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 11 days. Additionally, we document a key nonlinearity: release days with positive CPI surprises—i.e., inflation exceeding market expectations—generate more persistent news coverage, particularly on Fox News, and 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 and to the general public (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). 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. Unusual events, including high inflation episodes, may also result in additional coverage (Nimark 2014). 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 further makes it difficult to attribute changes in expectations to high-frequency changes in media coverage. Moreover, 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 therefore relies heavily on randomized control trials (RCTs) that directly expose some participants to selected media content (Binder 2021b; Coibion, Gorodnichenko, and Weber 2022). While 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. Our 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 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.

We first establish the strength and relevance of our instrument. We confirm that mentions of inflation indeed increase on CPI release dates. This is consistent with Binder 2021a, which 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. 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 and negative CPI surprises increase news coverage, but do so mildly 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). 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; McDermott, Fowler, and Smirnov 2008).

Using our instrument for news coverage, we find that an increase in inflation news coverage raises household inflation expectations, on average. A one standard deviation increase in coverage raises expectations by 0.13 percentage points at the peak on day 4, with the effect declining to zero on day 11. The magnitude of this overall effect is small, but it reflects the combined effects of inflationary and disinflationary news, which may 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 0.2 p.p. 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.

This asymmetry in the response of expectations to news coverage on positive versus negative surprise days is larger than the asymmetry in the response of coverage to positive versus negative surprises. The expectations response asymmetry is consistent with the work of Gambetti, Maffei-Faccioli, and Zoi 2023, which focuses on newspaper coverage of unemployment. They find that bad shocks have larger and more persistent effects than good shocks because of their higher information content—they lead to larger revisions and less disagreement in economic expectations.

The asymmetric response of expectations that we find 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 news media "convey information in two distinct ways: via the actual contents of their articles, and via their decisions on what events to cover" (p. 162). If the media choose to cover inflation, this indicates that inflation is likely high, regardless of the content of the news. When a story reports that inflation is low, this conflicts with a second signal coming from the fact that the media chose to cover inflation, suggesting that inflation is a problem. The conflicting signals mute the effect of disinflationary news on inflation expectations. The evidence that Chahrour, Shapiro, and Wilson provide in support of the news selection hypothesis is complementary to ours, as we use entirely different datasets and identification strategies. We use daily expectations data from the Federal Reserve Bank of New York's Survey of Consumer Expectations and an instrumental variables approach for identification. In contrast, they use monthly

Michigan Survey data and focus on the share of respondents who report hearing news about inflation in response to an open-ended question about news they have recently heard. They assume that respondents who list inflation first sought out the news deliberately, while those who list it second were exposed to inflation coverage more passively.

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 2021a; 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 focus on cable television coverage reflects its important role in the media landscape. Two decades ago, Krueger and Blinder 2004 found that television—especially cable television—was the most frequently-used source of information about the economy by a large margin. Cable TV still remains an important source of news for adults in the United States, used much more widely than either national or local newspapers.[1]

The paper is structured as follows. Section 2 presents the daily news coverage data, survey data on inflation expectations, and the construction of the CPI "surprise" series. Section 3 examines patterns in news coverage around CPI release days. Section 4 outlines our econometric framework and presents estimates of the dynamic causal effect of news on inflation expectations, emphasizing the asymmetric impact of positive

[1]An Economist/YouGov poll from March 2022 found that 39% of adults had used cable TV as a news source in the past week, versus 23% and 22% for national newspapers and local newspapers, respectively. See https://today.yougov.com/politics/articles/41957-trust-media-2022-where-americans-get-news-poll.

and negative inflation surprises. Section 5 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 includes all available data from the Biden presidency (January 20, 2021 to May 1, 2024), which included a rise and decline in inflation and major inflation surprises of both positive and negative sign.[2] In this period, cable television coverage of inflation was 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. Thus, our instrument is particularly relevant during this sample period.

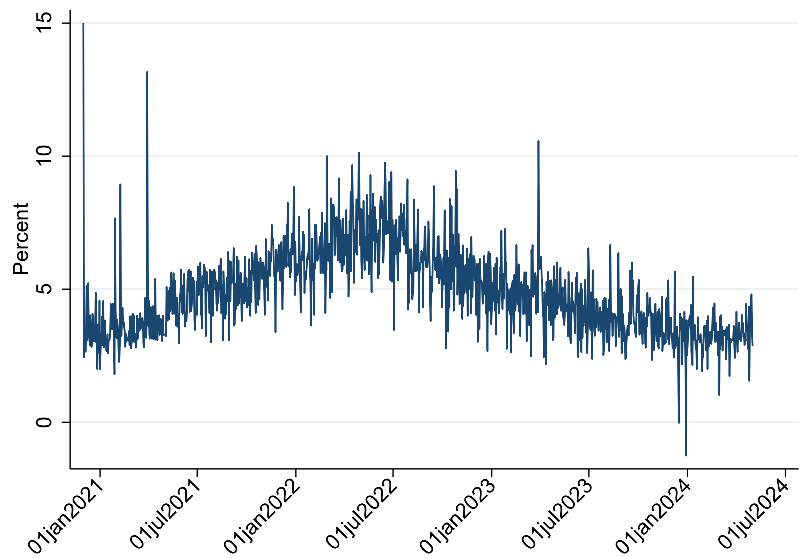
2.1 Expectations Data

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 several ranges (more than 12%, between 8% and 12%, between 4% and 8%, between 2% and 4%, between 0% and 2%, . . . , between -12%

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

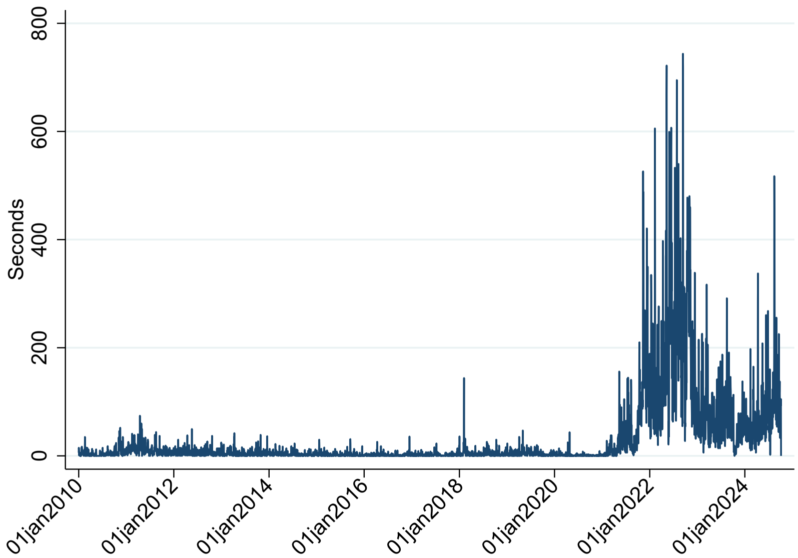
and -8%, and less than -12%). We use a method for fitting subjective probability distributions to density forecasts suggested by Ryngaert 2023, which makes use of data from both the point and density forecasts and allows for possibly asymmetric probability distributions. Figure 1 plots the daily median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

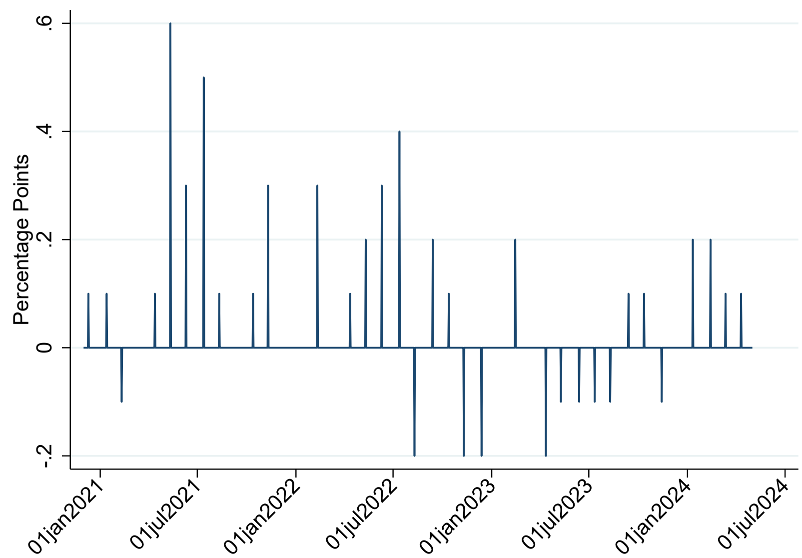
Figure 2: Cable Television Inflation Coverage



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

day that the word "inflation" is heard on cable television on each of the three stations. 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.

Since we plan to use the inflation surprises as an instrument, they should be contemporaneously uncorrelated with other structural shocks (Ramey 2016). Indeed,

Table A.1 demonstrates that the series is uncorrelated with other macroeconomic shock measures, such as monetary policy surprises and oil supply news surprises. Moreover, Table A.2 shows that the series cannot be forecasted using macroeconomic or financial variables.

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 will also be important for motivating the instrumental variables strategy that we will use in the next section.

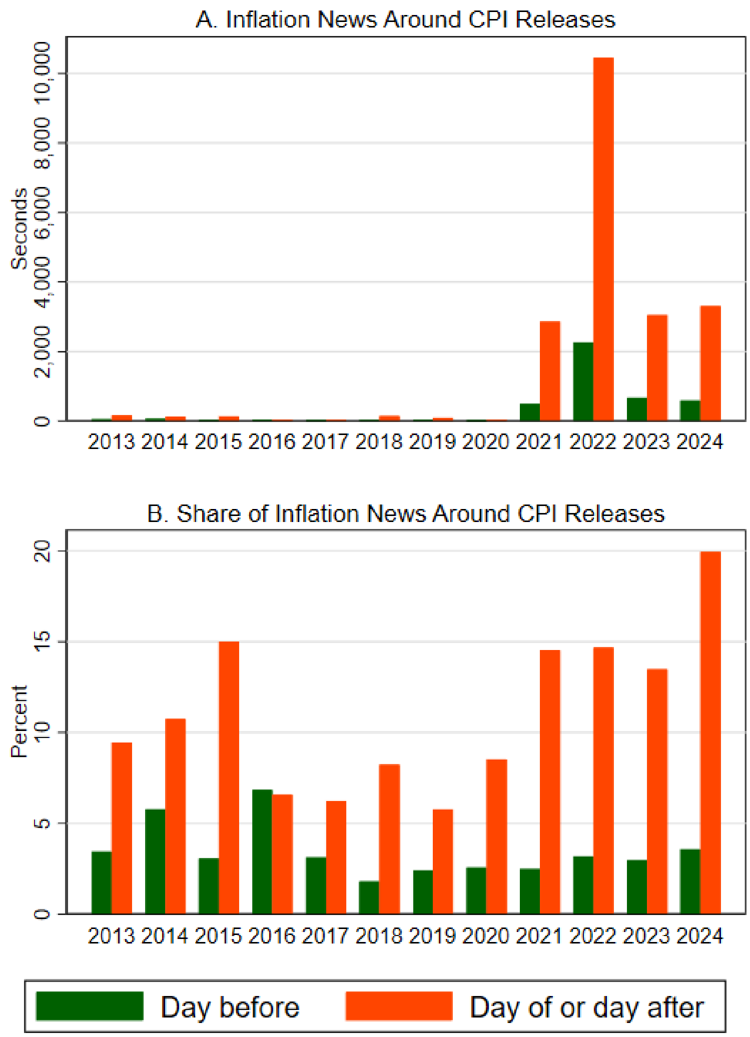
3.1 CPI Releases as Focal Point of Inflation Coverage

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, arose. Almost 15% of inflation news 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.

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.

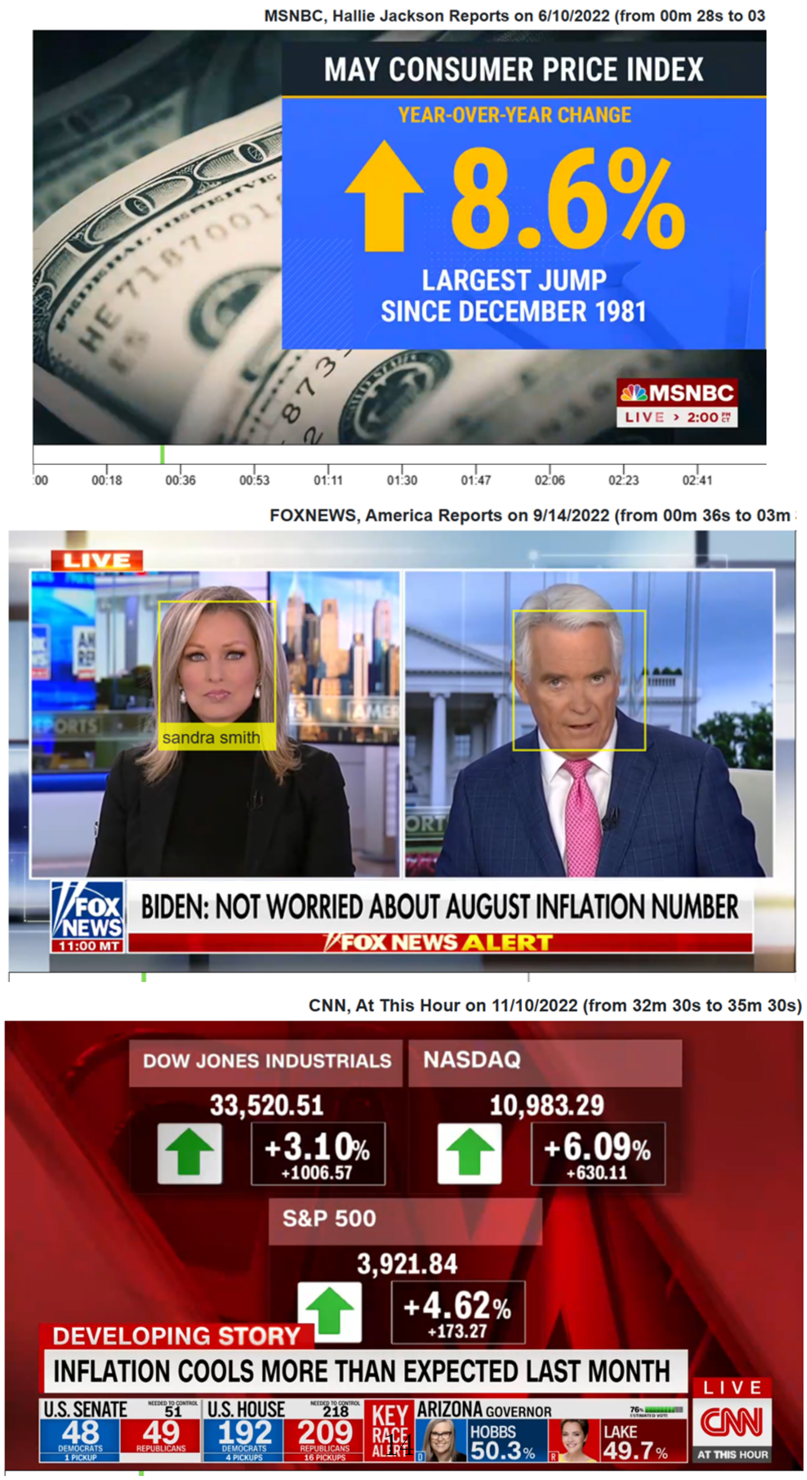
3.2 News Coverage of Inflation Surprises

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, 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.

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.

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:

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

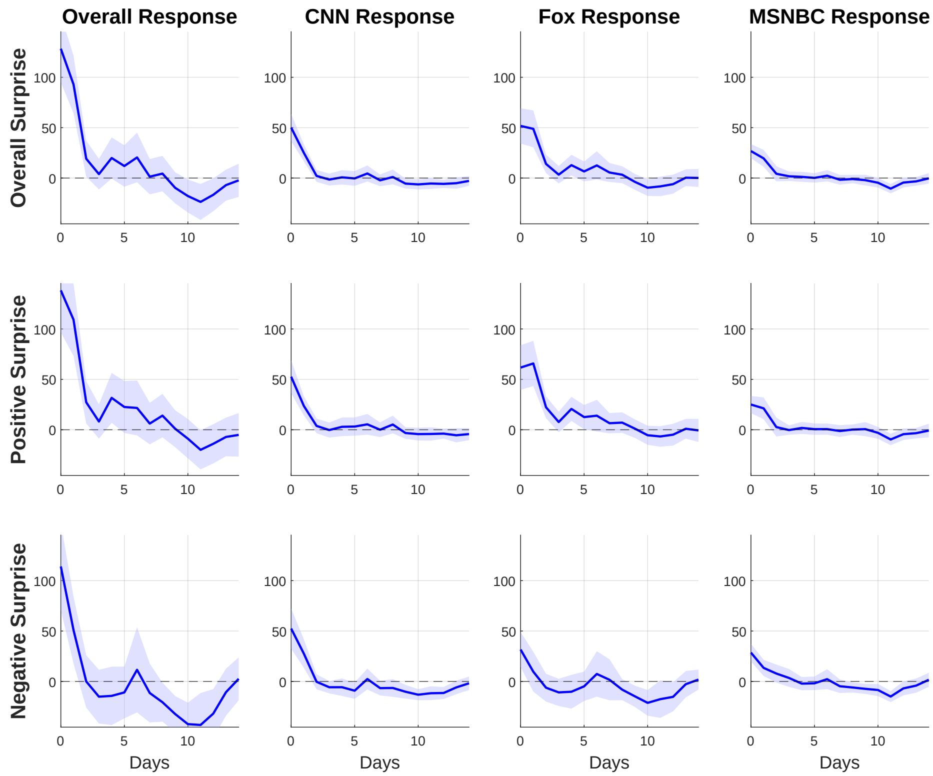
where $news_t$ measures the total daily news coverage of inflation in seconds. We employ two sources of "supply-driven" variation, $|surprise|_t$ is the absolute value of the inflation surprise series, while $\mathbb{1}_{\text{release}}$ is an indicator for CPI release dates. Our control set includes up to 30 lags of $news_t$ and daily inflation expectations, π_t^{exp}, to account for persistence in both news coverage and expectations.[3] 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 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, or 1.1 standard deviations. 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

[3]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.

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.[4] 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 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, this methodology enables us to test whether media responses to inflation surprises exhibit similar asymmetries in attention or framing.

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

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, but of somewhat different magnitudes: on release days with a 0.1 percentage point positive surprise, news coverage rises by approximately 138 seconds, whereas after a negative surprise, the increase is 114 seconds. This asymmetry is almost entirely driven by Fox News, which maintains elevated coverage of a positive surprise for an additional day. 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 and Results

This section outlines our empirical strategy for estimating the dynamic causal effects of inflation news coverage on daily household inflation expectations, and presents our results. 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:

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

where π^{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. That is, $\hat{news}_t$ are the fitted values from the following first-stage 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. This provides a strong first-stage relationship, with a first-stage F-statistic of 33.66, well above the conventional threshold for weak instrument concerns.

Instrument exogeneity: The validity of our instruments requires that they affect inflation expectations only via media coverage. Since CPI release dates are predetermined and the magnitude of the surprise is *ex ante* unpredictable, the surprise series is unlikely to be correlated with other unobserved shocks. Additionally, given that inflation news coverage reacts immediately to CPI releases—before households can update their expectations—concerns about simultaneity bias are mitigated. To further ensure exogeneity, we control for past expectations and past media coverage, preventing confounding effects 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 using 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.

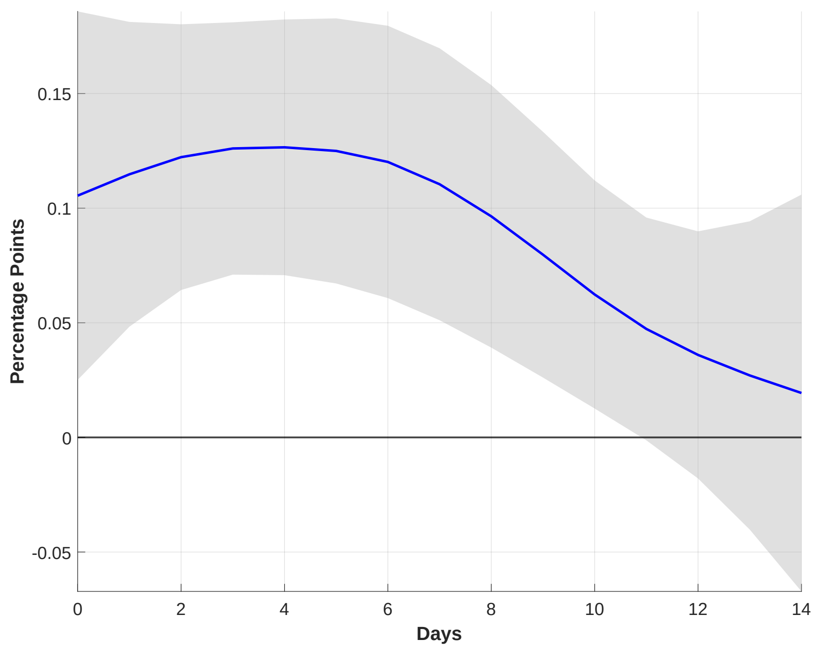
Following Barnichon and Brownlees 2019, we employ K-fold cross-validation, a resampling procedure, to select the parameters that minimize the average mean squared error (MSE). This procedure ensures that the penalization parameter λ is selected objectively to balance variance reduction and model flexibility. 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.

4.3 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 affects inflation expectations.

Figure 7 illustrates the smoothed dynamic response of inflation expectations to an exogenously induced 1 standard deviation increase in news coverage. Households significantly increase their inflation expectations in response to news, with the effect ranging between 0.1 and 0.13 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 11 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.

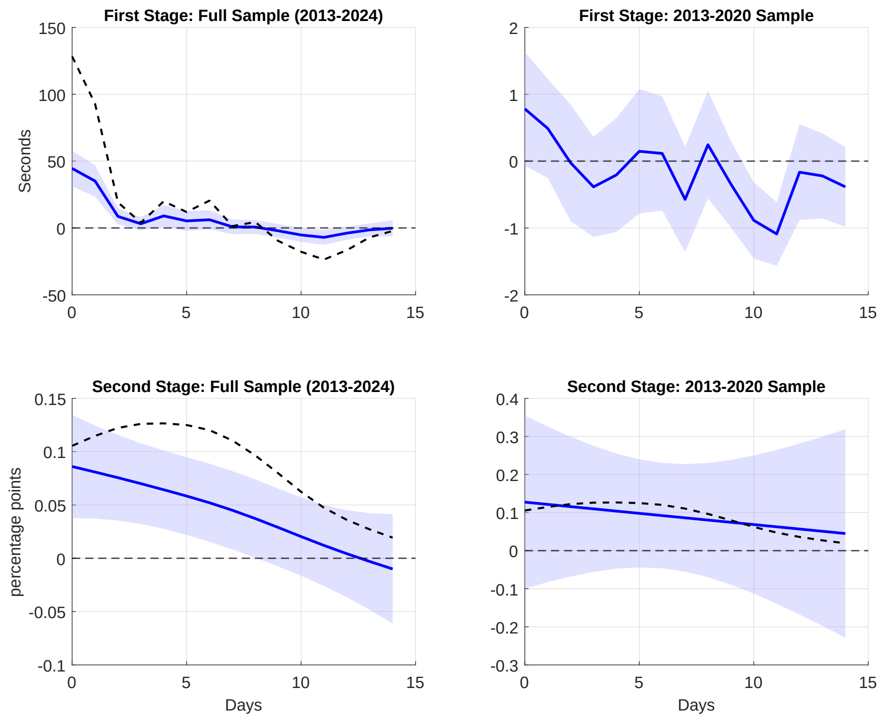
4.4 Alternative Sample Periods

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.

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.

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.

4.5 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. In our context, 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.[5]

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

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

where the instrumented news variable $\widehat{news}^+_t$ 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:

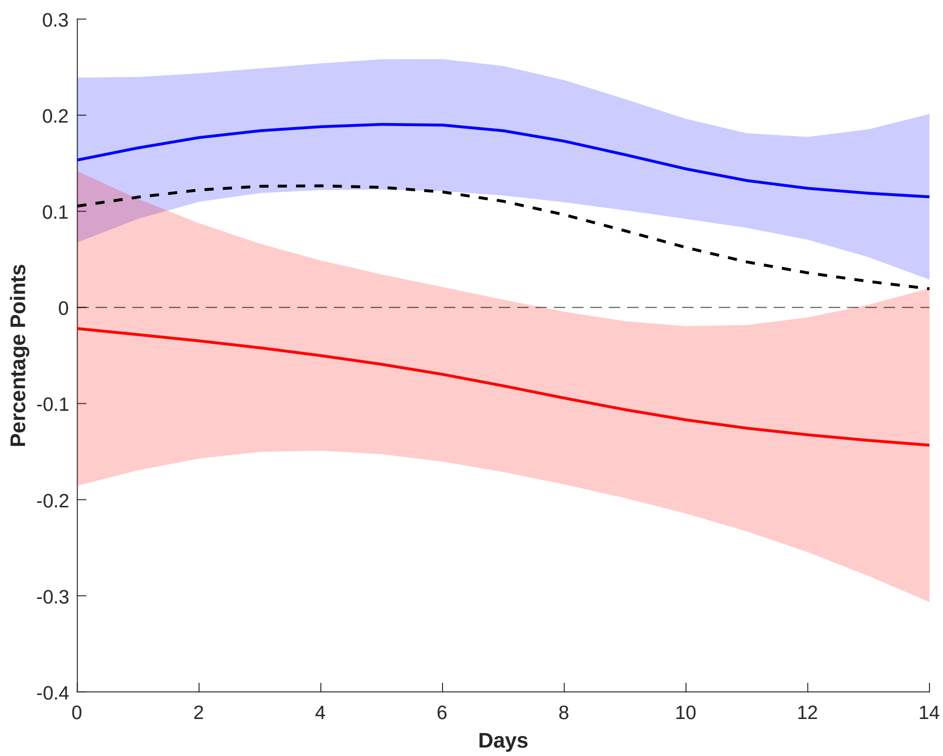
$$\pi^{\exp}_{t+h} = \beta^h_{0,-} + \beta^h_{1,-} \widehat{news}^-_t + \sum_{j=1}^{p} \Gamma^h_{j,-} \mathbf{X}_{t-j} + u_{t+h}, \quad h = 0, \dots, H. \tag{8}$$

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.

The responses exhibit a clear asymmetry. Following a positive surprise (blue), inflation expectations increase sharply and remain persistently elevated over the

[5] Our sign-based specifications may conflate sign and size effects given that the distribution of shocks is asymmetric (Caravello and Martinez-Bruera 2024). As a robustness check, we estimate LP-IVs using bins for small, medium, and large shocks to isolate size effects. Results are shown in Section 5.2.

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), respectively. The blue line represents responses to positive CPI surprises, while the red line represents responses to negative surprises. The black dashed line indicates the baseline response. Shaded areas denote 90% confidence intervals, based on Newey-West standard errors.

subsequent two weeks. By contrast, the response to a negative surprise (red) is muted: expectations remain essentially flat in the immediate aftermath and only begin to decline modestly after day 8. 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.

One concern raised by Caravello and Martinez-Bruera 2024 is 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.

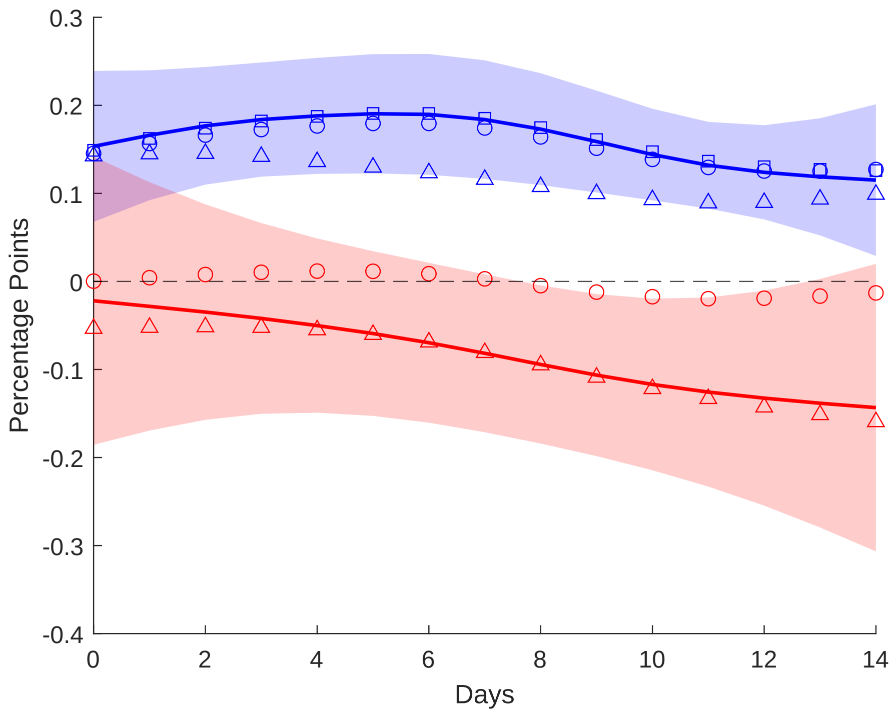
For each bin, we re-estimate the LP-IV specifications from Section 4.5, corresponding to Equations 7 and 8. We continue to use non-negative and non-positive release days as instruments, respectively, but now replace the absolute value of the CPI surprise with bin-specific indicators. This results in 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: 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.

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. 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.

4.6 Accounting Exercises

Median inflation expectations on the SCE peaked at 7.42% in June 2022, up from 3.80% at the end of 2020. Inflation news coverage from 2013 through 2021 averaged 2.3 seconds per day. Beginning in 2021, news coverage of inflation increased substantially, averaging 95 seconds per day. We conduct a few simple counterfactual accounting exercises to examine how the extra news coverage in the high inflation period contributed to the rise in inflation expectations. We define $\gamma_t = (news_t - 2.3)/112$, the difference between news coverage on day t and the average news coverage in the pre-2021 period, divided by 112 seconds since our coefficient estimates correspond to the effect of a 112 second increase in news coverage.

For the baseline exercise, we use the coefficient estimates β_1^h from Equation 6 that are plotted in Figure 7. We compute

$$\hat{\pi}_t = \sum_{h=0}^{14} \beta_1^h \gamma_{t-h}. \tag{11}$$

This $\hat{\pi}_t$ is the increase in inflation expectations on day t attributable to the above-baseline news coverage from days $t-14$ through t. Then $\pi_t^{exp} - \hat{\pi}_t$ is the counterfactual inflation expectation on day t if news coverage had remained at its pre-2021 average level. We find that inflation expectations would have risen to 7.13% at their peak in June 2022 instead of 7.4%. That is, the extra news coverage accounts for (7.42-7.13)/(7.42-3.80)=8% of the rise in inflation expectations over this period.

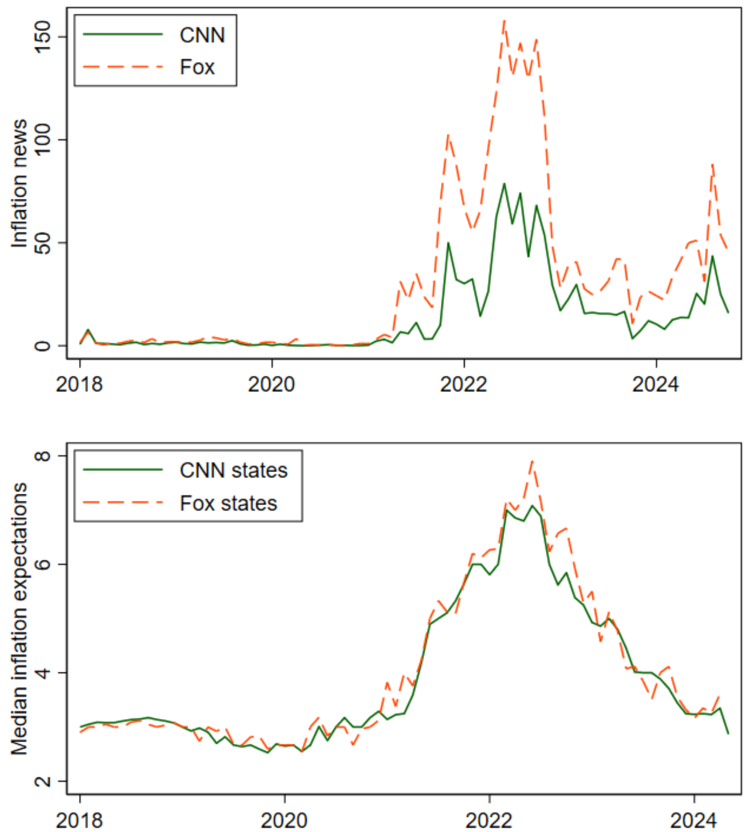
The baseline counterfactual exercise did not account for the asymmetric effects of positive and negative news. For the second counterfactual exercise, we also make use of the asymmetric effects estimates $\beta_{1,+}^h$ and $\beta_{1,-}^h$ from equations 7 and 8. If the most recent CPI release was a positive surprise, we let $\hat{\pi}_t = \sum_{h=0}^{14} \beta_{1,+}^h \gamma_{t-h}$. If it was a negative surprise, $\hat{\pi}_t = \sum_{h=0}^{14} \beta_{1,+}^h \gamma_{t-h}$. If it was a zero surprise, we use the baseline estimates and let $\hat{\pi}_t = \sum_{h=0}^{14} \beta_1^h \gamma_{t-h}$. We again compute $\pi_t^{exp} - \hat{\pi}_t$ as the counterfactual inflation expectation if news coverage had remained at its pre-2021 level. In this case, we find that expectations would have risen to 6.90% at their peak, implying that the extra news coverage accounts for 14% of the rise in inflation expectations over this period.

It is interesting to note that both of these accounting exercises yield estimates in the same range as the "back of the envelop" 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.

As an additional exercise, we consider the difference in inflation coverage between Fox and CNN in the high inflation period. Prior to 2021, Fox and CNN devoted virtually identical coverage time to inflation. Since 2021, Fox has devoted 30.7 seconds per day more coverage than CNN, on average (see the first panel of Figure 11). We replace γ_t with the difference between Fox coverage and CNN coverage on day t, and again compute $\hat{\pi}_t$ 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 0.13 percentage points compared to CNN viewers' expectations at the peak in June.

The Survey of Consumer Expectations does not ask for respondents' political affiliation or news source. However, it does provide their state of residence. We use data from Nationscape, a large public opinion survey conducted in 2020 (Tausanovitch and Vavreck 2021), on the share of Fox viewers and CNN viewers in each state. We categorize states according to whether the share of Fox viewers is greater than or less than the share of CNN viewers. In June 2022, the median inflation expectations in Fox-dominant states are 0.83 percentage points higher than those in CNN-dominant states (see the second panel of Figure 11). The difference in volume of inflation coverage thus explains about 16% (0.13/0.83) of that difference–again, this fits in the upper range of the back-of-the-envelop 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.

Figure 11: Inflation Coverage on Fox and CNN, and Expectations in Fox versus CNN-Dominant States



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

5 Conclusion

This paper provides new evidence on the effects of inflation news coverage on inflation expectations. We find that increased news coverage of inflation significantly raises household inflation expectations. Our use of daily data enables us to study the dynamics of this effect. 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. Our accounting exercises suggest that the additional news coverage of inflation after 2020 accounts for around 8 to 14% of the rise in inflation expectations at their peak.

Our results make use of a novel IV strategy relying on CPI release dates act as exogenous drivers of inflation news coverage. That is, news coverage is substantially higher on the day of and immediately after a CPI release, especially when the surprise content of the release is greater. This seems to be especially the case in recent years, as the news media seem to place high emphasis on these reports in an era in which inflation is highly salient. Using an instrument for identification was critical in our analysis. In particular, our OLS estimates were highly attenuated, likely due to measurement error in the news coverage variable. As most proxies for news coverage are likely to include substantial measurement error, strategies like ours that rely on exogenous drivers of coverage will be important for identifying the effects of news on expectations and other variables.

The nature of our instrument and the flexibility of the local projections approach that we use also enables us to document a key asymmetry: positive CPI surprises generate a stronger and more persistent response in expectations than negative surprises. 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 these asymmetries persist across different media channels or economic environments.

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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

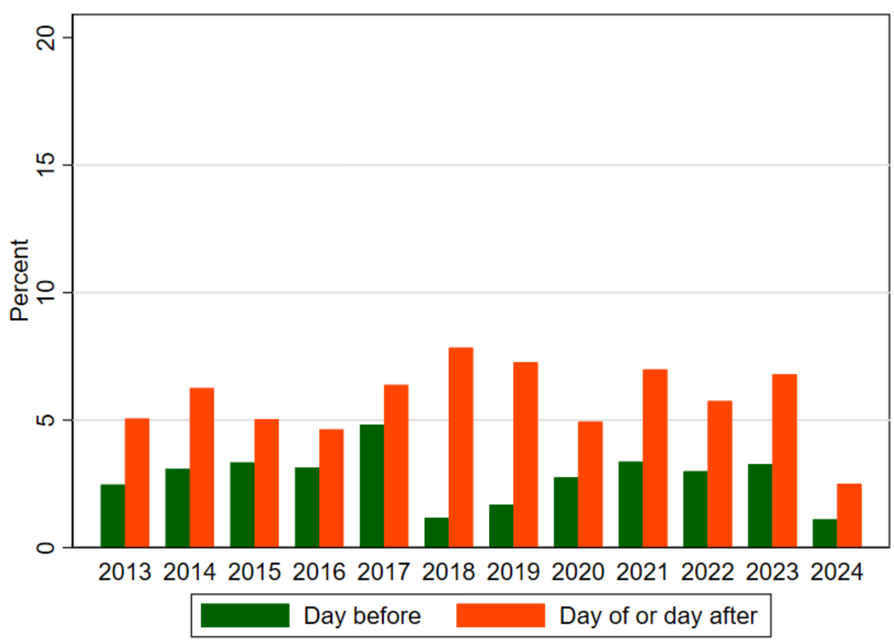
Notes: The table shows the correlation of the inflation surprise series with a range of different shock measures from the literature. For all series, we compute the Pearson correlation coefficient, the p-value corresponds to the test whether the correlation is different from zero. All shock measures, 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

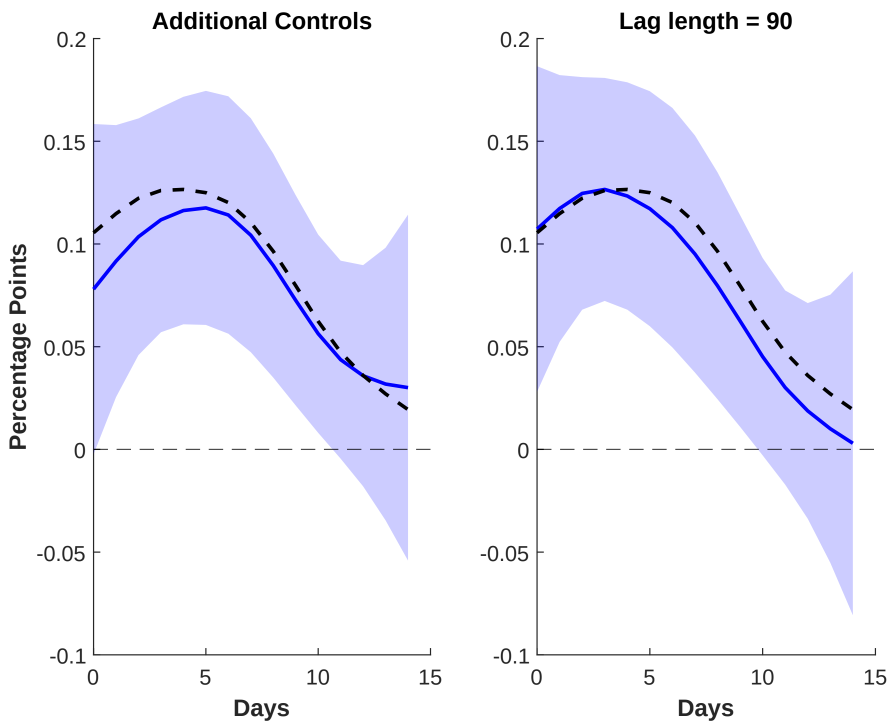
Notes: The table shows the p-values of a series of Granger causality tests of the inflation surprise series using a selection of macroeconomic and financial variables. The lag order is set to 90 days to capture longer-run relationships. Non-stationary series are made stationary by taking first differences. 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. The black dashed line indicates the baseline response. Shaded areas denote 90% confidence intervals, based on Newey-West standard errors.

B Smooth Local Projection Method Details and Robustness

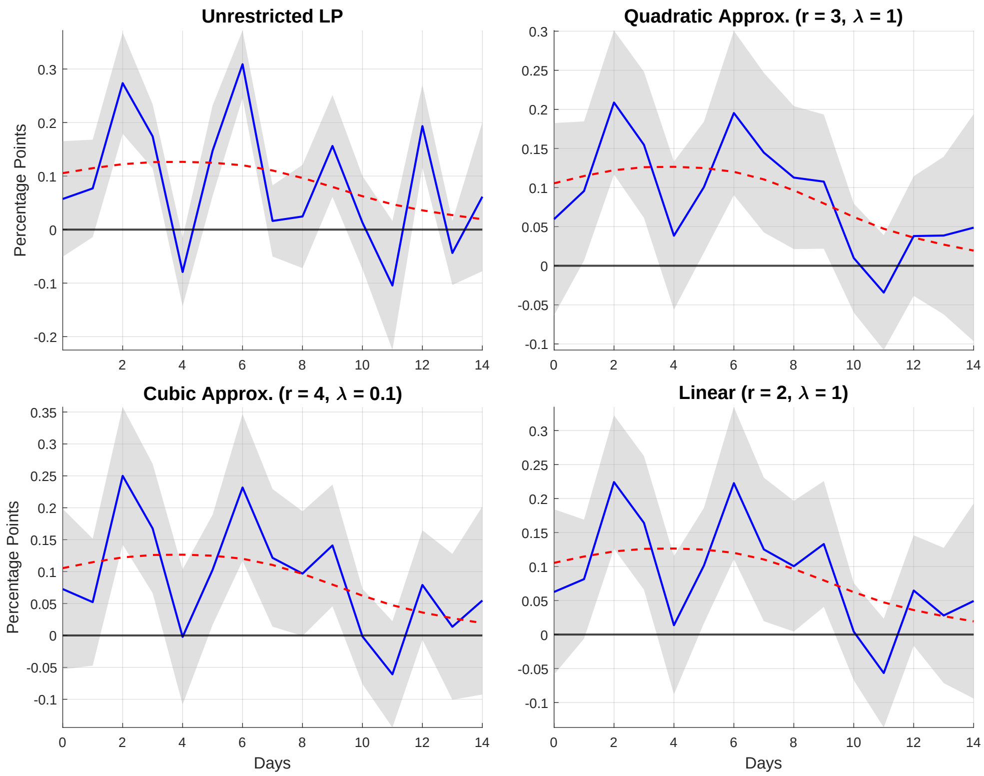
As discussed in Section 4.2, the smooth local projection method requires specification of the penalty parameter λ, and the polynomial degree $r-1$ to which the impulse response function shrinks as λ grows. The cross-validation procedure follows these steps:

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 $\lambda = 1$.
3. Cubic Approximation ($r = 4$): We approximate a cubic polynomial, allowing for two turning points. The cross-validation procedure now selects $\lambda = 0.1$.
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.

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

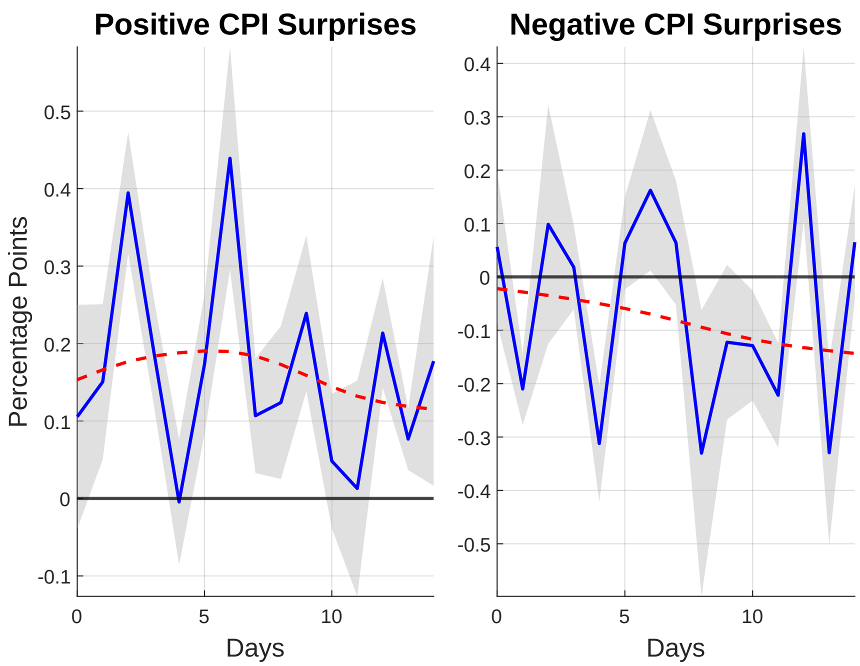


Notes: This figure presents smoothed IV-estimated response of inflation expectations to inflation news coverage under alternative parameterizations. The shaded area represents the 90% confidence interval, computed using Newey-West standard errors. The unit is percentage points. The red dashed line represents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

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 CPI release surprise of 0.1 percentage points. Despite some models producing more jagged estimates, the overall pattern is confirmed. The effect appears to peak within a few days and gradually dissipates after approximately 9-10 days.

Figure B.2 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 4.5 also holds when the LPs are not smoothed.

Figure B.2: 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.

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:

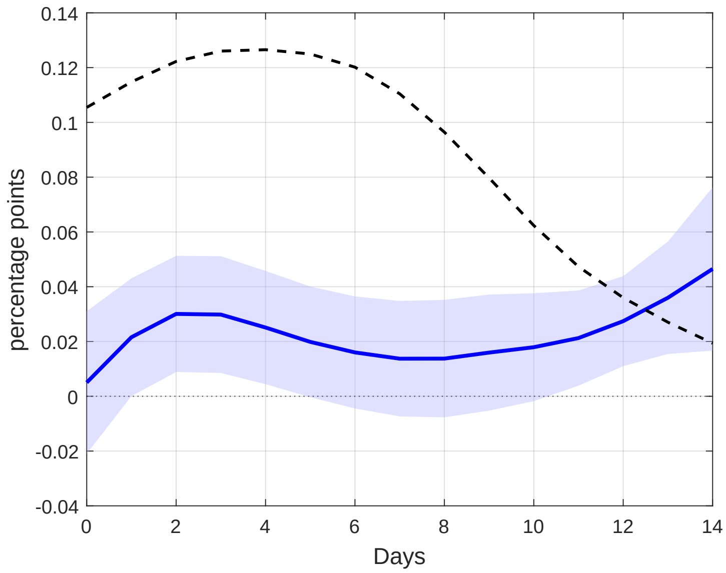
$$\pi^{\exp}_{t+h} = \gamma_0^h + \gamma_1^h news_t + \sum_{j=1}^{p} \phi_j^h \mathbf{X}_{t-j} + \epsilon_{t+h}, \quad h = 0, \ldots, H, \tag{12}$$

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.

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.[6]

[6]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 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.