)$$

Solving for  $\tau_t$ :

$$\frac{\gamma_t}{2} = \lambda_t (\tau_\pi + \tau_t)^2, \quad (15)$$

$$\sqrt{\frac{\gamma_t}{2\lambda_t}} = \tau_\pi + \tau_t, \quad (16)$$

$$\tau_t = \sqrt{\frac{\gamma_t}{2\lambda_t}} - \tau_\pi. \quad (17)$$

Since  $\tau_t \geq 0$ , the optimal precision is:

$$\tau_t^* = \max \left\{ 0, \sqrt{\frac{\gamma_t}{2\lambda_t}} - \tau_\pi \right\}. \quad (18)$$

## Interpretation

The optimal precision  $\tau_t^*$  balances the marginal benefit of reducing the expected loss against the marginal cost of acquiring more precise information.

- **Higher Marginal Value ( $\gamma_t$ ):** Increases optimal precision  $\tau_t^*$ .
- **Higher Marginal Cost ( $\lambda_t$ ):** Decreases optimal precision  $\tau_t^*$ .
- **Higher Prior Precision ( $\tau_\pi$ ):** Decreases optimal precision  $\tau_t^*$ , as the agent already has

---

<sup>1</sup>For example, when the cost function is quadratic ( $\alpha = 2$ ), the equation becomes  $\tau_t^3 + 2\tau_\pi \tau_t^2 + \tau_\pi^2 \tau_t - \frac{\gamma_t^2}{2\lambda_t} = 0$ . Solving this cubic equation analytically involves complex algebra (Cardano's formula). Or one can solve it numerically with numerical methods.

better prior information.

This framework captures the intuition that low-quality signals (e.g., observations from shopping or conversations) are inexpensive to acquire but offer low precision, while high-quality signals (e.g., detailed news reports) provide higher precision at a higher cost.

### **Implications for Attention**

The agent's attention to inflation-related information depends directly on the precision of the signals they choose to acquire, with greater precision requiring higher levels of attention. Attention is influenced by several factors. Higher information costs ( $\lambda_t$ ) discourage attention by making precision more expensive to achieve. In contrast, the perceived benefits of accurate information ( $\gamma_t$ ) increase attention, as the stakes of informed decision-making rise. Finally, improved accessibility to high-precision signals reduces information costs and encourages greater attention.

### **Policy and Media Influence**

Media coverage plays a critical role in shaping the cost and availability of high-precision information. Extensive media coverage can reduce the cost of acquiring precise information ( $\lambda_t$ ), thereby increasing attention. Conversely, barriers such as subscription paywalls elevate costs and diminish attention to high-quality signals. Media sensationalism or bias can also influence the perceived precision of available information, affecting an agent's choice of  $\tau_t$ .

By incorporating a cost function that depends on signal precision, I model how agents decide not just whether to pay attention but how much attention to pay, given the varying costs of acquiring information of different accuracies. Next I will test this empirically to see if more news coverage leads to higher attention.

## **3 Data**

In this section, I will describe the data construction for news coverage index and inattention index.



### 3.1 News articles

As news coverage often serves as the primary channel through which the public and markets interpret economic events, the interplay between media narratives and inflation expectations has garnered increasing attention. News articles not only report factual developments but also frame them in ways that can amplify or attenuate public sentiment and expectations. As Gentzkow, Kelly, and Taddy (2019) highlight, textual data offer unique opportunities to quantify these narratives, enabling researchers to move beyond traditional quantitative indicators and explore qualitative drivers of economic behavior.

#### Data Source

I use large-scale text analysis to study the evolution of inflation-related news coverage, with a focus on identifying and tracking shifts in topic content over time. The analysis rests on a few collection of newspaper datasets sourced from TDM Studio, including *The New York Times* (NYT), *The Wall Street Journal* (WSJ), *Washington Post* (WaPo), and other selected articles from US Newsstream.

Table 1: News articles from different sources

Name	Time period	Number of articles
New York Times	1980-2024	2,746,108
Wall Street Journal	1982-2024	2,232,788
Washington Post	1987-2024	2,024,792
Selected U.S. Newsstream papers	1966-2024	1,458,399
Total	1966-2024	8,552,087

Table 1 provides a summary of the data sources, time periods, and the number of articles included from each source.

For newspapers obtained through TDM Studio, the dataset includes both news articles and editorials. For the *New York Times*, the *Wall Street Journal*, and the *Washington Post*, I took the whole period where data are available. For the U.S. Newsstream papers, I selected a sample of articles using keyword-based filtering to focus on articles directly or indirectly related to inflation. Specifically, I identified articles containing terms such as "inflation," "price," "cost," "expensive," or "policy." This targeted approach allowed me to prioritize content likely to engage with economic and inflation-related themes, ensuring relevance

while maintaining a manageable dataset size. The U.S. Newsstream papers also extend the temporal scope of the data back to 1966, further enhancing the historical coverage of inflation narratives in U.S. media.

In total, the combined dataset includes 8.6 million articles spanning 1966-2024.

### **Topic classification**

To systematically analyze these datasets, I developed a *transformer*-based topic classifier using `distilroberta-base`, a lightweight and computationally efficient version of RoBERTa. Transformers, as Dell (2024) emphasizes, represent a significant advance in natural language processing (NLP), is capable of capturing contextual relationships and meaning in text. The choice of `distilroberta-base` balances computational efficiency with the ability to handle large-scale datasets.

I began the development of the topic classifier by creating a labeled training dataset. I sampled articles from TDM Studio and annotated them to classify if they discuss inflation, prices, or cost of living. Specifically, I use the following set of rules to decide if an article is on-topic: (a) articles that directly and centrally discuss inflation, price changes, or the cost of living (b) articles analyzing monetary authority responses to inflation (e.g., interest rate changes, bond purchases) or the role of inflation in shaping central bank policies (c) discussions of how inflation interacts with global economic trends, such as supply chain disruptions, labor shortages, or the impact of specific events (e.g., COVID-19) or (d) coverage of inflation metrics (e.g., CPI, PPI) and their implications for individuals, businesses, or economies. Any articles that tangentially discuss inflation, prices or costs of living are not on topic.

I did two rounds of labeling. In the first round, I used OpenAI's GPT-4o-mini model to label a large number of articles<sup>2</sup>. In the second round, I sampled a balanced number of articles that were predicted to be on topic and irrelevant by GPT-4o-mini and annotate them manually. Comparing the labels from GPT-4o-mini and my manual labels, GPT-4o-mini has a high recall (0.92) to identify news articles related to inflation, prices or costs of living, but has relatively low precision (0.78). I ended up with 4,382 labeled articles, 430 on topic and 3,952 irrelevant over the entire sample period (1940-2024).

---

<sup>2</sup>See Appendix A.1 for the prompts that were used.

Table 2: Topic classifiers

topic	num of labels	accuracy	precision	recall	F1 score
inflation	1,075	92.5	87.3	93.2	<b>90.2</b>
natural disasters	792	91.5	83.3	100.0	<b>90.9</b>

To fine-tune the `distilroberta-base` model, I took a balanced sample of these labels. I took all the 430 on topic articles and sampled 645 irrelevant articles so that the on topic articles made up about 40% of the total number of articles. In addition, through multiple rounds of training, I optimized hyperparameters, such as learning rate and batch size. The final model demonstrated strong predictive performance, achieving 90.2 F1 on a held-out test set.

Similarly, I trained another classifier for news coverage of natural disaster. The performance is shown in Table 2.

Figure 1 shows the coverage of inflation, prices and cost of living in *The New York Times* and *Washington Post* aggregated on a monthly level. Overall, the coverage of inflation in these two papers track each other well historically, and the attention to inflation is correlated with the rate of inflation.

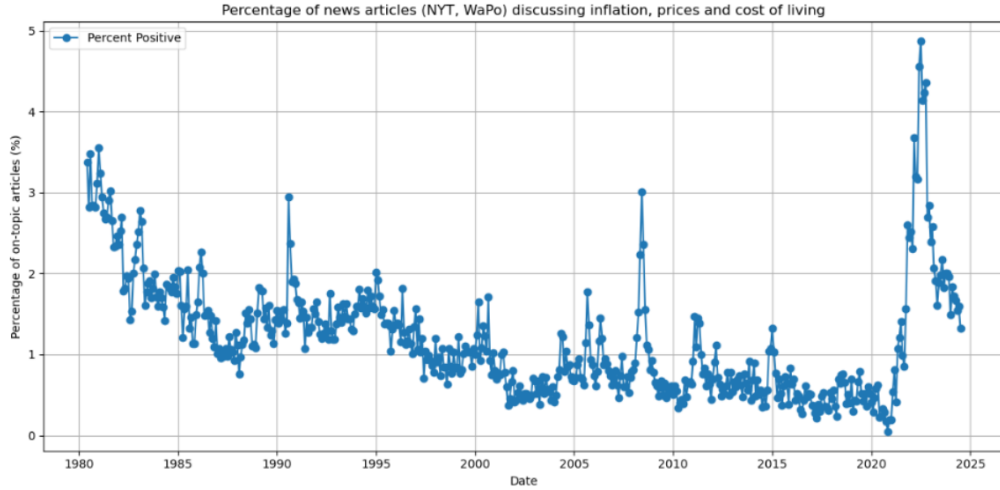


Figure 1: Percentage of news articles (NYT, WaPo) discussing inflation

Figure 2 shows the same coverage in *The Wall Street Journal*. The coverage differs slightly from NYT and WaPo especially in the 1980s. This is likely due to the fact that *The Wall Street Journal* was initially established with a primary focus on business and financial news, catering to business professionals, investors, and traders. In the following

empirical analysis, I will use these two series separately.

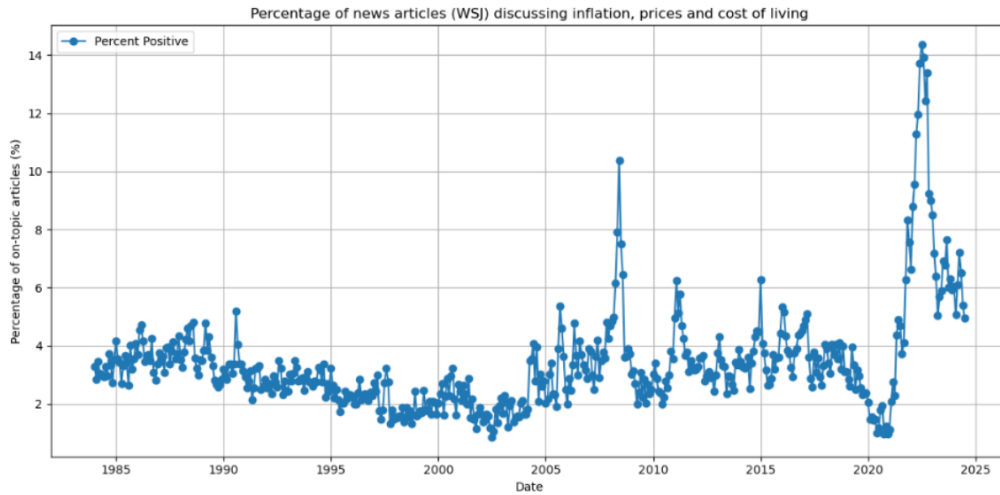


Figure 2: Percentage of news articles (WSJ) discussing inflation

### 3.2 Measure of inattention

I follow Bracha and Tang (2024) to construct measures of inattention that focus on a unique subset of respondents from the Michigan Survey of Consumers (MSC)<sup>3</sup> who expect inflation to stay the same in the next year.

The MSC employs a two-step questioning process: initially, respondents are asked qualitatively whether they think prices will go up, stay the same, or go down over the next year (Q13). The “Same-Up” group comprises respondents who indicate they expect prices to go up at the same rate as now—that is, they anticipate the rate of inflation to remain steady.

In the next question (Q13a), the “Same-Up” group were asked to provide a numeric expectation of the inflation rate, or answer “Don’t know.” Since they expect the future inflation to be the same as the current rate of inflation, their estimate of *future* inflation allows us to obtain their estimate of *current* inflation. Specifically, individuals who are not paying close attention to inflation will either provide an inaccurate estimate or not be able to answer at all. The share of respondent answering “Don’t Know” (I will refer to this as “DK share” later) gives us a proxy of inattention.

I follow Bracha and Tang (2024) and reconstruct and extend their inattention index (DK share index) to 2024.

<sup>3</sup>See Page 8 of the survey at <https://data.sca.isr.umich.edu/fetchdoc.php?docid=75445>

## 4 Empirical Methodology

### 4.1 Identification Strategy

To identify the causal impact of inflation news coverage on public attention to inflation, I exploit the exogenous variation in media coverage induced by natural disasters. Media outlets operate within a constrained capacity for content, with significant news events such as natural disasters often dominating coverage and displacing other topics. This crowding-out effect provides a natural instrument for inflation-related news coverage. Natural disasters, while unrelated to inflation, reduce the likelihood of inflation stories reaching the headlines or receiving prominent placement in media outlets. This methodology draws on many prior research, such as Eisensee and Strömberg (2007), who demonstrated that key newsworthy events, such as the Olympic Games, can crowd out other content.

The key identifying assumption is that natural disaster news coverage affects public attention to inflation solely through its impact on inflation news coverage. Specifically, the assumption is that natural disasters make fewer inflation-related articles reach the front page or lead stories, thereby reducing the visibility of inflation news to the public. While it is true that some natural disasters can have short-lived effects on supply chains, potentially influencing inflation expectations, these effects are typically localized and brief. The limited geographic and temporal scope of such disruptions implies that they are unlikely to drive systematic shifts in nationwide public attention to inflation. This is supported by studies such as Strobl (2011) and other reviewed by Dell, Jones, and Olken (2014). They highlight that while natural disasters can have localized economic impacts, their broader effects on macroeconomic outcomes tend to be minimal.

### 4.2 First-Stage Regression

The first stage of my analysis estimates the relationship between natural disaster news coverage ( $NDNC_t$ ) and inflation news coverage ( $INC_t$ ), controlling for relevant macroeconomic factors. The regression is specified as:

$$INC_t = \pi_0 + \pi_1 NDNC_t + \pi_2 X_t + \nu_t, \quad (19)$$

where  $INC_t$  is the share of inflation-related news articles in month  $t$ , and  $NDNC_t$  is

the share of articles focused on natural disasters in the same month. The vector  $X_t$  includes control variables (the unemployment rate, consumer sentiment index) to account for macroeconomic conditions that might influence both public attention and media reporting. A significant and negative coefficient on  $\pi_1$  will provide evidence of the crowding-out effect, whereby increased natural disaster coverage reduces the prominence of inflation news.

### 4.3 Second-Stage Regression

In the second stage, I use the predicted values of inflation news coverage ( $\widehat{INC}_t$ ) from the first stage to estimate its causal effect on public attention to inflation, measured by the Inflation Attention Index (IAI<sub>*t*</sub>) or "DK Share". This is also a proxy for  $m_t$  in the theoretical framework in Section 2. The second-stage regression is specified as:

$$IAI_t = \alpha + \beta \widehat{INC}_t + \gamma' X_t + \epsilon_t, \quad (20)$$

where IAI<sub>*t*</sub> represents public attention to inflation in month *t*, derived from aggregated responses in the Michigan Survey of Consumers. The variable  $\widehat{INC}_t$  captures the exogenous variation in inflation news coverage attributable to natural disaster news coverage. The vector  $X_t$  includes the same control variables as in the first stage, ensuring consistency. The coefficient  $\beta$  represents the causal effect of inflation news coverage on inflation attention, and  $\epsilon_t$  captures unobserved shocks to public attention unrelated to news coverage.

## 5 Results

### 5.1 Inflation and news coverage

As a simple test at first, I regress the share of news coverage dedicated to inflation (INC<sub>*t*</sub>) on current inflation measures. Table 3 presents the results of this regression, which confirm a strong and positive relationship between inflation rates and the extent of media attention devoted to inflation-related topics, such as prices and the cost of living.

In specification (1), the coefficient for the inflation rate is 0.252 ( $p < 0.01$ ), indicating that a 1 percentage point increase in the inflation rate is associated with a 0.252 percentage point increase in the share of total news coverage focused on inflation (the average is 1.5%

Table 3: News Coverage

	(1)	(2)
	$INC_t$	$INC_t$
Inflation	0.252*** (0.00901)	
Core inflation		0.275*** (0.00978)
const	0.385*** (0.0356)	0.294*** (0.0383)
R-Squared	0.598	0.599
Observations	530	530

Standard errors in parentheses

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

in my sample period; intuitively, a 6 percentage point increase in inflation will double the inflation news coverage). Similarly, specification (2) shows a slightly higher coefficient of 0.275 ( $p < 0.01$ ) when using core inflation as the independent variable. This result suggests that core inflation, which excludes more volatile components like food and energy prices, is also a strong predictor of inflation-related news coverage.

## 5.2 News coverage and attention

Next, I will present the 2SLS regression result whether news coverage of inflation affect people's attention to inflation.

### First stage

Table 4 reports the first-stage regression results. The first-stage regression results confirm the expected "crowding out" effect of natural disaster news coverage on inflation-related news coverage. The coefficient for  $NDNC_t$  (or `percent_nat`, percentage of news coverage on natural disaster) is statistically significant and negative ( $\beta = -0.0746, p < 0.01$ ). This implies that for every one percentage point increase in natural disaster coverage, inflation-related news coverage decreases by approximately 0.0746 percentage points, holding other factors constant.

This finding aligns with the hypothesis that media outlets operate within a limited news space. When natural disasters dominate the headlines, they displace other topics,

Table 4: First Stage Regression Results

Variable	Coefficient	t-statistics	p-value
NDNC <sub>t</sub> (percent_nat)	-0.0746***	-2.85	0.0046
const	1.4993***	13.76	< 0.001
R-squared	0.0151		
Observations	530		
F-statistic	8.119		

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

including inflation. The strong F-statistic ( $F = 8.119$ ) and the significance of the coefficient suggest that the relationship is robust.

Additionally, the constant term ( $\beta_0 = 1.4993, p < 0.001$ ) indicates that inflation-related news occupies an average of 1.5% of total news coverage over the time period.

### Second stage

The second-stage regression results provide insights into the relationship between inflation news coverage and inattention, as measured by "DK share" (*sharedk*). Recall that "DK share" represents the share of the Same-Up group who responded that they do not know the current rate of inflation (by choosing "Don't know") (i.e. those considered inattentive to inflation). Specifically, they initially indicated that they expect prices to rise at the same annual rate as today but, when asked to provide a specific figure for the current rate, admitted they "Don't know." This sequence of responses indicates a lack of awareness or engagement with inflation-related information.

Table 5 reports the results. The fitted value of inflation news coverage ( $\widehat{\text{INC}}_t$ ) has a statistically significant and negative effect on inattention across all set-ups. In specification (1), the coefficient for  $\widehat{\text{INC}}_t$  is  $-2.697$  ( $p < 0.05$ ), indicating that an increase in inflation news coverage is associated with a reduction in the share of individuals exhibiting inattention. Specifically, for every 1 percentage point increase in the share of total news coverage focused on inflation, there are 2.7 percentage points less inattentive individuals who answer "Don't Know".

This result remains consistent when controls for macroeconomic variables are added in specification (2), where the coefficient becomes  $-3.459$  ( $p < 0.05$ ).



Table 5: Second-Stage Regression Results

	(1)	(2)	(3)	(4)
	sharedk	sharedk	sharedk	sharedk
$\widehat{\text{INC}}_t$	-2.697** (1.268)	-3.459** (1.286)	-2.656** (1.609)	-3.062* (1.594)
Unemployment rate		-0.263* (0.143)		-0.261* (0.144)
Real GDP growth		-0.462*** (0.135)		-0.465*** (0.135)
Consumer sentiment		0.0597** (0.0232)		0.0607*** (0.0234)
$\widehat{\text{INC}}_{t-1}$			-0.0779 (2.316)	-0.797 (2.301)
const	10.46*** (0.242)	8.150*** (2.316)	10.46*** (0.242)	8.058*** (2.333)
R-Squared	0.00369	0.0371	0.00369	0.0374
Observations	509	509	509	509

Standard errors in parentheses

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

The macroeconomic controls included in specifications (2) and (4) also show significant effects. The unemployment rate has a small but significant negative impact on "DK share," with a coefficient of  $-0.263$  ( $p < 0.10$ ), suggesting that higher unemployment is associated with lower inattention. Real GDP growth has a highly significant and negative effect ( $-0.462$ ,  $p < 0.01$ ), indicating that economic expansion may improve focus on inflation-related issues. On the other hand, consumer sentiment has a positive and significant effect ( $0.0597$ ,  $p < 0.05$ ), implying that increased optimism or confidence might reduce attention to inflation.

Interestingly, lagged inflation news coverage ( $\widehat{\text{INC}}_{t-1}$ ) does not have a statistically significant effect on inattention in specifications (3) and (4). This result is somewhat surprising, as one might expect past news coverage to have a lingering impact on public attention. Two interpretations could explain this outcome:

1. Individuals may only remember the qualitative content of last month's news coverage but not the exact details, such as specific inflation numbers. This qualitative recall may not translate into measurable changes in attention.

2. Inflation tends to be reasonably persistent over time. Intuitively, it's unlikely for inflation to drastically change from 10% one month to 0% the next. This "stickiness" in inflation may also apply to news coverage and individuals' memory. As a result, the current month's news coverage captures most of the variation in attention, absorbing the potential effect of lagged news coverage.

The constants in all models are statistically significant, reflecting baseline levels of inattention when inflation news coverage and macroeconomic factors are held constant.

Finally, the  $R^2$  values indicate that the models explain a modest portion of the variation in "DK share," with the inclusion of macroeconomic controls improving the explanatory power from 0.00369 in specification (1) to 0.0374 in specification (4). This suggests that while inflation news coverage significantly affects inattention, other unobserved factors may also play a role.

## 6 Discussion

My analysis highlights the significant role of news media in shaping public attention to inflation by lowering the informational costs associated with understanding economic conditions. This effect operates not only on the consumer side but also has profound implications for firms and their pricing strategies. In this discussion, I explore two interconnected dimensions: the influence of media narratives on public economic perceptions, and the behavioral elements affecting firms' price adjustments in the context of inflation.

### 6.1 The Power of Media Narratives in Shaping Economic Perceptions

Recent research underscores a gap between textbook economic theories and the public's understanding of macroeconomic phenomena. For instance, Binetti, Nuzzi, and Stantcheva (2024) finds that individuals often hold misconceptions about fundamental economic relationships, such as the effects of interest rate changes on inflation. Similarly, Andre, Pizzinelli, Roth, and Wohlfart (2022) demonstrate that people can form economic expectations based on salient narratives from news media.

While news media serve as a key information source, their signals can be biased due to simplifications or sensationalism, significantly influencing how consumers perceive and

react to economic conditions. In economic models, consumers update their beliefs based on new information, but noisy or biased news can lead to inaccurate perceptions. For example, early 2021 media underestimated persistent inflation, causing consumers to be less vigilant about inflationary pressures and delaying adjustments in spending and saving.

Overly pessimistic media tones can make consumers unnecessarily cautious, reducing spending and potentially contributing to economic slowdowns. These effects have significant implications for aggregate demand and inflation dynamics. Extending models that include imperfect information and heterogeneous agents can help incorporate media's impact on consumer expectations.

Biased media signals can cause systematic deviations in consumer expectations, leading to suboptimal decisions and affecting macroeconomic outcomes. Policymakers must consider these perception gaps when designing monetary policies to manage inflation expectations effectively.

Advancements in computational text analysis allow researchers to examine macroeconomic narratives across extensive media content (Gentzkow et al., 2019). Quantifying media sentiment and content helps understand how narratives spread and influence consumer behavior. For instance, tracking terms like "transitory inflation" versus "persistent inflation" can identify media biases, and correlating these with consumer surveys provides evidence of media's influence.

Media narratives can create feedback loops that impact economic outcomes. Underestimating inflation risks can delay consumer adjustments, exacerbating inflation if it persists. Conversely, media pessimism can heighten inflation expectations, leading to higher wage demands and price increases.

These dynamics underscore the importance of accurate media reporting and effective communication from policymakers. Media distortions can undermine central banks' efforts to manage public expectations through tools like forward guidance. Integrating the role of biased media signals into economic models allows for better prediction of outcomes and more effective policy interventions, acknowledging that consumers are influenced by narratives and do not operate with perfect information.

## 6.2 Behavioral Elements in Firms' Price Adjustment Strategies

While my primary focus has been on consumers, it is equally important to consider how firms respond to media-influenced consumer perceptions. Traditional menu cost models suggest that firms adjust prices in response to changes in costs and demand, accounting for the physical and managerial costs of changing prices (Mankiw, 1985). However, these traditional models often overlook the micro-behavioral elements that influence firms' pricing decisions in a competitive landscape.

An illustrative example is the behavior of certain retailers during the post-COVID inflation period. Notably, some businesses that had maintained stable prices for years chose to raise prices amid heightened inflation concerns. For instance, a well-known pizza establishments in New York City, 2 Bros, famous for their longstanding \$1 slices, increased prices to \$1.50. This shift occurred despite relatively modest increases in overall price levels (5% in 2021) compared to previous decades (50% cumulative between 2001 and 2020) when these firms did not adjust their prices.

One plausible explanation is that high inflation environments alter the perceived fairness of price increases. Consumers may attribute price hikes to external economic conditions rather than to firms' desire to increase profits. This attribution reduces the risk of consumer backlash against individual firms (Kahneman, Knetsch, & Thaler, 1986). As a result, firms find it "easier" to adjust prices without damaging customer relationships or brand reputation.

This behavioral aspect introduces a microfoundation for the adjustment costs in menu cost models. The "cost" of changing prices can consist of the potential negative perception by consumers. When inflation is high and widely publicized, the consumer's threshold for acceptable price changes shifts, effectively lowering the adjustment cost for firms.

Moreover, the degree to which firms adjust prices may vary depending on the competitive environment. In markets with many substitutable options (e.g. many similar pizza spots in a city), firms might be more hesitant to raise prices for fear of losing customers to competitors. Conversely, in markets with fewer alternatives, firms may have more leeway to adjust prices without significant customer attrition.

Understanding these behavioral dynamics is crucial for accurately modeling price adjustment mechanisms. It suggests that firms' pricing strategies are influenced not only

by economic fundamentals but also by consumer psychology and media-driven narratives. Incorporating these elements into economic models could improve predictions of how firms and consumers will respond to policy changes and economic shocks.

## 7 Conclusion

This paper demonstrates the significant role of media in shaping public attention to inflation by reducing the informational costs associated with understanding economic conditions. Using a novel dataset of over 8 million news articles and a rational inattention framework, I show that media coverage of inflation substantially decreases public inattention. Specifically, my baseline result shows that a 1 percentage point increase in the share of total news coverage dedicated to inflation leads to a 2.7% reduction in inattentive individuals. These findings highlight how access to timely and precise information can bridge the gap between economic reality and public perceptions.

Future research should also look at the media's influence beyond consumers, but to firms and policymakers. High inflation periods, paired with heightened media attention, shift consumer tolerance for price adjustments, making firms more likely to revise prices without fear of reputational damage. These behavioral responses suggest that inflation narratives are not just passive reflections of economic reality but active drivers of expectations and actions across all economic agents.

Policymakers should take these dynamics into account, especially when designing communication strategies to manage inflation expectations. Media narratives can amplify or dampen public responses to inflation, creating feedback loops that influence aggregate demand and inflationary pressures. Future research could delve deeper into the framing and sentiment of inflation-related news to further understand how media shapes economic behavior and expectations.

To conclude, I examine the news coverage of inflation, offering valuable insights into how information dissemination impacts public attention and decision-making in the context of inflation. By integrating rational inattention theory with empirical evidence on media coverage, this paper provides a foundation for more informed policy interventions in managing inflation expectations.

## References

- Andrade, P., & Le Bihan, H. (2013). Inattentive professional forecasters. *Journal of Monetary Economics*, 60(8), 967-982.
- Andre, P., Pizzinelli, C., Roth, C., & Wohlfart, J. (2022, 02). Subjective models of the macroeconomy: Evidence from experts and representative samples. *The Review of Economic Studies*, 89(6), 2958-2991.
- Baker, S. R., McElroy, T. S., & Sheng, X. S. (2020, 05). Expectation formation following large, unexpected shocks. *The Review of Economics and Statistics*, 102(2), 287-303.
- Binetti, A., Nuzzi, F., & Stantcheva, S. (2024). *People's understanding of inflation*. Retrieved from <https://www.stefanie-stantcheva.com/research/> (Harvard University Working Paper)
- Bracha, A., & Tang, J. (2024, 06). Inflation levels and (in)attention. *The Review of Economic Studies*, rdae063.
- Carroll, C. D. (2003, 02). Macroeconomic expectations of households and professional forecasters\*. *The Quarterly Journal of Economics*, 118(1), 269-298.
- Coibion, O., & Gorodnichenko, Y. (2015, August). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, 105(8), 2644-78.
- Dell, M. (2024). Deep learning for economists. *Journal of Economic Literature*. (Forthcoming)
- Dell, M., Jones, B. F., & Olken, B. A. (2014, September). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature*, 52(3), 740-98.
- Eisensee, T., & Strömberg, D. (2007, 05). News droughts, news floods, and u. s. disaster relief\*. *The Quarterly Journal of Economics*, 122(2), 693-728.
- Gabaix, X. (2019). Chapter 4 - behavioral inattention. In B. D. Bernheim, S. DellaVigna, & D. Laibson (Eds.), *Handbook of behavioral economics - foundations and applications 2* (Vol. 2, p. 261-343). North-Holland.
- Gentzkow, M., Kelly, B., & Taddy, M. (2019, September). Text as data. *Journal of Economic Literature*, 57(3), 535-74.
- Kahneman, D., Knetsch, J. L., & Thaler, R. (1986). Fairness as a constraint on profit seeking: Entitlements in the market. *The American Economic Review*, 76(4), 728-741.
- Mackowiak, B., & Wiederholt, M. (2009, June). Optimal sticky prices under rational inat-

- tention. *American Economic Review*, 99(3), 769–803.
- Mankiw, N. G. (1985, 05). Small menu costs and large business cycles: A macroeconomic model of monopoly\*. *The Quarterly Journal of Economics*, 100(2), 529-538.
- Nakamura, E., & Steinsson, J. (2008, 11). Five facts about prices: A reevaluation of menu cost models\*. *The Quarterly Journal of Economics*, 123(4), 1415-1464.
- Pfäuti, O. (2024). Inflation—who cares? monetary policy in times of low attention. *Journal of Money, Credit and Banking*, n/a(n/a). (Forthcoming)
- Powell, J. H. (2022, August 26). *Monetary policy and price stability*. Retrieved from <https://www.federalreserve.gov/newsevents/speech/powell20220826a.htm> (Speech transcript)
- Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics*, 50(3), 665-690. (Swiss National Bank/Study Center Gerzensee Conference on Monetary Policy under Incomplete Information)
- Soroka, S. N. (2012). The gatekeeping function: Distributions of information in media and the real world. *The Journal of Politics*, 74(2), 514–528.
- Strobl, E. (2011, 05). The economic growth impact of hurricanes: Evidence from u.s. coastal counties. *The Review of Economics and Statistics*, 93(2), 575-589.
- Woodford, M. (2003). Imperfect common knowledge and the effects of monetary policy. In P. Aghion, R. Frydman, J. Stiglitz, & M. Woodford (Eds.), *Knowledge, information, and expectations in modern macroeconomics: In honor of edmund s. phelps* (pp. 25–58). Princeton, NJ: Princeton University Press.

## A Appendix

### A.1 Classification Prompts

I used the following prompts with GPT-4o-mini to obtain preliminary sets of articles for labeling.

#### Topic: Inflation

**Prompt:** You are a text classification assistant tasked with determining if a news article is primarily about inflation, prices, or the cost of living.

Classify the article as either 'On-Topic' or 'Off-Topic' based on the following criteria:

- On-Topic: Articles that directly and centrally discuss inflation, price changes, or the cost of living. Articles analyzing monetary authority responses to inflation (e.g., interest rate changes, bond purchases) or the role of inflation in shaping central bank policies. Discussions of how inflation interacts with global economic trends, such as supply chain disruptions, labor shortages, or the impact of specific events (e.g., COVID-19). Coverage of inflation metrics (e.g., CPI, PPI) and their implications for individuals, businesses, or economies.
- Off-Topic: Articles where inflation, prices, or the cost of living are mentioned only tangentially. Broader discussions of economic trends, monetary policies, or global issues where inflation is secondary or peripheral to the main focus.

Example Clarifications: Article discussing "the Federal Reserve's measures to reduce inflation, focusing on the impact on food and energy prices": On-Topic. Article discussing "economic growth slowing down, with inflation as one of many factors analyzed": Off-Topic.

Your task is to classify each article strictly according to these criteria. Provide only one of the two labels: `true` if on topic, `false` if off-topic.

#### Topic: Natural Disasters

**Prompt:** You are a text classification assistant tasked with determining if a news article is primarily about a natural disaster or not.

You will be provided with a full news article. Your task is to classify it as either:



- On topic: Articles describing the occurrence of an ongoing natural disaster or an event that just happened (implicitly including its ongoing impacts). Example events include earthquakes, hurricanes, floods, etc.

- Off Topic: Articles that do not directly discuss a natural disaster.

Please note: Articles discussing tangentially related topics, such as insurance companies or policy analysis, without direct focus on ongoing or just-occurred disasters are considered off-topic.

Your task is to classify each article strictly according to these criteria. Provide only one of the two labels: `true` if on topic, `false` if off-topic.

## A.2 Natural Disaster News Coverage

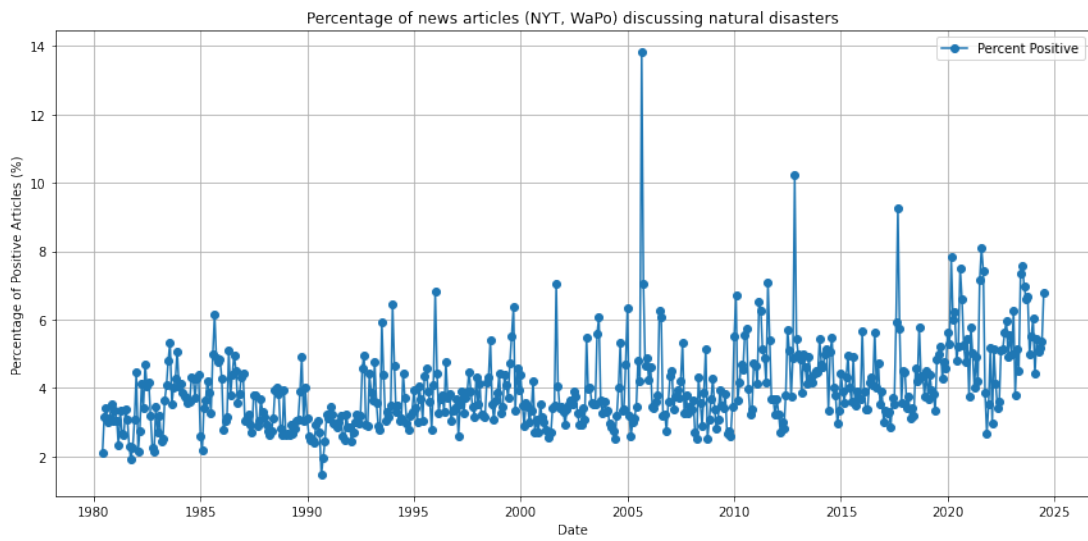


Figure 3: Percentage of news articles (NYT, WaPo) discussing natural disasters

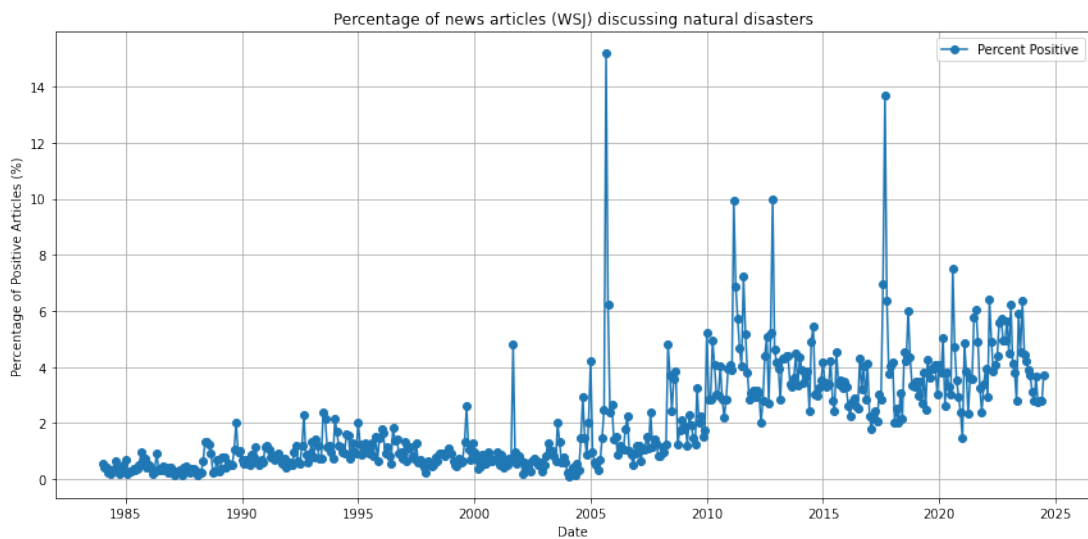


Figure 4: Percentage of news articles (WSJ) discussing natural disasters