The Causal Effect of News on Inflation Expectations*

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Abstract

This paper studies the response of household inflation expectations to television news coverage of inflation. We analyze news data from CNN, Fox News, and MSNBC alongside a daily measure of inflation expectations. Using a local projection instrumental variables approach, we estimate the dynamic causal effect of inflation news coverage on household inflation expectations at a daily frequency. Increased media coverage of inflation raises expectations, with effects peaking within a few days and fading after approximately 10 days. Additionally, we document a key nonlinearity: release days with positive CPI surprises—i.e., inflation exceeding market expectations— lead to stronger expectation responses than release days with negative surprises.

Keywords: Inflation expectations; expectations surveys; daily data; cable television; news coverage; local projection
JEL Codes: D83, D84, E31

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1 Introduction

The news media play a large role in transmitting economic news to the general public.[1] News about monetary policy and macroeconomic data often reach consumers primarily through the media. This means that media coverage of inflation is likely to have important implications for inflation expectations and, in turn, for consumer behavior and inflation dynamics.

Assessing the *causal* impact of news coverage on inflation expectations poses challenges. When inflation and expected inflation are high, the demand for news coverage of inflation rises.[2] Consequently, time-series correlations of the quantity of coverage and expectations do not imply a causal effect of inflation coverage on expectations. The relatively low frequency of most available survey data makes it difficult to attribute changes in expectations to high-frequency changes in media coverage. Finally, news coverage of inflation may contain information suggesting upward or downward pressure on prices, which may have effects of opposite sign and asymmetric magnitude on inflation expectations (Chahrour, Shapiro, and Wilson 2024). Current research on the effect of news on inflation expectations relies heavily on randomized control trials (RCTs) that directly expose some participants to media content (Binder 2021a; Coibion, Gorodnichenko, and Weber 2022). Although such studies provide clean identification, it is unclear how generalizable their results are to news encountered outside of an experimental setting.

We make use of daily data and an instrumental variables strategy to overcome these challenges. Specifically, we study the effect of cable news coverage of inflation on household inflation expectations at daily frequency using a local projections instrumental variables (LP-IV) approach. The primary endogeneity concern is that the quantity of inflation news increases due to expectations-driven demand for such news. The ideal instrument should therefore be a "supply shock" to inflation news—an

[1]See for example Carroll (2003), Krueger and Blinder (2004), Binder (2017b), Coibion et al. (2020), Larsen, Thorsrud, and Zhulanova (2021), Chahrour, Nimark, and Pitschner (2021), Binder (2017a), Ehrmann, Pfajfar, and Santoroc (2017)

[2]Unusual events, including high-inflation episodes, may also result in additional coverage (Nimark 2014).

increase in coverage driven by something other than audience demand. We argue that the release of a CPI report as well as the magnitude of the "surprise" it constitutes relative to the professional consensus forecast for that month matches this description. The release date of a CPI report is predetermined and exogenous and, *ex ante*, the surprise is not foreseeable and not driven by consumer expectations. We then use our instrument in a local projection model to study the dynamic response of consumer expectations to news coverage of inflation.

The proposed instrument is both strong and relevant. We confirm that mentions of inflation indeed increase on CPI release dates.[3] Moreover, we find that cable television coverage on CPI release dates frequently mentions the CPI report itself and indicates whether inflation was higher or lower-than-expected. More surprising reports generate more news coverage. Both positive (inflation higher-than-expected) and negative (inflation lower-than-expected) CPI surprises increase news coverage, but do so asymmetrically. Positive surprises generate a slightly larger and longer-lasting response. This asymmetry in news coverage is driven by Fox News, which covers positive surprises more intensively, and for an extra day. These results are in line with previous findings that, in general, the mass media tends to emphasize negative news, including news of crime, conflict, and crises (Harrington 1989, Altheide 1997).[4]

Using our instrument for news coverage, we find that an increase in news mentions of inflation raises household inflation expectations. A one standard deviation increase in coverage raises expectations by 0.12 percentage points at the peak on day 4, with the effect declining to zero on day 10. The magnitude of this overall effect is small, but it reflects the combined effects of inflationary and disinflationary news, which may

[3]This is consistent with Binder (2021b), who found that consumers surveyed shortly after the June 2021 CPI release were 11 percentage points more likely to report having heard news about inflation compared to those surveyed shortly before.

[4]This asymmetry in coverage of negative versus positive news likely reflects both supply-driven and demand-driven explanations. On the supply side, the media may choose to focus on unfavorable news in its role as "watchdog," in order to hold the government and companies accountable for errors and bad outcomes (Merrill and Lowenstein 1971). On the demand side, consumers may demand negative news more than positive news because of loss aversion (Kahneman and Tversky 1979), risk aversion (McCluskey, Swinnen, and Vandemoortele 2015) or a variety of other psychological, neurological, or evolutionary biological reasons (Rozin and Royzman 2001, Herwig et al. 2007, mcdermott2008).

have opposite and also asymmetric effects on expectations. Indeed, we find that after an inflationary CPI surprise, expectations rise immediately and persistently. The response is highest in the first week after the release—with a one standard-deviation increase in news coverage leading to a 0.19 ppt rise in expectations—and then declines slightly in the second week. In contrast, negative surprises have a weaker and less robust effect on expectations, indicating that households respond differently to such news when forming their expectations.

To contextualize these numbers, we consider how the trends in inflation news during the 2021-2024 inflation period may have contributed to both the increase in expectations and to the partisan gap in expectations. We find that increased media coverage can explain 8 to 12% of the increase in expectations at their peak in June 2022. Furthermore, we show that the volume of news coverage was higher on Fox news, a right-leaning news source, than on CNN, a left-leaning news source. The median inflation expectation in states that are primarily Fox-viewing was also higher than that in states that are primarily CNN-viewing. We document that the effect of the additional coverage on Fox–even without accounting for differences in tone–can explain 14% of the measured gap in expectations in these states.

Prior literature also documents an asymmetric response of macroeconomic expectations to good and bad news. Gambetti, Maffei-Faccioli, and Zoi 2023 analyze newspaper coverage of unemployment and find that bad shocks have larger and more persistent effects than good shocks because of their higher information content. Such asymmetry is also consistent with the work of Nimark and Pitschner (2019) and Chahrour, Shapiro, and Wilson (2024) on "news selection functions." A key insight of Nimark and Pitschner is that even the media's choice of *what* to cover conveys information. That is, if the media chooses to cover inflation, this indicates that inflation is likely high, regardless of the content of the news. News of low inflation therefore provides conflicting signals: the content of the news suggests lower inflation and the existence of the story suggests higher inflation. Chahrour, Shapiro, and Wilson (2024) use a news selection model to predict asymmetric responses of inflation expectations to news about higher and lower prices and document such an asymmetry in the Michigan Survey of Consumers using information about news respondents have recently heard. Our evidence, using a daily time series and instrumental variable approach to identification, reinforces this finding.

Our work is also related to a growing literature using high frequency data to assess the response of inflation expectations to macroeconomic data releases (Bauer 2015, Binder (2021b), Binder, Campbell, and Ryngaert 2024, Binder, Kamdar, and Ryngaert 2024, York 2023). Binder, Campbell, and Ryngaert (2024) find that CPI releases have mixed effects on consumer inflation expectations, and suggest that releases with larger effects may have been more newsworthy. Our results lend credence to that suggestion. Binder, Kamdar, and Ryngaert (2024) find that Republicans' and Democrats' inflation expectations moved in opposite directions following several CPI reports with large positive surprises in 2021, and point to different coverage of inflation on Fox versus CNN. In the German context, Hack and Rostam-Afschar (2025) find that firms' price setting plans respond to news releases about inflation, employment, and the trade balance.

Our estimation approach builds on studies that use high-frequency daily data to estimate the dynamic causal effects of monetary policy within a local projections framework, including Jacobson, Matthes, and Walker (2023) and Buda et al. (2023). We also relate to work on asymmetric dynamic effects identified within a local projections instrumental variables approach, such as Ben Zeev, Ramey, and Zubairy (2023) and Jordà, Singh, and Taylor (2024), typically applied to monetary and fiscal policy. Finally, by employing the smooth local projections framework of Barnichon and Brownlees (2019), we address excessive variability in impulse response estimates while preserving the flexibility of the local projections approach, following the recommendations of Jordà (2023).

The paper is structured as follows. Section 2 describes the daily news coverage data, the survey data on inflation expectations, and the construction of the CPI "surprise" series. Section 3 analyzes patterns in news coverage around CPI release days. Section 4 details our econometric framework. Section 5 presents the main empirical findings, including estimates of the dynamic causal effects of news on inflation expectations and evidence on the asymmetric impact of positive versus negative inflation surprises. Finally, Section 6 concludes.

2 Data

We use three sets of data: survey data on consumer inflation expectations, cable television coverage data, and data from CPI releases and professional forecasts used to construct the instrument. The sample begins on January 1, 2021 and extends to May 1, 2024. This period featured a rise and subsequent decline in inflation and major inflation surprises of both positive and negative sign.[5]

As we argue in Section 4.1, the strength of the relationship between CPI surprises and news coverage - and thus the relevance of the instrument - is conditional on increased attention to inflation, which was much more pronounced during this high-inflation episode. Cable television coverage of inflation was also more prominent than in prior years, and CPI releases were especially important focal points of inflation coverage. Even as inflation declined, the prominence of CPI releases remained elevated: in 2024, 20% of inflation coverage in a month occurred on the day of or the day after a CPI release, compared to less than 10% in most years prior to 2020. Kroner (2025) similarly finds that market-based expectations respond more strongly to CPI releases when market attention to inflation is high.

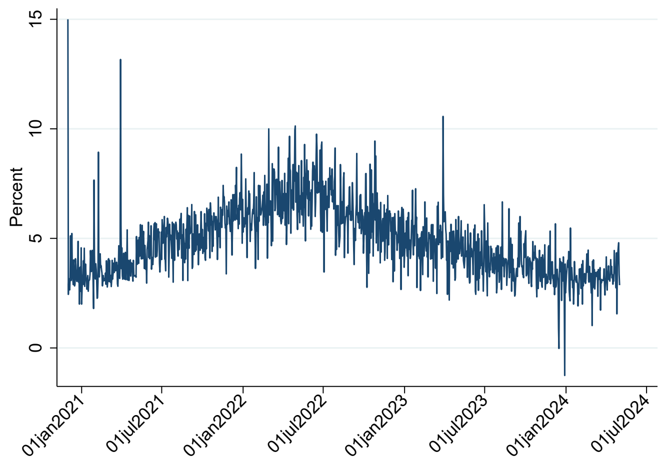
2.1 Expectations Data

Our data on inflation expectations comes from the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE). As documented in Binder, Campbell, and Ryngaert (2024), though this is a monthly survey, respondents take the survey throughout the month, and respondent characteristics are consistent across the month. They also show that respondents do not appear to select into taking the survey around particular events, like FOMC announcements or data releases. Thus, we make use of the survey at daily frequency.

Survey respondents provide forecasts in two formats: numerical point forecasts and density forecasts. In the latter, respondents are asked to assign probability to outcomes that inflation falls into several ranges (more than 12%, between 8% and

[5]The instrument includes all release dates during this period. To accommodate the inclusion of lags in our model, we use data extending to December 1, 2020.

Figure 1: Daily Consumer Inflation Expectations



Notes: Figure shows the interpolated median 1-year ahead inflation expectations of households on the daily frequency. Data from Survey of Consumer Expectations.

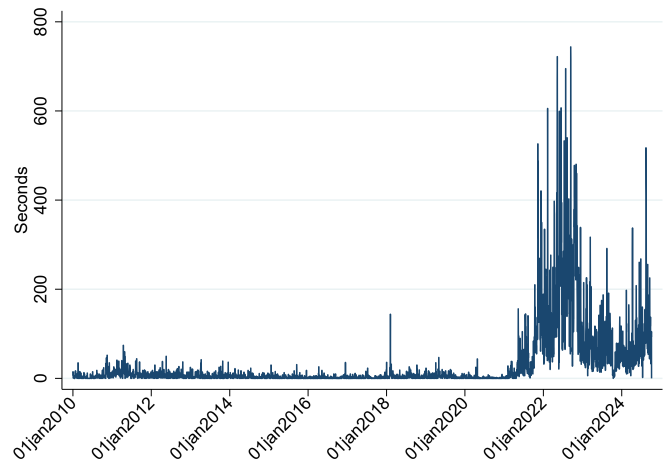
12%, between 4% and 8%, between 2% and 4%, between 0% and 2%, ..., between -12% and -8%, and less than -12%). We use a method for fitting subjective probability distributions to density forecasts suggested by Ryngaert (2023), which makes use of data from both the point and density forecasts and allows for possibly asymmetric probability distributions. Figure 1 plots the daily median inflation expectation series.

2.2 Cable Television Data

The Stanford Cable TV News Analyzer allows researchers to write queries to compute the length of time that words are spoken on the three major cable news stations: CNN, Fox, and MSNBC (Hong et al. 2021). The underlying dataset, provided by the Internet Archive's TV News Archive, includes nearly 24-7 video coverage of these stations, with accompanying transcripts, beginning on January 1, 2010.

Our primary measure of interest from this dataset is the number of seconds per day that the word "inflation" is heard on cable television on each of the three stations.

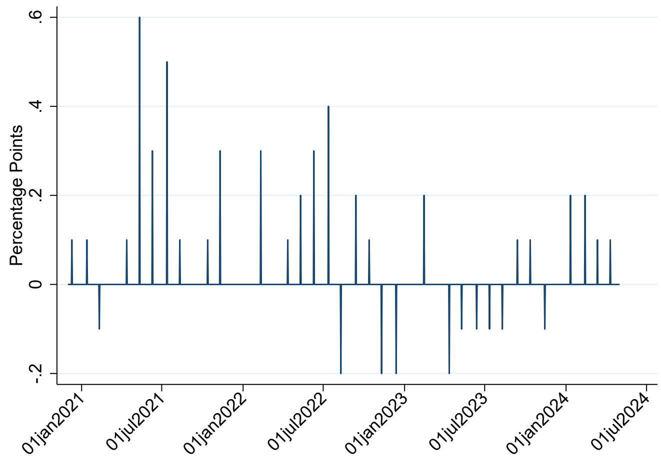
Figure 2: Cable Television Inflation Coverage



Notes: Figure shows the seconds per day that the word "inflation" is said on Fox News, CNN, and MSNCB, combined.

Note that for text searches, the recorded time is only the time in which the word or phrase is said, not the time of the whole discussion of the topic. Thus, if the word "inflation" takes roughly one second to say, then each second of coverage corresponds to one mention of inflation. Figure 2 shows this daily measure from January 1, 2010 to October 5, 2024. Most days prior to 2021 feature minimal mentions of inflation: 24% of days have zero mentions. On 69% of days, inflation is mentioned for at most 4 seconds. Average coverage is 4 seconds per day. From 2021 through 2024, coverage of inflation is much higher. Only 2% of days have zero mentions of inflation, and on 6% of days, inflation is mentioned for at most 4 seconds. Over the sample period we use in our subsequent analysis, average coverage is 99 seconds per day, with a standard deviation of 112 seconds.

Figure 3: Inflation Surprise Series



Notes: Daily inflation surprise series. We compute the difference between the CPI release and the Blue Chip Forecast as the inflation surprise. Data from December 1, 2020 to May 1, 2024.

2.3 Inflation Surprise Series

Our inflation surprise series measures the surprise content on each CPI release date. The series is zero on days without a CPI release. On release dates, the surprise is defined as the percentage point difference between headline year-over-year CPI and the most recent Blue Chip Forecast for its value. Figure 3 presents the inflation surprise series over our sample period. As shown, the largest positive surprise occurred on May 12, 2021, when it was reported that April CPI inflation was 0.6 percentage points higher than expected. Inflation continued to surprise forecasters to the upside for most of 2021 and the first half of 2022, with some negative surprises occurring in late 2022 and in 2023.

We use inflation surprises to instrument for variation in news coverage of inflation. These surprises are reduced-form objects that reflect underlying structural shocks leading to inflation outcomes that deviate from expectations. Importantly, our aim is not to isolate a single macroeconomic shock, but rather to capture unexpected inflationary developments more broadly. Therefore, Table A.1 shows that our series is not correlated with commonly studied shock measures, such as monetary policy surprises or oil supply news shocks, indicating that it does not simply track one particular type of macroeconomic disturbance. This lack of correlation is partly mechanical, as CPI releases generally occur on different days than the announcements driving these other shocks. Furthermore, Table A.2 demonstrates that our surprise series cannot be forecasted using macroeconomic or financial variables, underscoring its exogeneity relative to prior information.

3 Coverage of Inflation News

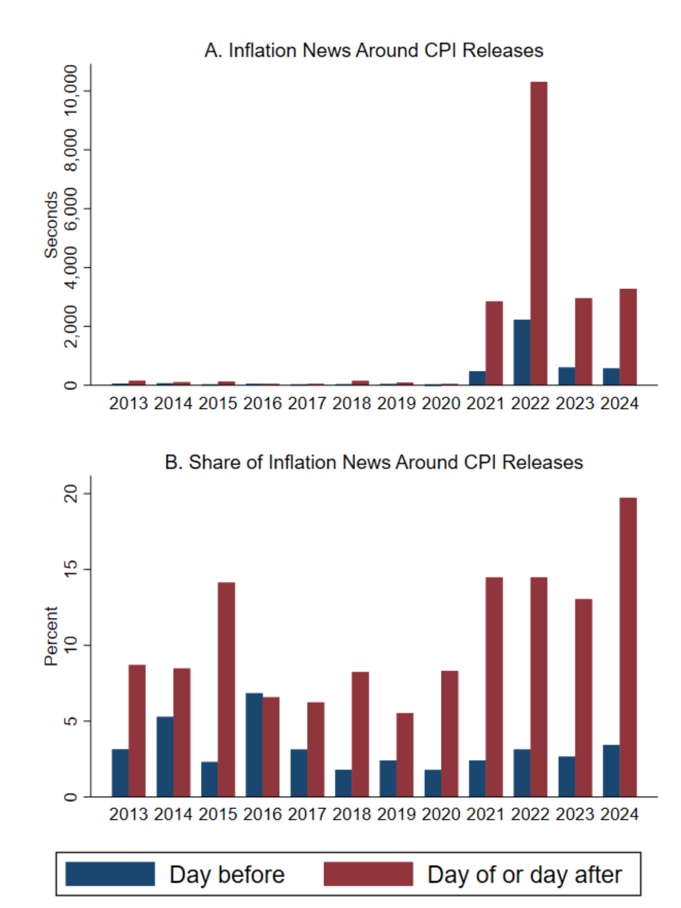
This section documents patterns of news coverage around CPI releases. While we think that the response of news to CPI reports is interesting in its own right, these results are also important for motivating the instrumental variables strategy that we use in the next section.

3.1 CPI Releases as Focal Point of Inflation Coverage

Inflation coverage on cable television frequently occurs on or near CPI release dates. In fact, the two highest coverage dates in our sample, May 11, 2022 and September 13, 2022, are both associated with CPI releases. Figure 4 shows how the volume and share of coverage that occurs around release dates has changed over time. As shown in Panel A, before 2021, total cable news coverage of inflation was sparse. Panel B shows the proportion of coverage that occurs on the day before and on the day of or following a CPI release. Since there are 12 CPI releases per year, 3.3% of days are CPI release dates. If more than 6.6% of inflation news occurs on the day of or after a CPI release, then those dates account for a disproportionate share of inflation coverage. From 2013 through 2015, around 9 to 15% of inflation coverage occurred on the day of or after a CPI release, while from 2016 through 2020, these days received coverage that was proportional to non-release days.

Beginning in 2021, not only the total news coverage of inflation, but also the share of coverage that occurred near CPI releases, rose. Almost 15% of inflation news

Figure 4: Inflation Coverage Around CPI Release Dates



Notes: The figure depicts inflation coverage around CPI release dates, using data from the Stanford Cable TV News Analyzer. Panel A shows the number of seconds spent discussing inflation on the day before and the day of and after the release. Panel B expresses this coverage as a share of coverage for the month.

occurred on the day of or immediately following a CPI release in 2021, 2022, and 2023. In 2024, CPI releases became an even larger focal point of inflation news, with 20% of inflation mentions occurring the day of or following a release. These results motivate our focus on the years 2021 through 2024 as our baseline sample period.

CPI releases are also a much stronger driver of inflation coverage than personal consumption expenditures (PCE) inflation releases, which occur on different days than CPI releases. As shown in Appendix Figure A.1, the share of inflation coverage on the day of or after PCE release dates is usually around 5 to 7%, which is not more than a typical day. Thus, even though the Federal Reserve's inflation target is officially defined in terms of PCE inflation, CPI inflation–which tends to be higher than PCE inflation, and is widely used to index Social Security payments, tax brackets, and state minimum wages (Janson, Verbrugge, and Binder 2020)–appears to be more salient for the media.

3.2 News Coverage of Inflation Surprises

Cable news reports often mention the CPI reports as well as the direction of surprise in the report. For example, following the release of the May 2022 CPI report, which was 0.3 percentage points higher-than-expected, the MSNBC program "Hallie Jackson Reports" referred to "this morning's worse than expected read on inflation, now 8.6. There were hopes today that it would bring signs that price spikes were easing. Instead, they got worse, led by that record surge in gas prices."

On September 14, 2022, the August CPI report came in 0.2 percentage points higher-than-expected. "America Reports" on Fox News reported, "We begin with President Biden brushing off August inflation report insisting the economy is still strong despite high prices hammering families nationwide," and referred to the "higher-than-expected inflation number." The same day, "Newsroom" on CNN reported on "Tuesday's inflation numbers, driving home the reality that the Fed still has a long way to go to get inflation under control."

A negative inflation surprise occurred on November 10, 2022, with CPI inflation 0.2 percentage points lower than expected. CNN's "At This Hour" reported, "Finally,

Figure 5: Examples of Cable TV Inflation Coverage

Notes: Examples of screenshots from the Stanford Cable TV News Analyzer. These images are from MSNBC on June 10, 2022, Fox News on September 14, 2022, and CNN on November 10, 2022.

we get some good inflation news. This might be one of the most positive economic developments we've seen all year. Month over month, we saw prices go up by 0.4. That is encouraging because it was supposed to get worse than that and it didn't. That was flat. Year over year, consumer prices up 7.7. Normally, that is terrible news but we're obviously not in normal times now." Another negative CPI shock occurred on July 12, 2023, when the CPI report was 0.1 percentage points lower than expected. CNN reported on the "better than expected inflation report we got in the U.S." with the "consumer price index showing that inflation slowed to 3% on an annual basis making June the 12th straight month that inflation has slowed. Let's look at some of the categories. Gas from a year ago down 27, used cars 5, meat fractionally, but airfare off almost 19." Examples of screenshots from some of these video clips appear in Figure 5.

3.3 Dynamic Response of News to Inflation Surprises

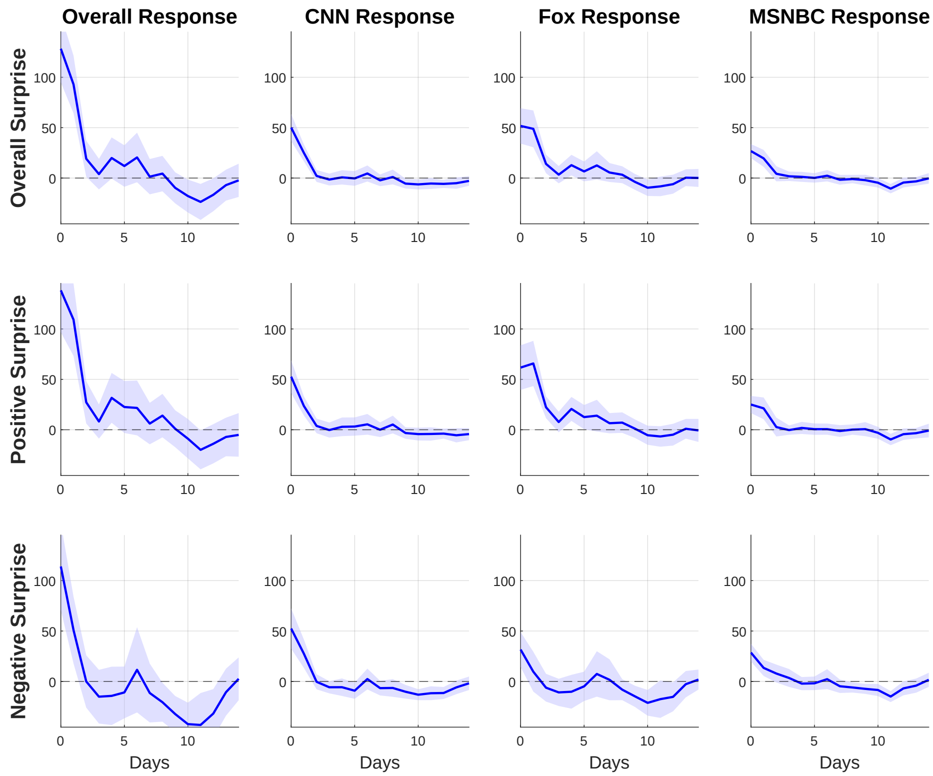
To estimate the dynamic effect of inflation surprises on cable news coverage of inflation, we apply a local projections (LP) framework following Jordà 2005. Specifically, we estimate:

$$news_{t+h} = c^h + \alpha_1^h |surprise|_t + \alpha_2^h \mathbb{1}_{\text{release}} + \sum_{j=1}^{p} \Phi_j^h \mathbf{X}_{t-j} + \varepsilon_{t+h}, \quad h = 0, \ldots, H, \quad (1)$$

where $news_t$ measures the total daily news coverage of inflation in seconds. We employ two sources of "supply-driven" variation, $|surprise|_t$ is the absolute value of the inflation surprise series, while $\mathbb{1}_{\text{release}}$ is an indicator for CPI release dates. Our control set includes up to 30 lags of $news_t$ and daily inflation expectations, π_t^{exp}, to account for persistence in both news coverage and expectations.[6] We estimate this model for a maximum horizon of 14 days, capturing the immediate impact on inflation news coverage. The impulse response function (IRF) is given by the sequence

[6]The choice of 30 lags follows existing studies using daily macroeconomic data, such as Jacobson, Matthes, and Walker 2023.

Figure 6: Dynamic Responses of News Coverage



Notes: This figure shows the estimated dynamic effects of CPI surprises and release dates on news coverage in seconds. The shaded area represents the 90% confidence interval based on heteroskedasticity and autocorrelation consistent (HAC) standard errors, approximated with the delta method. The on-impact effect is normalized to correspond to a 0.1 ppt inflation surprise on a release day.

of coefficients $\{0.1 \times \alpha_1^h + \alpha_2^h\}_{h=0}^{H}$.

We estimate Equation 1 for total news coverage and separately for CNN, Fox News, and MSNBC. The first row of Figure 6 presents the impulse response functions, normalizing the response to a 0.1 percentage point inflation surprise on a CPI release day. That is, on a CPI release day with a 0.1 percentage point inflation surprise, total news coverage increases significantly by approximately 128 seconds. Recall that this means that the actual word "inflation" is spoken for an additional 128 seconds, approximately 1.1 standard deviations in news coverage.

We find that the extensive margin—the mere occurrence of a CPI release day—accounts for about 85% of this on-impact response, while the size of the inflation surprise explains the remainder. Notably, this response is short-lived, dissipating within two to three days.

Breaking down the responses by news channel, CNN and Fox News contribute nearly equally to the on-impact increase in coverage, while MSNBC plays a smaller role. Coverage on CNN and MSNBC returns to baseline within two days, whereas Fox News coverage remains elevated for an additional day, suggesting a slightly more persistent response.

3.4 Asymmetric Response of Coverage to Positive and Negative Surprises

The flexibility of local projections also allows us to test for asymmetric effects on news coverage depending on whether inflation surprises are positive or negative. We modify Equation 1 and separately estimate the impact of positive surprises and negative surprises. Let $\mathbb{1}^{+}_{\text{release}}$ denote CPI release dates with non-negative surprises, and $\mathbb{1}^{-}_{\text{release}}$ with non-positive surprises.[7] Then we estimate:

$$news_{t+h} = c^h_+ + \alpha^h_{1,+}|\max(0, surprise)|_t + \alpha^h_{2,+}\mathbb{1}^{+}_{\text{release}} + \sum_{j=1}^{p} \Phi^h_{j,+}\mathbf{X}_{t-j} + \varepsilon_{t+h}, \quad (2)$$

and

$$news_{t+h} = c^h_- + \alpha^h_{1,-}|\min(0, surprise)|_t + \alpha^h_{2,-}\mathbb{1}^{-}_{\text{release}} + \sum_{j=1}^{p} \Phi^h_{j,-}\mathbf{X}_{t-j} + \varepsilon_{t+h}. \quad (3)$$

These specifications model asymmetries by splitting the instruments based on the sign, enabling the estimation of distinct dynamic responses. This approach follows

[7]We define the CPI release dummies weakly: $\mathbb{1}^{+}_{\text{release}}$ includes all days with non-negative surprises (i.e., surprise ≥ 0), and $\mathbb{1}^{-}_{\text{release}}$ includes all days with non-positive surprises (i.e., surprise ≤ 0). Thus, zero-surprise release days enter both specifications.

recent developments in the literature on government spending multipliers, where researchers emphasize the importance of accounting for sign-dependent effects. For instance, Barnichon, Debortoli, and Matthes (2022) and Ben Zeev, Ramey, and Zubairy (2023) employ local projections to study whether the effects of fiscal shocks vary by the sign of the shock measure. Similarly, Jordà, Singh, and Taylor (2024) apply this methodology to uncover asymmetric effects of monetary policy shocks. The overarching insight is that modeling by sign captures economically meaningful non-linearities that would otherwise be missed in linear or symmetric frameworks. In our context, we apply this sign-split methodology to test for asymmetries in how inflation surprises affect media coverage.

The second and third rows of Figure 6 show the responses to positive and negative surprises. Both lead to an immediate increase in news coverage, though of somewhat different magnitudes: on release days with a 0.1 percentage point positive surprise, coverage rises by approximately 138 seconds, compared to 114 seconds after a negative surprise. Thus, we do not find a pronounced asymmetry on impact. However, Fox News coverage remains elevated for an extra day following positive surprises, suggesting that inflationary news differs in the duration of coverage. Beyond this immediate effect, the persistence of media coverage also differs. Coverage following negative inflation surprises fades more quickly, turning statistically significantly negative after 9 days and remaining so for approximately five days. This reversal suggests that while negative surprises initially receive attention, media outlets reduce coverage more rapidly than in response to positive inflation shocks. These results are consistent with broader patterns in media reporting, where negative economic news (in our case, a positive inflation surprise, during a period of high inflation) tends to receive more coverage (Altheide 1997, Harrington 1989, Soroka 2006, Soroka 2012, Heinz and Swinnen 2015).

Our results, in addition to contributing to the literature on media coverage of economic conditions, also lend themselves to the construction of a useful instrument for inflation news coverage. Recall that we wish to study the effects of news coverage on inflation expectations, but face endogeneity and reverse causality issues. We have now shown that CPI release dates, which have exogenous and predetermined timing, significantly increase news coverage, and more so when they are associated with larger inflation surprises. We will use these insights to construct our instrument for news coverage in the next section.

4 Empirical Strategy

This section outlines our empirical strategy for estimating the dynamic causal effects of inflation news coverage on daily household inflation expectations. We employ a local projections instrumental variables (LP-IV) approach, following Stock and Watson (2018), which enables us to flexibly trace the response of expectations to exogenous variation in media coverage induced by CPI release dates and inflation surprises. As demonstrated in Section 3, these have a strong impact on news coverage, making them well-suited for identifying causal effects.

4.1 LP-IV Framework

The LP-IV method allows us to estimate impulse responses flexibly without imposing strong structural assumptions. We implement this framework by instrumenting inflation-related media coverage with CPI surprises and scheduled CPI announcement dates, which provides the following IV regression:

$$\pi^{\exp}_{t+h} = \beta^h_0 + \beta^h_1 \widehat{news}_t + \sum_{j=1}^{p} \Gamma^h_j \mathbf{X}_{t-j} + u_{t+h}, \quad h = 0, \dots, H, \tag{4}$$

where $\pi^{\exp}_t$ represents median one-year-ahead household inflation expectations, and $\mathbf{X}$ includes lagged controls for expectations and media coverage. We instrument for $news_t$, the total seconds of inflation coverage on day t, using two instruments: the absolute value of the CPI surprise on day t and an indicator that takes value 1 if t is a CPI release date.[8] That is, $\widehat{news}_t$ are the fitted values from the following first-stage

[8]Alternative potential instruments, such as monetary policy decisions on FOMC meeting days or monetary policy surprises, also influence news coverage of inflation. However, they do not satisfy the exclusion restriction in our setting, as they are likely to directly affect household inflation expectations through channels other than news coverage. We explore this relationship in Appendix D.

regression:

$$news_t = c + \alpha_1 |surprise|_t + \alpha_2 \mathbb{1}_{\text{release}} + \sum_{j=1}^{p} \Phi_j \mathbf{X}_{t-j} + \varepsilon_t \tag{5}$$

Instrument relevance: As shown in Section 3, CPI surprises and release dates lead to an immediate increase in inflation news coverage, yielding a strong first-stage relationship with a first-stage F-statistic of 21.66.[9] This value is well above conventional thresholds to guard against concerns of weak instruments. However, when considering the low-inflation sample period from 2013 to 2020, the relationship between CPI surprises on release days and news coverage is insignificant: the F-statistic drops to 1.85, and there is no significant on-impact effect on news coverage (see also Section 5.2 for a comparison of sample periods). The fact that instrument relevance is regime-dependent aligns with the findings of Kroner (2025), who documents that heightened investor attention during the 2021-2023 high-inflation period dramatically amplified market reactions to CPI releases. This evidence suggests that in high-inflation regimes, attention to CPI releases intensifies, thereby magnifying the economic impact of the information. For this reason, we focus on the 2021-2024 sample period, when CPI release days more strongly shape inflation news coverage. The causal effect we estimate is inherently conditional on periods of elevated attention. However, substantial news coverage of inflation is a hallmark of such high-attention periods. This is precisely the causal effect of interest, as these are the moments when households are most exposed to and influenced by inflation-related news.

Instrument exogeneity: The validity of our instruments requires that the inflation surprise at a CPI release day affect inflation expectations only through media coverage. Since CPI release dates are predetermined and the magnitude of surprises is *ex ante* unpredictable, the surprise series is unlikely to be correlated with other unobserved shocks. Moreover, because inflation news coverage reacts immediately to CPI releases—before households have time to update their expectations—concerns

[9] We compute the first-stage F-Statistic as Wald test on the instruments after estimating Equation 5, using Newey-West standard errors.

about simultaneity bias are mitigated.

We acknowledge that the volume of news coverage is also shaped by an upward shift in audience demand for inflation-related information during a high-inflation regime: in this period, attention to news about inflation is higher, leading to more extensive reporting on release days. Importantly, however, the timing of CPI release days and the size of the surprises are fully exogenous, as an elevated level of attention has no impact on the release schedule. By focusing on very short windows around these releases, our high-frequency approach isolates the immediate impact of this exogenous information arrival, before confounding factors can affect expectations. To strengthen exogeneity, we also control for past expectations and past media coverage, thereby mitigating confounding from forward-looking expectation adjustments.

4.2 Smooth Local Projections

The impulse responses could be estimated via OLS, with standard errors that are robust to heteroskedasticity and autocorrelation. However, it is well known that the impulse response estimator from unrestricted local projections can have high variability (Ramey 2016). The relatively high noise in our daily data is likely to exacerbate this issue (Binder, Campbell, and Ryngaert 2024). Adding mild constraints to the local projection can improve efficiency quite substantially while largely preserving flexibility (Jordà 2023).

One such approach, which we adopt, is the smooth local projections methodology of Barnichon and Brownlees (2019), which is based on the penalized B-splines of Eilers and Marx (1996). Specifically, we approximate the sequence of coefficients $\{\beta_1^h\}_{h=0}^H$ using a B-spline basis function expansion:

$$\beta_1^h \approx \sum_{k=1}^{K} b_k B_k(h), \tag{6}$$

where $B_k(h)$ are B-spline basis functions that span the forecast horizon. The coefficients b_k are estimated using a generalized ridge estimator, which we implement building on the `SmoothLP` package provided by Bousquet (2024). Smoothing the impulse responses requires specification of a penalty parameter λ that controls the degree of smoothing, and also a parameter r. The impulse response function shrinks to a polynomial of degree $r - 1$ as λ grows large.

Following Barnichon and Brownlees (2019), we employ K-fold cross-validation, a resampling procedure, to select the parameters that minimize the average mean squared error (MSE). This procedure ensures that the penalization parameter λ is selected objectively to balance variance reduction and model flexibility. We test a vector of λ values ranging from 0.1 to 1000 and consider $r = 2, 3$ or 4, allowing the impulse response to shrink toward a linear, quadratic, or cubic polynomial, respectively. The resampling procedure selects $\lambda = 1000$ for $r = 2$–in other words, a high degree of smoothing, with the polynomial shrinking towards a linear function. Further details of the K-fold cross-validation and results using alternative parameterizations are in Appendix B.

5 Results

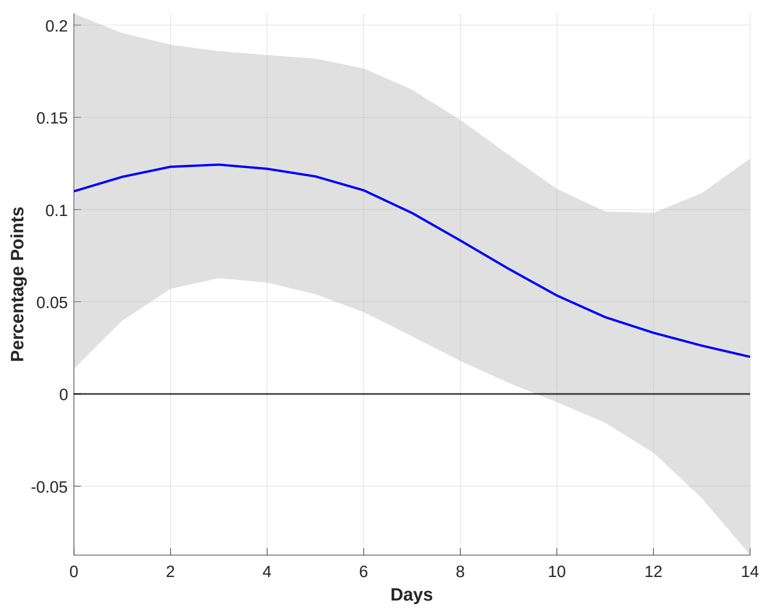
In this section, we present our main empirical findings on how inflation news coverage affects household inflation expectations. We begin by showing the baseline dynamic effects using our LP-IV framework and then explore alternative sample periods to assess the state-dependent relevance of our instruments. We next examine the existing asymmetries in household responses to inflationary versus disinflationary news and conclude by quantifying the broader contribution of news coverage to the rise in inflation expectations through an accounting exercise.

5.1 Baseline Results

We estimate the effect of inflation news coverage on household inflation expectations by estimating Equation 4 for horizons up to 14 days. Specifically, we analyze how a one standard deviation increase in inflation news coverage—equivalent to 112 seconds—induced by exogenous variation on CPI release dates affect inflation expectations.

Figure 7 illustrates the smoothed dynamic response of inflation expectations to an exogenously-induced one standard deviation increase in news coverage. Households significantly increase their inflation expectations in response to news, with the effect ranging between 0.1 and 0.12 percentage points. The response follows a hump-shaped pattern, a typical feature in the transmission of news shocks to subjective expectations (Coibion and Gorodnichenko 2012), before gradually fading out around 10 days after the shock. Note that results are virtually identical if we augment the control set in Equation 4 to include additional macro-financial indicators: the daily S&P 500 Index, the WTI Oil Price, and the VIX, a standard measure of market volatility. Results are also highly robust to extending the lag length from 30 to 90 days. Both of these robustness checks are shown in Appendix Figure A.2.

Figure 7: Dynamic Response of Household Inflation Expectations

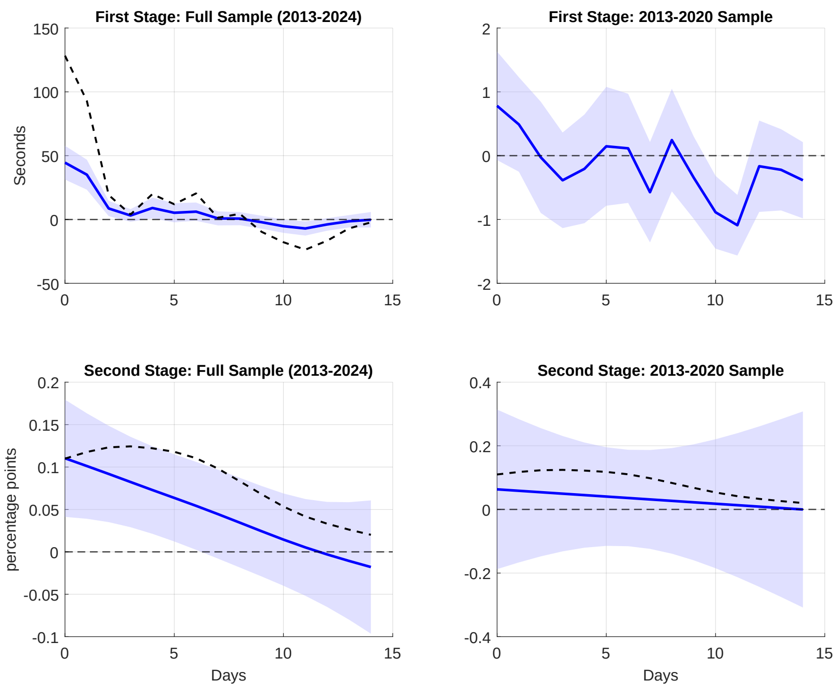


Notes: This figure presents the smoothed IV-estimated response of inflation expectations to a 1 standard deviation increase in news coverage (112 seconds). The shaded area represents the 90% confidence interval, based on heteroskedasticity and autocorrelation consistent standard errors.

5.2 Alternative Sample Periods

In our baseline specification, we focus on the sample period from 2021 to 2024, a time characterized by elevated inflation rates. This choice reflects the state-dependent nature of our identification strategy. Our instruments are more relevant in high-inflation regimes, where news coverage of inflation, especially on CPI release dates, is pronounced.

Figure 8: Results for Alternative Sample Periods



Notes: This figure presents results for alternative sample periods: the full sample period (June 1, 2013 to May 1, 2024) and the pre-2021 sample period (June 1, 2013 to November 30, 2020). The first row shows the dynamic response of news coverage to a 0.1 percentage point inflation surprise on a release day. The second row shows the impulse response of inflation expectations to a one standard deviation shock to news coverage, using our LP-IV approach. The shaded areas indicate the 90% confidence intervals, and the dashed lines represent the baseline point estimates, included for comparison.

If we instead use the full available sample period, from June 1, 2013 to May 1, 2024, we find a weaker response of news coverage in the first stage, just as one would expect from Figure 4. These results are presented in Figure 8. In the first panel, we see that the response of news coverage to a 0.1 percentage point inflation surprise on a release day is a little less than half of the response in the 2021 to 2024 sample. In the second stage, the response of expectations to a shock to news coverage is qualitatively similar, but somewhat muted.

However, if we focus only on the pre-2021 period, from June 1, 2013 to November 30, 2020, we find no significant response of news coverage to CPI releases and surprises, indicating that our instrument is irrelevant in a regime of relatively low and stable inflation. Correspondingly, we do not identify an effect of news on expectations in that period, but that reflects our lack of instrument relevance and not necessarily a lack of true effect.

5.3 Asymmetric Effects

Our baseline model assumes a symmetric response of household inflation expectations to news coverage. However, prior research (Soroka 2006, Gambetti, Maffei-Faccioli, and Zoi 2023, Chahrour, Shapiro, and Wilson 2024) suggests that consumers react more strongly to negative than to positive news. This implies that households should respond more to reports of rising inflation than to news of a slower price increase. To test for such asymmetries, we extend the LP-IV framework in Equation 4 by estimating separate responses for positive and negative inflation surprises.

First, we estimate the effect of an increase in news coverage using the positive surprises as an instrument:

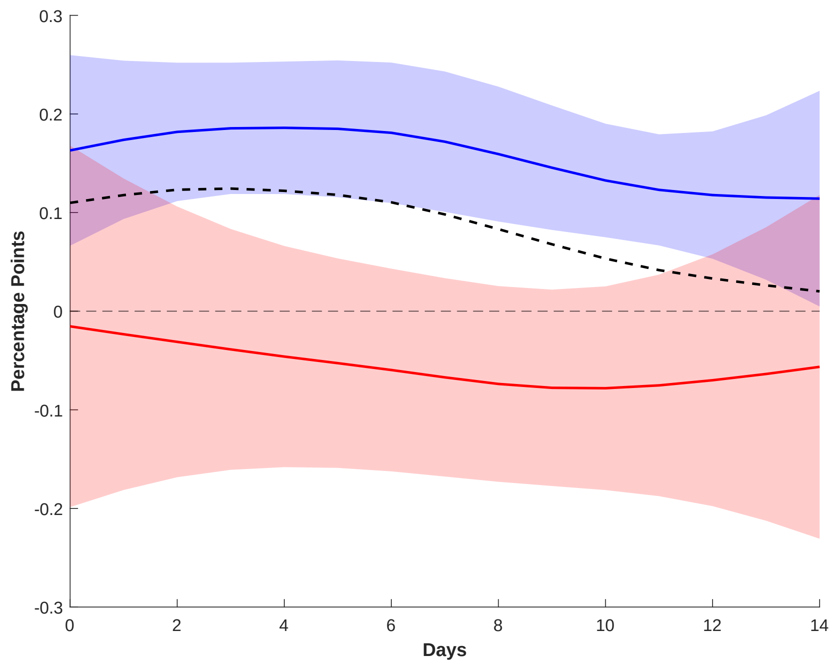
$$\pi^{\exp}_{t+h} = \beta^h_{0,+} + \beta^h_{1,+} \hat{news}^+_t + \sum_{j=1}^{p} \Gamma^h_{j,+} \mathbf{X}_{t-j} + u_{t+h}, \quad h = 0, \ldots, H. \tag{7}$$

where the instrumented news variable $\hat{news}^+_t$ is obtained from the first-stage regression, using the absolute value of positive CPI surprises and an indicator variable for release days with non-negative surprises. Similarly, we estimate the effect of an increase in news coverage using the negative surprises as an instrument:

$$\pi^{\text{exp}}_{t+h} = \beta^h_{0,-} + \beta^h_{1,-} \hat{news}^-_t + \sum_{j=1}^{p} \Gamma^h_{j,-} \mathbf{X}_{t-j} + u_{t+h}, \quad h = 0, \ldots, H. \tag{8}$$

Figure 9 displays the estimated impulse responses of household inflation expectations to positive and negative CPI surprises, scaled to a one standard deviation increase in inflation news coverage. These estimates are based on the smooth local projections IV approach introduced in Section 4.

Figure 9: Dynamic Response of Inflation Expectations: Positive vs. Negative Surprises



Notes: The figure presents the LP-IV impulse responses of inflation expectations to a one standard deviation increase in news coverage (112 seconds). The blue line shows responses to positive CPI surprises, the red line to negative surprises, and the black dashed line indicates the baseline. Shaded areas denote 90% confidence intervals.

The responses exhibit a clear asymmetry. Following a positive surprise (blue), inflation expectations increase sharply and remain persistently elevated over the subsequent two weeks. By contrast, the response to a negative surprise (red) is muted: expectations remain essentially flat in the subsequent two weeks. The dotted black line shows the baseline (linear) response to a CPI surprise, which lies between the two non-linear specifications but closer to the positive response.

Caravello and Martinez-Bruera (2024) raise the concern that specifications using sign-split transformations may conflate sign and size non-linearities when the distribution of the shock variable is asymmetric. In our case, CPI surprises are highly skewed (skewness = 8.48) and heavy-tailed (kurtosis = 117.78), raising the possibility that larger positive surprises may be driving the observed asymmetry in responses. To assess this, we group all non-zero CPI surprises into five bins based on sign and magnitude: medium negative (-0.2 ppt), small negative surprises (-0.1 ppt), small positive (0.1 ppt), medium positive (0.2 ppt), and large positive (0.3 ppt or greater). Note that all surprises are multiples of 0.1 ppt due to rounding.

For each bin, we re-estimate the LP-IV specifications from Equations 7 and 8. We continue to use non-negative and non-positive release days as instruments, respectively, but now replace the absolute value of the CPI surprise with bin-specific indicators. This results in the following first-stage equations:

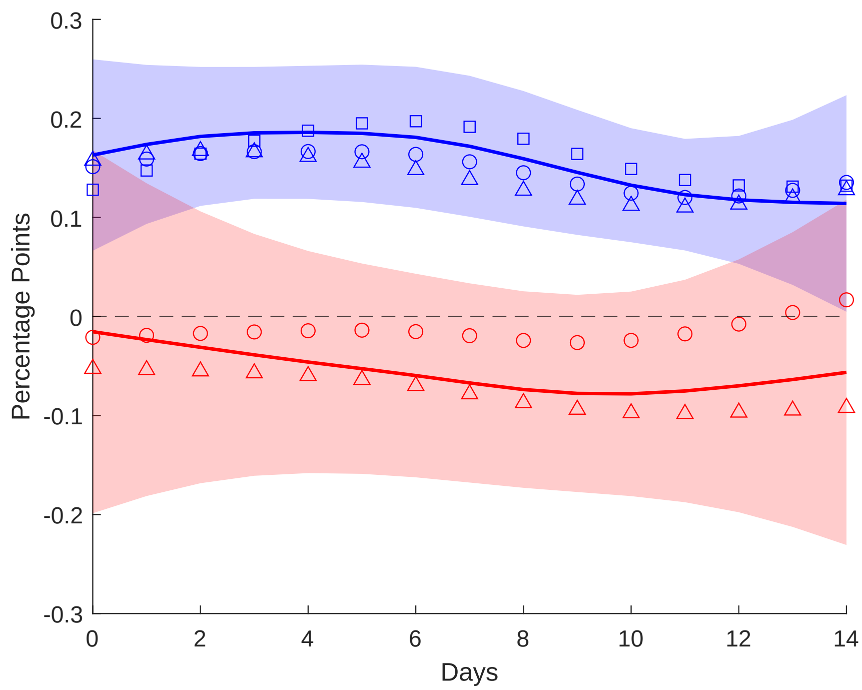
$$news_{t+h} = c_{+}^{h} + \alpha_{1,+}^{h} S_{+,t} + \alpha_{2,+}^{h} \mathbb{1}_{\text{release}}^{+} + \sum_{j=1}^{p} \Phi_{j,+}^{h} \mathbf{X}_{t-j} + \varepsilon_{t+h}, \tag{9}$$

$$news_{t+h} = c_{-}^{h} + \alpha_{1,-}^{h} S_{-,t} + \alpha_{2,-}^{h} \mathbb{1}_{\text{release}}^{-} + \sum_{j=1}^{p} \Phi_{j,-}^{h} \mathbf{X}_{t-j} + \varepsilon_{t+h}, \tag{10}$$

where $S_{+,t}$ and $S_{-,t}$ are categorical indicators denoting the three bins for positive surprises and the two bins for negative surprises, respectively. In each case, we estimate a separate LP-IV specification using one of the bins as the instrument. This enables a symmetric comparison across magnitudes (e.g. +0.1 ppt vs. -0.1 ppt), while also isolating the influence of large positive surprises (>0.2 ppt), allowing us to assess the role of size asymmetries more directly.

Figure 10 plots the resulting impulse responses across bins. The findings confirm that the asymmetric reaction of expectations is not driven by outlier shocks: even at comparable magnitudes, positive news consistently elicits stronger and more persistent responses than negative news.

Figure 10: Dynamic Response of Inflation Expectations: Estimation by Size Category



Notes: Solid lines show impulse responses to positive (blue) and negative (red) CPI surprises, with shaded 90% confidence intervals. Markers represent point estimates from bin-specific LP-IV models: circles for CPI surprises of $\pm$ 0.1 percentage points (ppt), triangles for $\pm$ 0.2 ppt, and squares for surprises of $\geq$ 0.3 ppt. All responses reflect the effect of a one standard deviation increase in news coverage.

This confirms that the observed asymmetry in responses is primarily driven by the sign of CPI surprises rather than their size. Positive surprises consistently trigger a pronounced and persistent increase in inflation expectations in the days following the release. In contrast, negative surprises result in little to no response. This pattern holds across different magnitudes of surprises.

How should this asymmetry in the response of expectations to positive and negative inflation news be interpreted? We note that it is not primarily driven by the mildly asymmetric news coverage of positive and negative surprises. Recall from Figure 6 that news coverage increases immediately after both positive and negative CPI surprises, with peak responses of similar magnitudes occurring on the day of the release in both cases. The fact that inflation expectations rise sharply after positive surprises but only negligibly after negative ones thus suggests that the asymmetry stems not from differences in the amount of media coverage, but rather from how households process the information. Our results are consistent with the news selection hypothesis (Chahrour, Shapiro, and Wilson 2024). On days with negative inflation surprises (i.e. disinflationary news), some households will interpret the additional coverage of inflation as a signal that inflation is high, counteracting some of the signal that comes from the content of the news.

5.4 Accounting Exercises

The high-inflation period 2021-2024 featured an increase in inflation expectations as well as an increase in political polarization. In this section, we use our estimated coefficients to examine how increased news coverage may have contributed to these phenomena.

We first use the coefficient estimate β_1^0 from Equation 6.[10] Define γ_t as the increase in inflation expectations on day t attributable to coverage on that date:

$$\gamma_t = \beta_1^0 news_t. \tag{11}$$

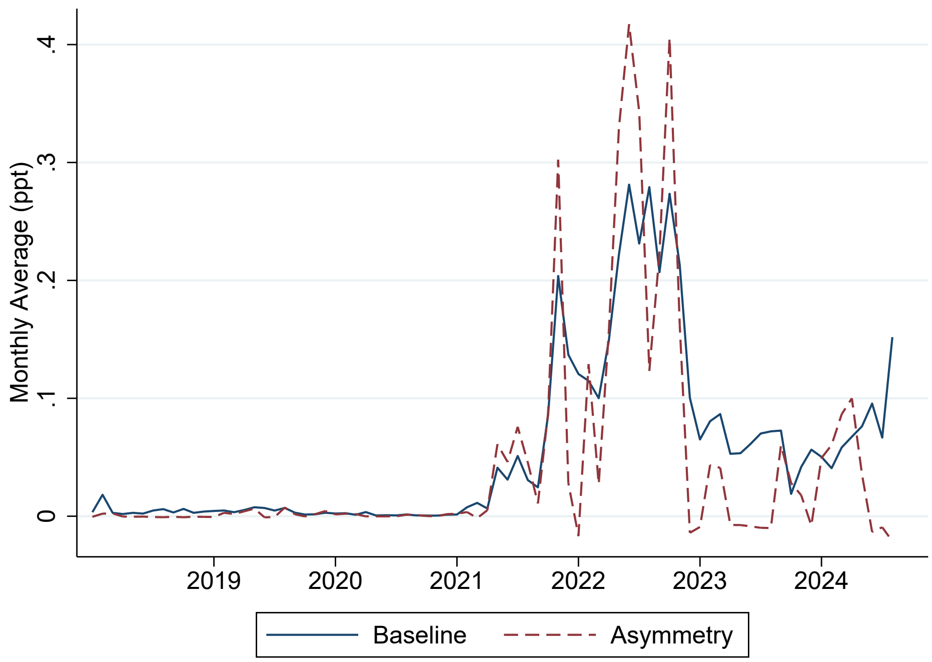
Although our evidence suggests that news increases expectations for a few days, it is unclear how to account for the accumulating effect of news over multiple days. Here, we assume that the effect of news on expectations is eliminated almost immediately. In this case, news coverage of inflation must remain high if inflation expectations are to remain elevated. This calculation does not account for the asymmetric effects of

[10]This is multiplied by 112 before they are plotted in Figure 7 to show the effect of a one standard deviation change in inflation news coverage.

inflationary and disinflationary news. We also make use of the estimates of asymmetric effects $\beta^0_{1,+}$ and $\beta^0_{1,-}$ from equations 7 and 8. If the most recent CPI release was a positive surprise, we let $\gamma_t = \beta^0_{1,+} news_t$. If it was a negative or zero surprise, $\gamma_t = \beta^0_{1,-} news_t$.

We plot the monthly averages of both estimates in Figure 11.

Figure 11: Effect of News Coverage on Inflation Expectations



Notes: The figure shows the monthly average of the effect of news coverage on household inflation expectations using the estimated on-impact effect from the baseline estimation, and the estimated effects for the asymmetric case.

Both series peak in June 2022, the same month as the peak median inflation expectation in the SCE. The baseline estimates imply a 0.28 percentage point increase in expectations due to news and while the estimates incorporating asymmetry imply a 0.42 percentage point increase. The median inflation expectation in the SCE was 7.42% in June 2022, up from 3.80% at the end of 2020. This means that the extra news coverage accounts for 8 to 12% of the overall increase in expectations. It is interesting to note that our accounting exercises yield estimates in the same range as the "back-of-the-envelope" calculations of Chahrour, Shapiro, and Wilson (2024). Using an entirely distinct dataset and identification strategy from ours, they find that "news media could account for somewhere between 4 and 18% of the increase in aggregate inflation expectations" in the rising inflation period.

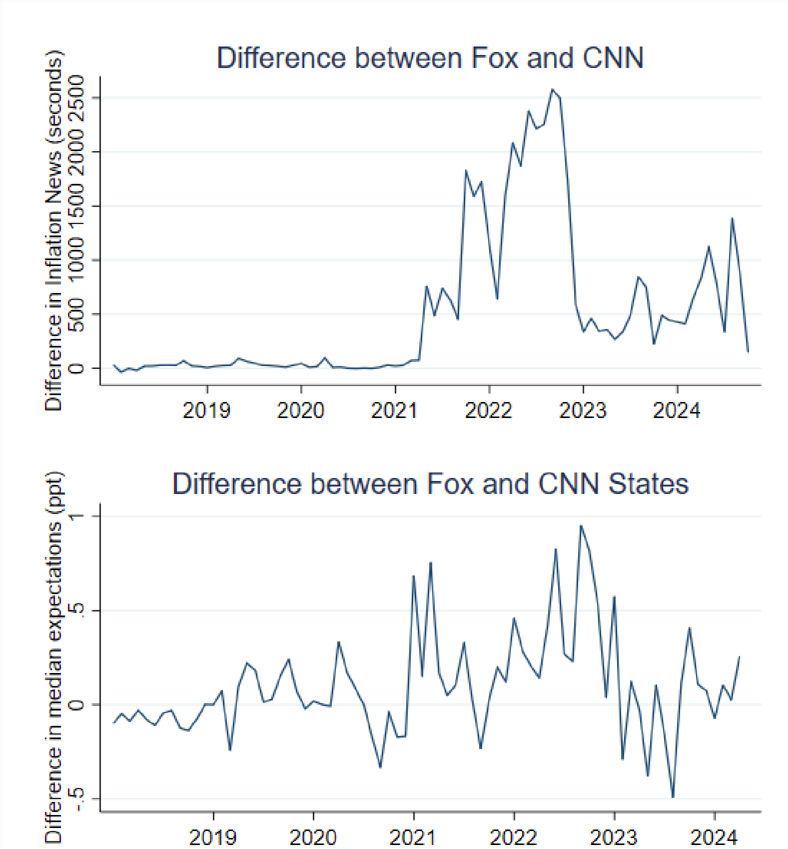
Accounting for asymmetry has important implications for understanding the effect of news on expectations. We see in Figure 11 that in 2022, which featured repeated inflationary news, we predict a larger increase in expectations than when we use our baseline specification. Conversely, while coverage remained elevated in 2023, CPI releases were more likely to come in as expected or lower-than-expected. This implies a moderated effect of news on expectations.

As expectations rose in 2022, the partisan gap in inflation expectations also expanded. Binder, Kamdar, and Ryngaert (2024) document that, in this period, Republican expectations increased by more than Democrat expectations and Republican expectations were more responsive to CPI releases. The first panel of Figure 12 shows that Fox News–a news source consumed primarily by Republicans–covered inflation more intensively than more left-leaning sources like CNN in this period.[11] As an additional exercise, we consider how the difference in inflation coverage between Fox and CNN may explain the partisan divergence in inflation expectations.

We replace γ_t with the difference between Fox coverage and CNN coverage on day t, and again compute γ_t as we did in the previous exercise (accounting for asymmetric effects). We find that the additional volume of inflation coverage on Fox would have increased Fox viewers' expectations by about 0.12 percentage points compared to CNN viewers' expectations at the peak in June 2022.

[11] Prior to 2021, Fox and CNN devoted virtually identical coverage time to inflation.

Figure 12: Inflation Coverage on Fox and CNN, and Expectations in Fox vs. CNN-Dominant States



Notes: The top panel shows the difference in inflation news coverage (seconds per month) on Fox and CNN, using data from the Stanford Cable TV News Analyzer. The bottom panel shows the difference in the median inflation expectations in states with more CNN viewers than Fox viewers (CNN states) and vice versa (Fox states). Expectations data from the Survey of Consumer Expectations; viewership data from Nationscape.

The Survey of Consumer Expectations does not ask for respondents' political affiliation or news source. It does, however provide their state of residence. Using data from Nationscape, a large public opinion survey conducted in 2020 (Tausanovitch and Vavreck 2021), on news viewership in each state, we categorize states as either predominantly Fox-viewing or predominantly CNN-viewing. In June 2022, the median inflation expectation in Fox-dominant states was 0.83 percentage points higher than that in CNN-dominant states (see the second panel of Figure 12). The difference in volume of inflation coverage thus explains about 14% (0.12/0.83) of that difference–again, this fits in the upper range of the back-of-the-envelope calculations from Chahrour, Shapiro, and Wilson (2024). Note that this is just the difference attributable to the *volume* of coverage on Fox versus CNN. The difference in coverage content and tone likely explains even more of the difference in expectations.

6 Conclusion

This paper provides new evidence on the effects of inflation news coverage on inflation expectations. A daily time series of inflation expectations and inflation news coverage allow us to study the dynamics of this effect. Using a novel IV strategy relying on CPI release dates as exogenous drivers of inflation news, we find that increased news coverage of inflation significantly raises household inflation expectations. The effect peaks within the first few days and gradually fades thereafter, so that expectations remain elevated for just under two weeks following a news shock. The effect sizes that we estimate are nontrivial. A one standard deviation increase in news coverage raises expectations by around 0.1 to 0.2 percentage points. This suggests that the increase inflation news can account for approximately 8 to 12% of the peak increase in inflation expectations.

The nature of our instrument and the flexibility of the local projections approach that we use also enables us to document a key asymmetry: higher-than-expected CPI releases generate a stronger and more persistent response in expectations than lower-than-expected releases. This suggests that inflationary news exerts a greater influence on household expectations than disinflationary news.

Our findings contribute to the growing literature on the role of the media in shaping macroeconomic expectations and highlight the usefulness of high-frequency data in understanding the transmission of economic news. Future research could explore whether the results we document appear in other economic environments. It may also consider how other measures of reporting - such as content and tone - may impact expectations.

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Online Appendix

A Additional Tables and Figures

Table A.1: Correlations of the Inflation Surprise Series with Other Shock Measures

Shock Measure	Source	Correlation	p-value	Sample
Monetary Policy	Bauer and Swanson (2023)	-0.003	0.9211	Jan 1, 2021 - Dec 31, 2023
	Nakamura and Steinsson (2018)	-0.0039	0.8932	Jan 1, 2021 - May 1, 2024
Uncertainty	Baker, Bloom, and Davis (2016)	-0.0258	0.3682	Jan 1, 2021 - May 1, 2024
Oil supply news	Känzig (2021)	-0.0009	0.9763	Jan 1, 2021 - May 1, 2024

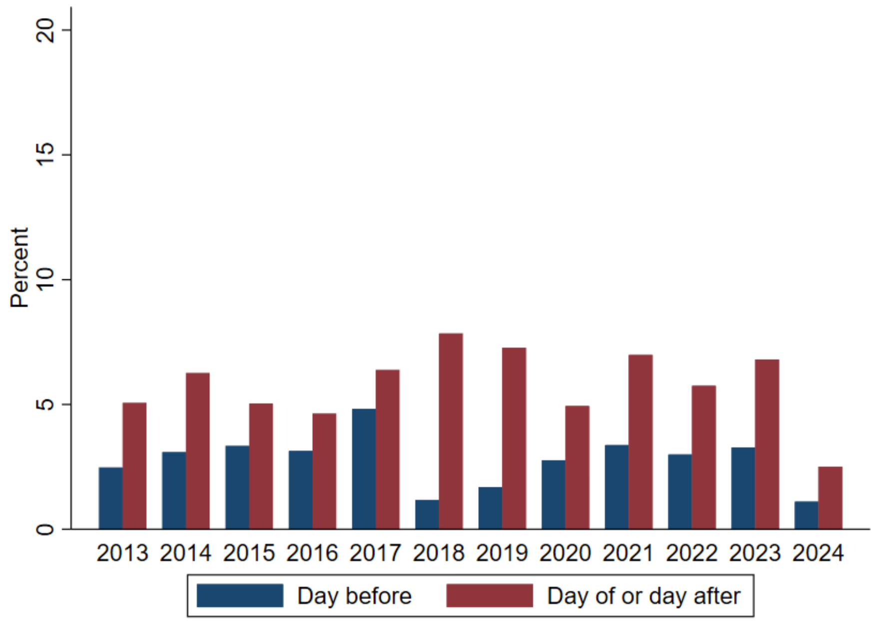
Notes: The table shows the correlation of the inflation surprise series with a range of different shock measures from the literature. For all series, we compute the Pearson correlation coefficient, the p-value corresponds to the test whether the correlation is different from zero. All shock measures, with the exception of Bauer and Swanson (2023), are available at the daily frequency for the sample period from Jan 1, 2021 to May 1, 2024. Bauer and Swanson (2023) is available up until December 2023.

Table A.2: Granger causality tests

Variable	p-value
S&P 500	0.8439
Geopolitical risk	0.8350
CBOE Volatility Index: VIX	0.0932
WTI Oil Price	0.4793

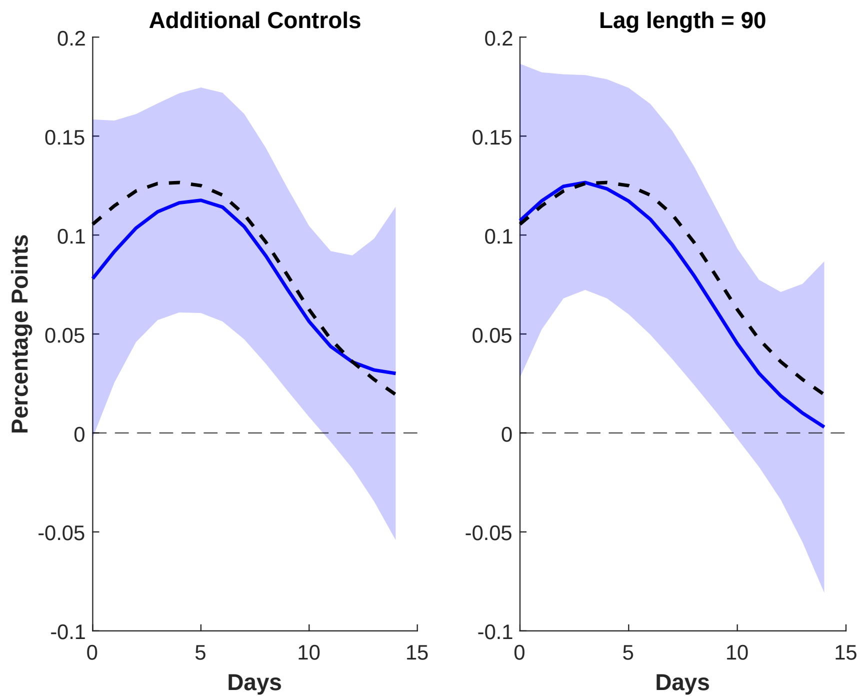
Notes: The table shows the p-values of a series of Granger causality tests of the inflation surprise series using a selection of macroeconomic and financial variables. The lag order is set to 90 days to capture longer-run relationships. Non-stationary series are made stationary by taking first differences. The regressions include a constant term.

Figure A.1: Inflation Coverage Around PCE Release Dates



Notes: The figure depicts inflation coverage around PCE release dates, using data from the Stanford Cable TV News Analyzer. The coverage is expressed as a share of news coverage for the month.

Figure A.2: Dynamic Response of Inflation Expectations: Robustness Checks



Notes: The figure displays smoothed LP-IV impulse responses of inflation expectations to a one standard deviation increase in news coverage. The left panel shows the response from a model with additional controls, while the right panel corresponds to a model with a longer lag specification. The black dashed line shows the baseline response. Shaded areas denote 90% confidence intervals, based on Newey-West standard errors.

B Smooth Local Projection Method Details and Robustness

As discussed in Section 4.2, the smooth local projection method requires specification of the penalty parameter λ, and the polynomial degree $r - 1$ to which the impulse response function shrinks as λ grows. The cross-validation procedure follows these steps:

1. The dataset is split into K equally sized folds.

2. The model is trained on $K-1$ folds, leaving one fold as the test set.

3. The MSE is computed on the left-out test fold.

4. This process is repeated across all K folds, ensuring each serves as the test set once.

5. The average MSE across folds is computed for each candidate λ.

6. The optimal λ is chosen as the one that minimizes the average MSE.

We find the lowest MSE for $K = 11$, $\lambda = 1000$, and $r = 2$, which we use for our baseline specification. As robustness checks, we estimate the following:

1. Unrestricted Local Projections: We estimate the IRF without any smoothing, using the standard LP-IV approach.

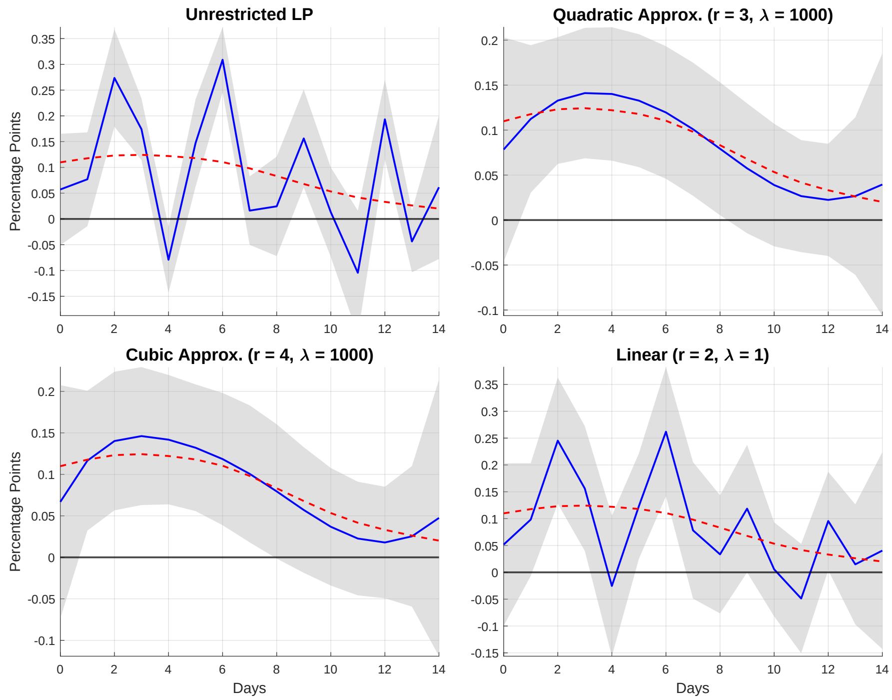
2. Quadratic Approximation ($r = 3$): Here, we approximate a quadratic polynomial, allowing for one turning point. In this case, the cross-validation procedure selects $\lambda = 1000$.

3. Cubic Approximation ($r = 4$): We approximate a cubic polynomial, allowing for two turning points. The cross-validation procedure selects $\lambda = 1000$.

4. Low Smoothing ($r = 2, \lambda = 1$): We revert to our baseline polynomial order ($r = 2$) but force a low penalization level ($\lambda = 1$) to explore the sensitivity of the results.

These alternatives are shown in Figure B.1. Each figure also includes the baseline estimate (red dashed line) for reference. Across all model specifications, we consistently find a significant increase in inflation expectations in the days following a one standard deviation in news. Despite more jagged estimates for the unrestricted estimator and when using a low λ, the overall pattern is confirmed. The effect appears to peak within a few days and gradually dissipates after approximately 9 to 10 days.

Figure B.1: Robustness: Dynamic Response of Household Inflation Expectations

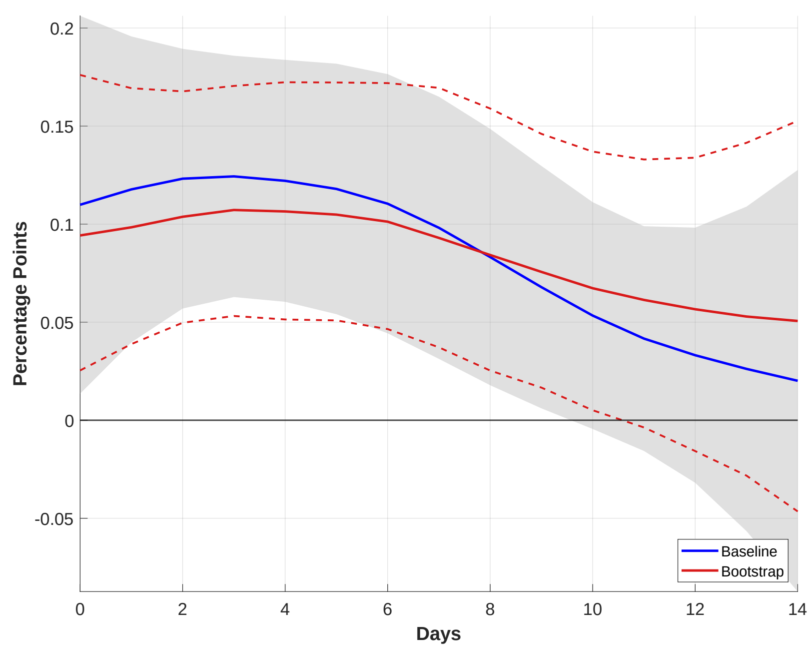


Notes: This figure presents smoothed IV-estimated responses of inflation expectations to inflation news coverage under alternative parameterizations. The shaded area represents the 90% confidence interval, computed using Newey-West standard errors. Units are percentage points. The red dashed line represents our baseline impulse response ($r = 2$ and $\lambda = 1000$).

We follow the empirical approach in Barnichon and Brownlees (2019) and estimate the LP-IV model by using the fitted value of news coverage from the first stage in the second stage. As noted by Barnichon and Brownlees (2019), inference in this context remains an open issue, with the asymptotic theory only partially developed. To address the first stage estimation uncertainty, we rely on a standard moving-block bootstrap procedure (see, for example, Kuensch 1989). This involves selecting blocks of length l randomly with replacement.

In the context of local projections, the block length should at least cover $H + p$ to account for both the forecast horizon and the number of lags. While Lusompa (forthcoming) cautions that this requirement creates a bias-variance tradeoff, making it generally undesirable to tie the block length directly to $H+p$, our use of high-frequency data—and thus a substantially larger sample than in conventional macroeconomic studies—helps to mitigate this concern. We therefore implement the moving-block bootstrap with $n = 1,000$ replications, conservatively choosing a block length of $l = 100$ to comfortably accommodate our 30-day lag structure and 14-day horizon. For each replication, we re-estimate the full LP-IV procedure.

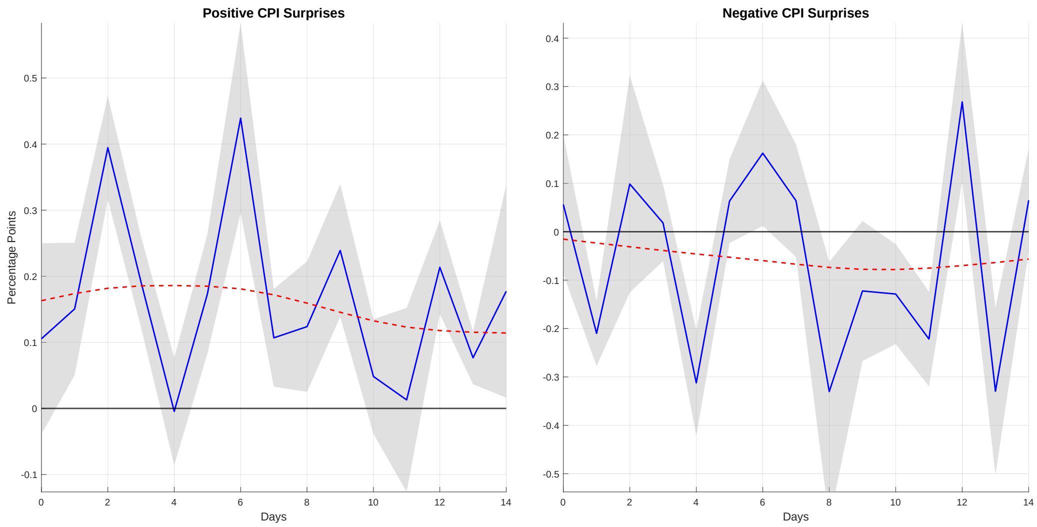
Figure B.2: Robustness using a Bootstrap Procedure



Notes: This figure presents the baseline LP-IV estimation in blue together with the median and the 90% confidence interval, based on the moving-block bootstrap. Units are percentage points.

Figure B.2 plots the median impulse response function along with the bootstrapped 90% confidence interval. This demonstrates that our results remain robust even when explicitly incorporating the first stage estimation uncertainty. Moreover, they are

Figure B.3: Robustness for the Asymmetric Case



Notes: This figure presents the unrestricted LP-IV estimation of positive and negative surprises, respectively. The shaded area represents the 90% confidence interval, computed using Newey-West standard errors. The unit is percentage points. The red dashed line represents our baseline impulse response.

stable to variations in the block length (ranging from 45 to 120) and when increasing the number of bootstrap replications to $n = 2,500$.

Finally, Figure B.3 shows the unrestricted LP-IV estimates together with the smoothed estimates for responses to positive and negative surprises. This figure confirms that the asymmetry documented in Section 5.3 also holds when the LPs are not smoothed.

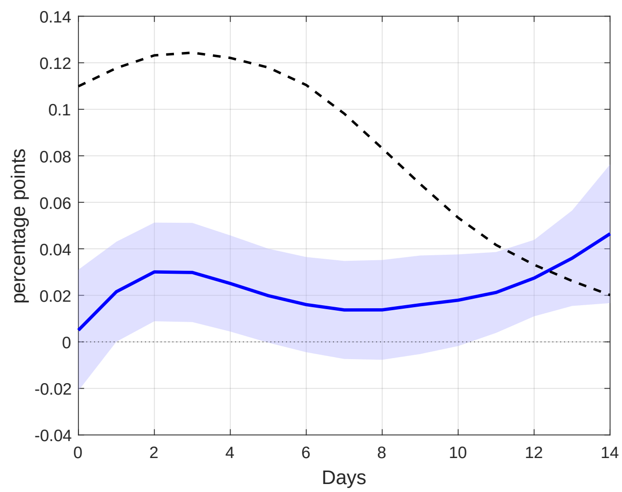
C Comparison of IV and Non-IV Estimates

It is informative to compare the results of our LP-IV to those from a non-instrumented LP model. That is, we compare our estimates from Equation 4 to those from the following equation:

$$\pi^{\exp}_{t+h} = \gamma^h_0 + \gamma^h_1 news_t + \sum_{j=1}^{p} \phi^h_j \mathbf{X}_{t-j} + \epsilon_{t+h}, \quad h = 0, \ldots, H, \tag{12}$$

where the difference is that we do not use an instrument for $news_t$. Figure C.1 compares these non-instrumented estimates to the baseline estimates from the LP-IV.

Figure C.1: Comparison of IV and non-IV Estimates



Notes: This figure presents results for a non-instrumented local projection of inflation expectations on news coverage. Dashed lines represent the baseline point estimates from the LP-IV, included for comparison.

The non-instrumented estimates are much smaller than the instrumented estimates. This is most likely due to measurement error in $news_t$. The variable $news_t$ measures the number of seconds that the word "inflation" is spoken. But this may be a noisy proxy for the total amount of coverage of inflation. For example, one news story may mention the word "inflation" one time in a brief, one-sentence discussion of inflation. Another story may mention the word "inflation" one time in a lengthier discussion. Other stories may discuss inflation using alternative terms like "CPI" or "price increases." It is well-known that classical measurement error in the independent variable leads to attenuation bias—the non-instrumented estimate is biased towards zero. When we use an instrument for $news_t$, the instrument isolates variation in true news coverage that is uncorrelated with the measurement error, so this attenuation bias is avoided.[12]

D The Role of Monetary Policy

Over the sample period of 2021-2024, the federal funds rate (FFR) cumulatively increased by 5.25 percentage points, drawing substantial media attention. Figure D.1 shows that a considerable share of inflation news has consistently occurred on or immediately after FOMC meeting days, not only during the recent high-inflation period.

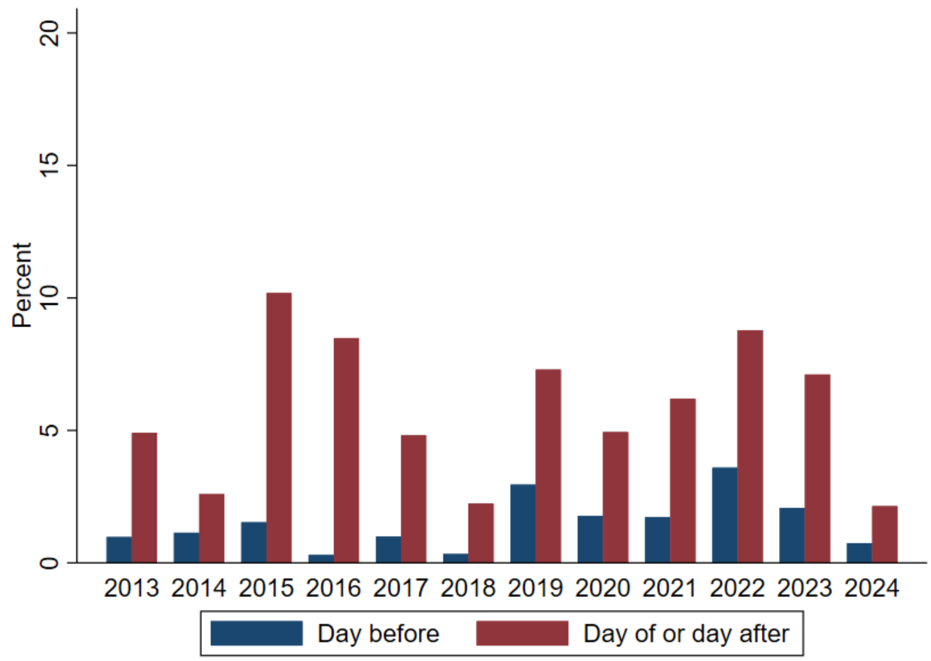
To account for the role of monetary policy in shaping news coverage of inflation, we estimate an alternative specification that replaces our baseline instruments (based on CPI release dates) with their monetary policy counterparts: an indicator for FOMC meeting days and a measure of the change in monetary policy at each meeting. We focus here particularly on the response of news to these meetings and argue that—while these meetings and substantial rate changes do drive media coverage—they do not satisfy the criteria for a valid instrument to study the effects on household inflation expectations via news coverage.

We estimate the impact of monetary policy on news coverage using the following local projection model:

$$news_{t+h} = c^h + \alpha_1^h |\Delta FFR|_t + \alpha_2^h \mathbb{1}_{\text{FOMC}} + \gamma_1^h |surprise|_t + \gamma_2^h \mathbb{1}_{\text{release}} + \sum_{j=1}^{p} \Phi_j^h \mathbf{X}_{t-j} + \varepsilon_{t+h}, \tag{13}$$

[12]Endogeneity concerns—e.g., reverse causality from expectations to news coverage—would typically bias the OLS estimates upward. Thus, they cannot explain the smaller non-instrumented coefficients we find.

Figure D.1: Share of Inflation News Occurring Around FOMC Meetings



Notes: The figure shows the share of total inflation-related news coverage occurring on the day before, day of, or day after FOMC meetings, from 2013 to 2024.

where $\mathbb{1}_{\text{FOMC}}$ is an indicator variable equal to one on the second day of the FOMC meeting, the date coinciding with the statement release and $|\Delta FFR|_t$ is equal to the absolute change in the Federal Funds rate at the meeting.[13] We also control for the instruments in Equation 5, as we know that these drive news coverage. Although changes in the FFR are not strictly exogenous - they are often being anticipated by markets - news coverage may well respond to the magnitude of the actual policy decision as it is relevant to consumers and easy to report.

For robustness, we confirm that the results are similar if we use the absolute value of the orthogonalized monetary policy surprise series from Bauer and Swanson (2023) in place of the absolute change in the FFR.[14] Bauer and Swanson (2023)

[13]All of the interest rate changes in our sample are increases, so for this period this is equal to the change in the policy rate.

[14]Note that the identified surprise series from Bauer and Swanson (2023) is only available up to

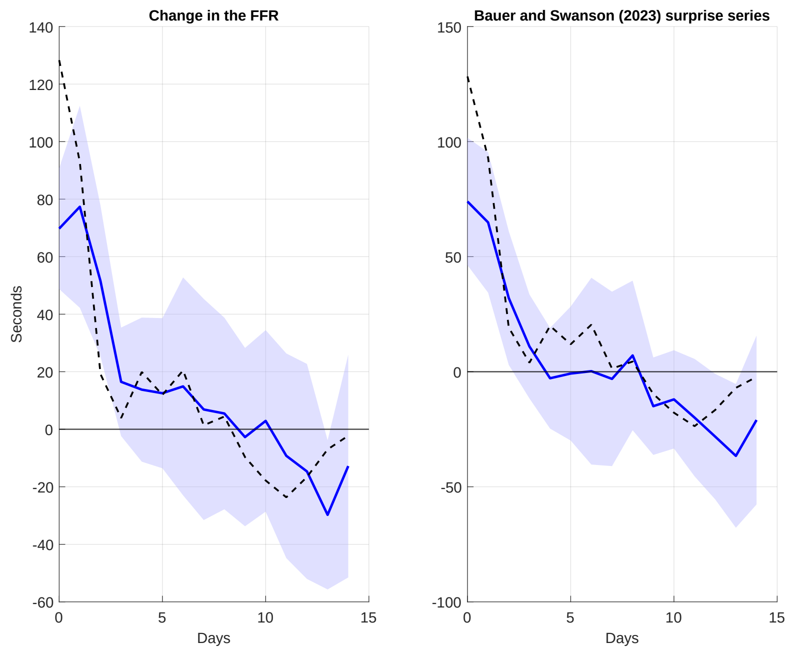
reassess the use of high-frequency monetary policy surprises to identify monetary policy surprises, addressing concerns that these surprises are not fully exogenous because they are correlated with publicly available macroeconomic and financial data known before the announcements. Specifically, they orthogonalize the surprises by regressing them on publicly available macroeconomic and financial variables (such as stock market moves, yield curve changes, and commodity prices) observed before the FOMC announcements, and then take the residuals. These residuals are interpreted as orthogonalized monetary policy surprises, purged of predictable components tied to prior economic conditions. This approach produces a monetary policy shock series that is more plausibly exogenous and satisfies the exclusion restriction more robustly.

News coverage increases significantly on the day of the FOMC meeting and dissipates quickly in the days that follow. The left panel of Figure D.2 shows the results using the absolute change in the FFR as instrument, while the right panel displays results using the absolute value of the orthogonalized surprises from Bauer and Swanson (2023). The figure illustrates the dynamic response of news coverage of inflation to a 25 basis point increase in FFR (one standard deviation change in the relevant surprise series) on a FOMC meeting day. We find that news coverage rises significantly by approximately 70 to 74 seconds. This effect is insignificant by the third day, mirroring the short-lived response observed following CPI releases.

Although monetary policy announcements appear to drive news coverage, they are not suitable instruments for estimating the causal effect of news on inflation expectations. FOMC meetings and policy decisions do not satisfy the exclusion restriction, as changes in the federal funds rate may influence inflation expectations through channels other than news. If consumers understand the contractionary purpose of higher rates, the rate changes themselves may drive their inflation expectations downward.

December 2023, so we adjust the sample period for this exercise accordingly.

Figure D.2: Dynamic Response of News Coverage to Monetary Policy

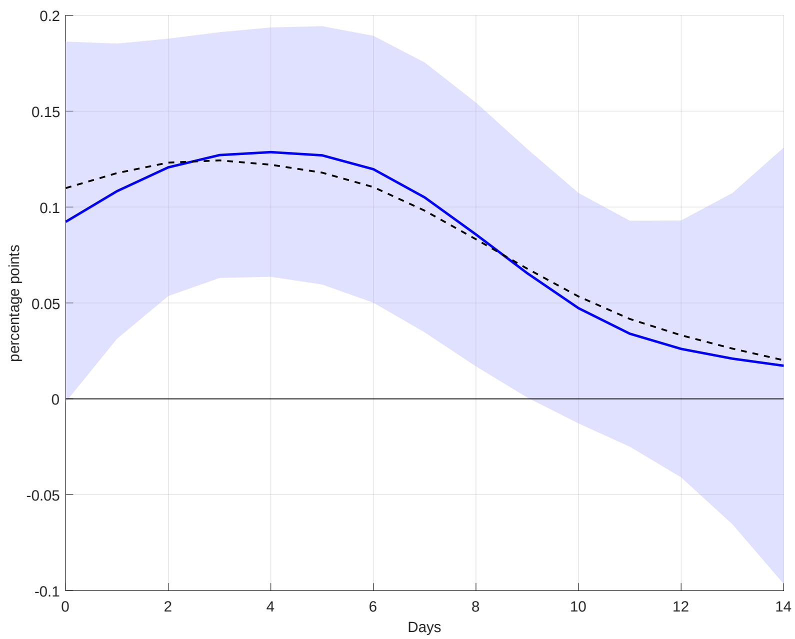


Notes: The left panel shows results using the absolute change in the federal funds effective rate together with an indicator for the FOMC meeting day, scaled to a 25 basis point increase. The right panel shows the news response to a one standard deviation in the absolute value of the orthogonalized monetary policy surprise series from Bauer and Swanson (2023) on an FOMC meeting day. Shaded areas indicate 90% confidence intervals, based on Newey-West standard errors. The dashed black lines represent estimates from our baseline specification.

Consumers may also interpret higher rates as bad news and increase their inflation expectations due to the well-documented link between pessimism and inflation expectations (Kamdar and Ray 2024). These alternative effects undermine the validity of these instruments in isolating the causal impact of news on expectations. Furthermore, our results from Section 5.3 as well as the results of Chahrour, Shapiro, and Wilson (2024) imply that the response of inflation to news will depend on the information content of the news. Consumers respond more strongly and in an opposite direction to inflationary news than to disinflationary news. It is unclear how to designate the informational interpretation of a monetary policy decision to consumers.

The significance of monetary policy announcements in generating news coverage may worry that omitting these announcements and measurements of changes in policy is biasing our main LPIV analysis. As a final robustness check, we show that our analysis is robust to including controls for FOMC meetings and the change in the federal funds rate. Figure D.3 shows that the estimated dynamic effect of news coverage on inflation expectations remains virtually unchanged, alleviating concerns that monetary policy announcements confound our baseline results.

Figure D.3: Robustness Check: Including Controls for Monetary Policy



Notes: The figure shows the dynamic effect of news coverage on inflation expectations, using the baseline LP-IV model with additional controls for FOMC meeting days and the change in the FFR. Shaded areas indicate 90% confidence intervals, based on Newey-West standard errors. The dashed black lines represent estimates from our baseline specification.