# Inflation and Attention: Evidence from the Market Reaction to Macro Announcements*

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**Abstract**

I present new evidence on the formation of investors' inflation expectations by exploiting the releases of macroeconomic data. Using intraday financial market data, I show that the Consumer Price Index (CPI) emerges as the most impactful data release during the 2021–2023 inflation surge. Bond yields and market-implied inflation expectations, as well as stocks and foreign asset prices respond significantly stronger on impact to a surprise about CPI inflation, compared to the prior low-inflation period. This increase in market sensitivity is unique among macro releases. The joint response of asset prices to CPI releases points to a faster incorporation of inflation news into inflation expectations, consistent with investors paying more attention to the releases. I corroborate this interpretation by documenting that only around CPI releases trading volume and release-specific Google searches substantially increased during the inflation surge. My findings support theories of endogenous inattention and highlight the role of investor attention for the interplay between the macroeconomy and financial markets.

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# 1 Introduction

How do investors form their inflation expectations? Answering this question is crucial for both economists and policymakers, as investors' inflation expectations are not only central in understanding the link between inflation and asset prices—a perennial topic in finance (e.g., Cieslak and Pflueger, 2023)—but also determine longer-term interest rates in the economy and provide unique information of where inflation is headed (Bernanke, 2007, 2013).[1] While by now a large literature in monetary economics studies the formation of individuals' inflation expectations, our understanding with respect to investors is still fairly limited.

One insight of that literature—often summarized under the term "rational inattention" (Sims, 2003)—is the importance of the inflation environment for individuals' information acquisition and expectation formation. As discussed by Jerome Powell at the 2022 Jackson Hole symposium, rational inattention predicts that "[w]hen inflation is persistently high, households and businesses must pay close attention and incorporate inflation into their economic decisions. When inflation is low and stable, they are freer to focus their attention elsewhere."[2] Indeed, recent work finds empirical support for this mechanism for households and firms (Weber et al., 2023). However, as investors are usually seen as more sophisticated (e.g., Caballero and Simsek, 2022), it is ex-ante not clear how relevant this mechanism is for financial markets.

In this paper, I show that the inflation environment affects investors' attention to inflation and thereby changes how financial markets incorporate inflation news. I do this by studying the high-frequency effects of U.S. macroeconomic news announcements on asset prices during the 2021-2023 inflation surge. Consistent with a rise in investor attention to inflation, I find that surprises about the CPI have much larger effects on interest rates and on inflation expectations—as measured by inflation swap rates—in comparison to the prior low-inflation period. This increase in market sensitivity to CPI news can also be documented for a broad range of other asset prices. However, it is unique among macro releases. Overall, the evidence points towards a faster incorporation of inflation news into investors' inflation expectations due to increased attention. I further support this interpretation by a variety of evidence, from documenting an exceptional increase around CPI releases in trading volume and Google searches—two proxies of attention—to demonstrating that the results are not

[1] Diercks et al. (2023) shows that the 1-year inflation swap rate provides better forecasts of realized inflation than alternatives, in particular since the Great Recession. Mertens and Zhang (2023) shows similar evidence for longer-term inflation expectations.

[2] https://www.federalreserve.gov/newsevents/speech/powell20220826a.htm (accessed on Dec. 7, 2023).

driven by changes in risk premia.

As with almost any causal relationship, establishing one between the inflation environment and investors' inflation attention is econometrically challenging. In this paper, I employ a high-frequency event study design to try to accomplish that. My analysis is motivated by a simple model—along the lines of DellaVigna and Pollet (2009)—which illustrates how the immediate effect of a macro news release on yields and inflation expectations is increasing in the share of investors being attentive to the release. Intuitively, higher attention leads, on average, to a faster updating of investors' expected inflation and interest rates. Hence, if investors are indeed more attentive to inflation in a high-inflation environment, the market impact of inflation news should be larger as well.

I test this prediction by looking at the intraday effects of macro news releases, which—by the virtue of being prescheduled—provide a unique way of studying the interplay of attention and incorporation of new information. In particular, I compare the announcement effects across two periods: a low-inflation period, ranging from the Great Recession to May 2021, and a subsequent high-inflation period ending in July 2023. With the latter period having relatively few observations, the use of intraday windows is crucial as it reduces noise and hence allows me to have sufficient statistical power to detect, if existent, statistical differences across periods. In my analysis, I focus on the CPI release to test my prediction with respect to inflation news and look at 15 other major macro announcements, such as Nonfarm Payrolls, to disentangle common changes across announcements to inflation-related ones.[3] One way to think about my empirical analysis is in the context of a difference-in-differences setting. The first difference is low-inflation versus high-inflation environment, and the second difference is CPI (treatment group) versus non-CPI releases (control group).

Looking at asset prices within a 60-minute window, I find that CPI inflation surprises have more than an order of magnitude stronger effects on yields in the high-inflation period. The differences across periods are highly significant at the 1 or 5 percent level. Similarly, inflation expectations—measured by inflation swap rates—are also much more responsive, in particular at the 1- and 2-year horizons. In contrast, for none of the other macro announcements, I find a comparable rise in market impact in the high-inflation period. As a consequence, the CPI release emerges as the most powerful macro release in terms of its impact effects on interest rates and inflation swap rates during the inflation surge. The increased market sensitivity also holds when looking at stock markets, both domestic and

[3] I focus on the headline CPI because it is not only the most cited inflation measure but also the relevant number for inflation-related securities and is timelier than alternatives such as the personal consumption expenditures (PCE) price index.

international, foreign interest rates, as well as exchange rates. Qualitatively, the responses to CPI news during high inflation show a cohesive picture, consistent with the model intuition. A higher-than-expected CPI leads to an increase in inflation swap and interest rates, and a consequent decline in stocks. It also leads to an appreciation of dollar in line with the smaller increases of foreign interest rates relative to U.S. counterparts. In my analysis, I also show that the exceptional rise in CPI's market impact is robust across a wide variety of alternative specifications and not driven by particular choices in the baseline analysis.

In the remainder of the paper, I provide additional evidence to support the attention-based interpretation of the main findings. To closer link the increase in CPI's market impact to investor attention, I look at two proxies of investor attention: trading volume (e.g., Barber and Odean, 2008) and Google searches (e.g., Da, Engelberg, and Gao, 2011). Specifically, I show that trading volumes of interest rate futures show an exceptional increase around CPI releases during the high-inflation period, both compared to average trading volumes and to other macro releases. Hence, the evidence suggests that more investors are trading around CPI releases, consistent with more of them paying attention to it. To confirm this, I also look at daily Google search indexes for release-specific topics such as "Consumer Price Index" or "Nonfarm Payrolls". Consistent with the other results, I find that searches around CPI releases for the topic "Consumer Price Index" increased dramatically since 2021, while very little on other days. I do not find any similar evidence for other topics on their respective release dates. Lastly, I employ the decompositions by Adrian, Crump, and Moench (2013), Kim and Wright (2005), and d'Amico, Kim, and Wei (2018)—each available at the daily frequency—to provide further evidence that the increased market sensitivity to CPI news is primarily driven by expected inflation and interest rates rather than risk premia.

**Related literature** My paper relates to various strands of prior work. First and foremost, I contribute to the work in macrofinance understanding the link between inflation and asset prices. There are old literatures on the effects of inflation on stocks (e.g., Fama and Schwert, 1977; Fama, 1981; Boudoukh and Richardson, 1993; Campbell and Vuolteenaho, 2004), and bonds (e.g., Fleming and Remolona, 1997; Balduzzi, Elton, and Green, 2001; Beechey and Wright, 2009; Gürkaynak, Levin, and Swanson, 2010; Bauer, 2015). There is also a set of papers which emphasizes the role of inflation in understanding the time varying stock-bond co-movements (e.g., David and Veronesi, 2013; Campbell, Pflueger, and Viceira, 2020). With the high inflation levels in the recent period, there has been renewed interest in how inflation gets priced in financial markets (Chaudhary and Marrow, 2022; Fang, Liu, and Roussanov, 2022; Gil de Rubio Cruz et al., 2022; Knox and Timmer, 2023; Pflueger, 2023; Bahaj et al., 2023). I contribute to the prior literature by showing that the inflation environment is crucial in understanding how inflation affects asset prices. As my paper emphasizes the interaction between the inflation environment and investors' change in behavior, it is also related to Braggion, Von Meyerinck, and Schaub (2023) which studies investors' behavior during the German Hyperinflation. Finally, my paper connects to recent work in macrofinance which deviations from full-information rational expectations to explain asset pricing movements (e.g., Adam, Marcet, and Beutel, 2017; Bordalo et al., 2019).

Another body of work—which my paper is related to—studies the importance of investors' attention for asset pricing. Various papers incorporate forms of limited attention into portfolio choice problems to study a variety of questions (e.g., Hirshleifer and Teoh, 2003; Peng and Xiong, 2006; Bansal and Shaliastovich, 2011; Andrei and Hasler, 2015; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016, among many others). On the empirical side, Huberman and Regev (2001) and Barber and Odean (2008) provide direct evidence of the importance of investor attention for the stock market. Da, Engelberg, and Gao (2011) show that an investor attention measure based on Google searches can predict stock prices. Closer to my paper, a variety of papers study scheduled information releases, such as macroeconomic and earnings announcements. DellaVigna and Pollet (2009) and Hirshleifer, Lim, and Teoh (2009) provide evidence that limited investor attention leads to initial underreaction to earnings announcements and subsequent post-announcement drifts. Ben-Rephael, Da, and Israelsen (2017) show, among other things, that post-earnings-announcement drifts can be connected to an insufficient amount of investor attention. More recent papers include Boguth, Grégoire, and Martineau (2019), Benamar, Foucault, and Vega (2021), Hirshleifer and Sheng (2022), Fisher, Martineau, and Sheng (2022), and Andrei, Friedman, and Ozel (2023). My paper contributes to this body of work by showing that the inflation environment plays a crucial role in how investors' attention is allocated. More generally, my findings emphasize the importance of macroeconomic conditions for investor attention.

Lastly, my paper relates to recent work in macroeconomics which provides support of "rational inattention" models (Sims, 2003) by documenting the relationship between the inflation environment and individuals' attention to inflation.[4] Bracha and Tang (2019) and Pfäuti (2021) show that key properties of survey data in the U.S. and Euro Area are consistent with higher inattention during low-inflation periods. Korenok, Munro, and Chen (2022) show for various countries that there is a positive relationship between country's inflation

[4] See Maćkowiak, Matějka, and Wiederholt (2023) for a survey on rational inattention models in monetary economics and beyond.

rate and inflation-related Google searches. Pfäuti (2023) directly estimates attention levels for the low- and high-inflation period from U.S. survey data which he then maps into a macroeconomic model to study the implications. Cavallo, Cruces, and Perez-Truglia (2017) conduct two randomized controlled trials, one in a low-inflation environment (U.S.), and one in a high-inflation environment (Argentina).[5] Providing information treatments about inflation, they show that households in Argentina change their inflation belief less, consistent with the idea that they were more informed prior to the treatment. Weber et al. (2023) confirm the findings by Cavallo, Cruces, and Perez-Truglia (2017) in a broader setting for both households and firms. Employing a set of randomized control trials across countries and over time, including the 2021-2023 inflation surge, the authors are also able to more directly link the difference in treatment responses to the inflation environment. My findings complement these papers by showing that the inflation environment also affects investors' attention to inflation and that this changes how fast new information gets incorporated into financial markets under high inflation.

**Roadmap** The remainder of the paper is structured as follows. In the next section, I discuss my empirical approach and introduce a simple, theoretical framework to guide it. Section 3 introduces the data, and Section 4 shows the main results for the high-frequency effects of macro news. In Section 5, I provide additional analyses in support of an attention-based explanation of the findings. Section 6 concludes.

## 2 Research Design

I am interested in assessing if people are more attentive to inflation news when inflation is high. To do so, I study the effects of surprises about U.S. macroeconomic data releases. In this section, I first explain the theoretical link between inflation news, attention, and the reaction of asset prices, before I discuss my empirical strategy.

### 2.1 Simple Model of Attention and Market Reaction to News

In the following, I lay out a simple, theoretical model which provides guidance for the empirical analysis in this paper. The main goal of this model is to illustrate how investors'

[5] The treatments by Cavallo, Cruces, and Perez-Truglia (2017) and Weber et al. (2023) are publicly available information which are easily accessible to individuals beforehand. Hence, more attentive people should have already incorporated this information, causing them to be less responsive. In contrast, my "information treatment" is new information about inflation which was not publicly available prior to the release. Thus, more attentive people should be more responsive.

attention affects the impact of macroeconomic announcements on financial markets in a typical high-frequency event study (see Gürkaynak and Wright, 2013, for a survey). The model will be agnostic about the underlying reasons why agents pay more or less attention to inflation news. However, under the premise that people might pay more attention to inflation news when inflation is high as suggested by theory (e.g., Sims, 2003) and recent evidence (e.g., Weber et al., 2023), the model yields predictions which I will test later in the empirical analysis.

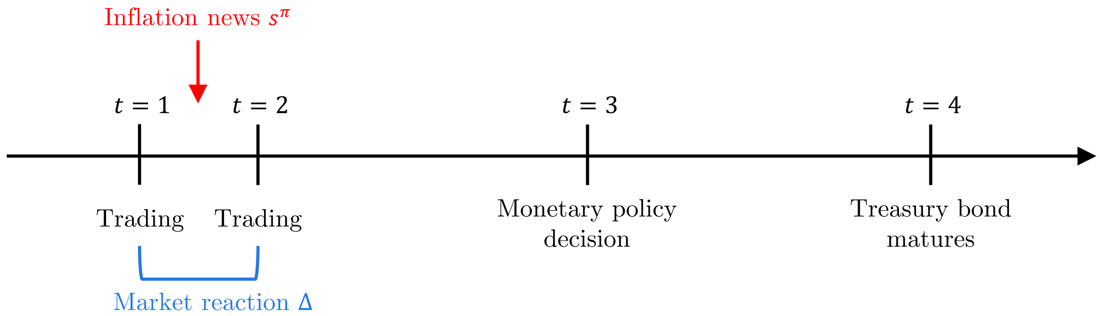
My framework is in the tradition of portfolio choice models under noisy information. Classic references are Grossman and Stiglitz (1980), Verrecchia (1982), Kim and Verrecchia (1991), Kandel and Pearson (1995), and Veronesi (2000). I model the news related to a macroeconomic announcement as a public, noisy signal. Following DellaVigna and Pollet (2009), I model the attention to the announcement as the share of investors incorporating the signal into their decisions. In the following, I lay out the setup of the model, the model solution, as well as the predictions for the empirical analysis. All technical details are relegated to Online Appendix A.

**Setup** The model has *four dates*, i.e., $t = \{1, 2, 3, 4\}$, and consequently three periods. Figure 1 outlines the timeline of the model. Dates 1 and 2 are depicting the trading dates around the public inflation signal, i.e., the model counterpart to the empirical "pre" and "post" timestamp around the macroeconomic release of interest. As the period from date 1 to 2 corresponds to 30-minute or 90-minute window in the empirical analysis later, it should be seen as very short. In contrast, the other two periods should be seen as substantially longer as depicted in the figure.

There is a continuum of investors in the model, $i \in [0, 1]$. At date 1, each agent $i$ invests $\lambda_1^i$ in a risky Treasury security, i.e., a longer-term government bond, in order to maximize her wealth at date 4. The Treasury security matures at date 4, pays a coupon of one dollar at maturity, and is in zero net supply. The risk in the bond's value comes from the possible change $\Delta R$ in the risk-free rate $R_f$ by the monetary policy authority at date 3. So investors are uncertain of how to discount the bond's coupon between date 3 and 4. Modeling the Treasury security as the risky asset in such a way is based on Benamar, Foucault, and Vega (2021) and the references therein, and is motivated by the empirical analysis which focuses on the bond market. I will come back to this below when I talk about the empirical approach.

In each period, an agent can also invest in a riskless asset (a cash account). This asset has a net return of $R_f$ in period two (from date 2 to date 3) and period three (from date 3 to date 4). Since period one (from date 1 to date 2) is supposed to be very short, I assume

Figure 1: Model Timeline




Notes: This figure illustrates the four dates in the model including a summary headline for each date. It also shows the arrival time of the inflation signal. Details are provided in the text.

there is no return on the cash account earned and hence no discounting in the model for that period. Further, as the level of the risk-free rate is not important for the model mechanism, I will assume that the risk-free rate is zero, $R_f = 0$, when I solve the model as done by other papers before. This makes the model very tractable.

Monetary policy is set according to a Taylor rule which is given by $\Delta R = \phi \Delta\pi$, where $\Delta\pi$ is the change in inflation from date 2 to 3, i.e., $\pi_3 = \Delta\pi + \pi_2$. $\Delta\pi$ is assumed to be normally distributed with mean zero, i.e., $\Delta\pi \sim N(0, \sigma_\pi^2)$. Similar to the risk-free, I also assume $\pi_2 = 0$. Investors cannot observe $\Delta\pi$ prior to the monetary policy decision at date 3. However, before date 2, investors receive a public, noisy signal about $\Delta\pi$, i.e., $s^\pi = \Delta\pi + \eta$, $\eta \sim N\big(0, \sigma_\eta^2\big)$. Following DellaVigna and Pollet (2009), I assume that only $\mu^\pi$ investors (attentive investors) incorporate signal $s^\pi$ into their expectations, while $1 - \mu^\pi$ inattentive investors ignore it.[6]

At date 2, each agent $i$ faces again a portfolio problem investing $\lambda_2^i$ in the risky Treasury security in order to maximize her wealth at date 4. The difference to date 1 is that $\mu^\pi$ investors make this decision based on signal $s$, which they incorporate based on the signal-to-noise ratio as they face a standard signal extraction problem. Both date 3 and 4 do not involve any portfolio optimization as the investors' wealth is assumed to be held in the risk-free asset.

**Solution** The model solution is derived by solving each investor's portfolio choice problem and then using market clearing conditions to obtain the equilibrium prices for date 1 and 2. Each investor is assumed to have a quadratic utility function with risk aversion parameter

[6]Note that in DellaVigna and Pollet (2009), $\mu$ actually denotes the share of inattentive investors as opposed to the share of attentive investors here.

$\gamma$. Further, let $\mathrm{E}_t^i[\cdot]$ and $\mathrm{Var}_t^i[\cdot]$ denote investor $i$'s expectation and variance conditional on date $t$ information, respectively. At date 1, investor $i$ solves

$$\max_{\lambda_1^i,\lambda_2^i} \mathrm{E}_1^i[W_4^i] - \frac{\gamma}{2}\mathrm{Var}_1^i[W_4^i] \tag{1}$$
$$\text{s.t. } W_4^i = \lambda_2^i\,(V - P_2) + \lambda_1^i\,(P_2 - P_1) + W_0^i,$$

where $W_t^i$ is $i$'s wealth at date $t$, and $P_t$ is the price of the Treasury security at date $t$. $V$ denotes the value of the Treasury security and is equal to the discounted bond coupon, i.e., $V = 1/\left((1+R_f)\,(1+R_f+\Delta R)\right)$. As shown in Online Appendix A.3, $V$ can be rewritten (up to first order) as

$$V = 1 - \phi\Delta\pi. \tag{2}$$

Solving $i$'s portfolio choice problem (1) leads to the $i$'s demand for the Treasury security at date 1 and 2 based on date 1 information, i.e.,

$$\lambda_1^i = \frac{\mathrm{E}_1^i[P_2] - P_1}{\gamma\mathrm{Var}_1^i[P_2]} \quad \text{and} \quad \lambda_2^i = \frac{\mathrm{E}_1^i[V] - \mathrm{E}_1^i[P_2]}{\gamma\mathrm{Var}_1^i[V]}. \tag{3}$$

Solving problem (1) at date 2 leads to investor $i$'s updated demand for the Treasury security based on date 2 information

$$\tilde{\lambda}_2^i = \frac{\mathrm{E}_2^i[V] - P_2}{\gamma\mathrm{Var}_2^i[V]}. \tag{4}$$

Imposing market clearing conditions $\int_0^1 \lambda_1^i di = 0$, $\int_0^1 \lambda_2^i di = 0$, and $\int_0^1 \tilde{\lambda}_2^i di = 0$ at date 1 and 2, yields the equilibrium prices

$$P_1 = \mathrm{E}_1[V] = 1 \quad \text{and} \quad P_2 = \mathrm{E}_2[V] = 1 - \frac{\mu^\pi\phi\xi}{1-\xi\,(1-\mu^\pi)}s^\pi. \tag{5}$$

Here, $\mathrm{E}_t[\cdot]$ denotes the average expectation across investors.[7] Note that the inflation expectations in the model are given by

$$\mathrm{E}_1[\Delta\pi] = 0 \quad \text{and} \quad \mathrm{E}_2[\Delta\pi] = \frac{\mu^\pi\xi}{1-\xi\,(1-\mu^\pi)}s^\pi. \tag{6}$$

Hence, bond prices, as shown in expression (5), can be rewritten in terms of the inflation

[7] Roughly speaking, attentive and inattentive investors are weighted by their population share relative to their contribution to the conditional variance of $V$. This is formally defined in Online Appendix A.5 and is similarly derived as in DellaVigna and Pollet (2009).

expectations, i.e.,

$$P_t = 1 - \phi \mathrm{E}_t[\Delta\pi]\,. \tag{7}$$

**Predictions for market reactions to news** With the model solution at hand, I can directly characterize the *market reaction to inflation news* in the model. In particular, note that the change in the bond price is given by

$$\Delta P = P_2 - P_1 = -\frac{\mu^\pi \phi \xi}{1 - \xi\,(1 - \mu^\pi)} s^\pi.$$

As mentioned earlier, the period from date 2 to 4 can be thought of a flexible time span depending on the maturity of the bond. In the empirical analysis below, I will use *bond yields* rather than the bond prices, as yields are more commonly referenced. Let $\tau$ be the modified duration of the bond.[8] Following Gürkaynak, Kısacıkoğlu, and Wright (2020) and others, I approximate the bond's yield change by the negative of its price change divided by its modified duration, i.e.,

$$\begin{aligned} \Delta y &= -\frac{\Delta P}{\tau} \\ &= \underbrace{\frac{1}{\tau}\frac{\mu^\pi \phi \xi}{1 - \xi\,(1 - \mu^\pi)}}_{\beta^{y|\pi}} s^\pi. \end{aligned} \tag{8}$$

Besides bond yields, the framework also makes a prediction for changes in *inflation expectations* around inflation news. In particular, they are given by

$$\begin{aligned} \Delta \mathrm{E}[\pi_3] &= \mathrm{E}_2[\pi_3] - \mathrm{E}_1[\pi_3] \\ &= \mathrm{E}_2[\Delta\pi] \\ &= \underbrace{\frac{\mu^\pi \xi}{1 - \xi\,(1 - \mu^\pi)}}_{\beta^{\pi|\pi}} s^\pi. \end{aligned} \tag{9}$$

As one can show that $\frac{\partial \beta^{y|\pi}}{\partial \mu^\pi} > 0$ and $\frac{\partial \beta^{\pi|\pi}}{\partial \mu^\pi} > 0$ holds (see Appendix A.6), the model relationship between investor attention and the market reaction to inflation news is as follows: For a period of higher attention to inflation versus one with lower attention, i.e., $\mu^\pi_H > \mu^\pi_L$, the model predicts an increased sensitivity of interest rates and inflation expectations to

[8] The modified duration measures the percentage decrease in the bond price if its yield increases by one percentage point.

inflation news, i.e., $\beta_H^{y|\pi} > \beta_L^{y|\pi}$ and $\beta_H^{\pi|\pi} > \beta_L^{\pi|\pi}$.

Notice how equation (11) is generically written for any macro series $k$, not just for inflation-related data releases. The rationale behind this is that the empirical analysis can test an implicit prediction of the theoretical framework: To the extent that a macro release is not informative about inflation, the attention to it and consequently the asset price sensitivity should be relatively constant across inflation environments. That is, $\beta_H^{y|\neg\pi} \approx \beta_L^{y|\neg\pi}$ and $\beta_H^{\pi|\neg\pi} \approx \beta_L^{\pi|\neg\pi}$, where $s^{\neg\pi}$ denotes news which is not unambiguously informative.

To summarize, the theoretical framework has the following predictions for the empirical analysis. If investors are more attentive to inflation news when is inflation is high, we should expect the following: (1) Bond yields should be more responsive. A positive inflation surprise should lead to larger increases in yields. (2) Inflation expectations should be more responsive. A positive inflation surprise should lead to larger increases in inflation expectations. (3) Measures of attention should be higher around inflation news.

## 2.2 Empirical Strategy

The previous section showed that, theoretically, higher attention should lead to stronger effects of inflation news on interest rates and inflation expectations. So the original question turns to: does high inflation lead to stronger market responses to inflation news, i.e., $\beta_H^{y|\pi} > \beta_L^{y|\pi}$ and $\beta_H^{\pi|\pi} > \beta_L^{\pi|\pi}$? To empirically answer this question, I first need a

First, I need to construct empirical counterparts to the signals $s^{\pi}$ and $s^{\neg\pi}$. To do so, I employ the new information arising from macroeconomic data releases. Consider the release of macroeconomic variable $k$ at time $t$. For example, the Bureau of Labor Statistics publishes the numbers on the Consumer Price Index at 8:30 am typically between the 10th and 15th of a given month. Here, CPI is the macroeconomic series of interest ($k$), and the announcement time $t$ is 8:30 am on a given day. I construct the surprise ("news") of a given release by subtracting from the macro series $k$ its forecast, that is,

$$s_t^k = \frac{k_t - \mathrm{E}[k_t|\mathcal{I}_{t-\Delta^-}]}{\hat{\sigma}^k}, \tag{10}$$

where $k_t$ is the released value and $\mathrm{E}[\cdot|\mathcal{I}_{t-\Delta^-}]$ is the expectation conditional on information available just prior to the release. To make the magnitudes of surprises comparable across macroeconomic series $k$, I also divide by the sample standard deviation of $k_{US,t} - \mathrm{E}[k_{US,t}|\mathcal{I}_{t-\Delta^-}]$, denoted by $\hat{\sigma}^k$.

With empirical measures of $s^{\pi}$ and $s^{\neg\pi}$ at hand, one can test the theoretical predictions

(X) and (Y) with the following specification:

$$\Delta x_t = \beta_L^{x|k} s_t^k \mathbb{1}_{t \in L} + \beta_H^{x|k} s_t^k \mathbb{1}_{t \in H} + \varepsilon_t^k, \tag{11}$$

where $x$ is either an interest rate or a measure of inflation expectations, i.e., $x \in y, \pi$, and $\Delta x_t$ denotes the corresponding change in $x$ in a narrow window around the announcement time $t$. Further, $s_t^k$ is news about macro series $k$, $\mathbb{1}_{t \in L}$ and $\mathbb{1}_{t \in H}$ are indicator functions denoting if the announcement $t$ is during high or low inflation, and $\beta_L^k$ and $\beta_H^k$ are the coefficients of interest. The error term $\varepsilon_t^k$ includes the effects of unmeasured news and/or noise on the asset price of interest.

**CPI release versus other macro releases** In order to test the prediction on the market reactions by running equation (11), one needs decide which macroeconomic releases should be chosen to reflect the arrival of inflation and non-inflation news. In general, all macroeconomic data releases will be provide new information about inflation to some extent. While certain releases, e.g., price indexes, might be theoretically closer linked to inflation, if they are not timely enough, people might choose to still not pay attention to them as other releases with similar information are released earlier.

In the following, I argue that the release of the *headline CPI* is ex-ante the cleanest release of inflation news $s^\pi$ for which one would expect investor attention to increase during high inflation. First, the CPI release is generally the most cited inflation measure by the press (e.g., Bullard, 2022). Second, the headline CPI inflation is used to index both inflation swaps and Treasury inflation-protected securities (TIPS). Third, the CPI release is relatively timely compared to other common inflation measures. For example, the PCE price index, the Federal Reserve's preferred measure of inflation, comes usually out two weeks after the CPI and is usually found to not lead to strong financial market reactions which I will confirm in my analysis. While other releases might also experience an increased attention allocation, the CPI release should be a priori the release for which this effect is the strongest.

*Other macro releases* will certainly also contain information about inflation, in particular other price releases such as the Producer Price Index (PPI). So one might also see an increased sensitivity for these releases, however it should be less pronounced if at all existent. Other releases which are less directly mapped into inflation should see least increase in sensitivity. If investors have limited capacity, one might even think that attention and thus the market reaction decreases during the high inflation period.

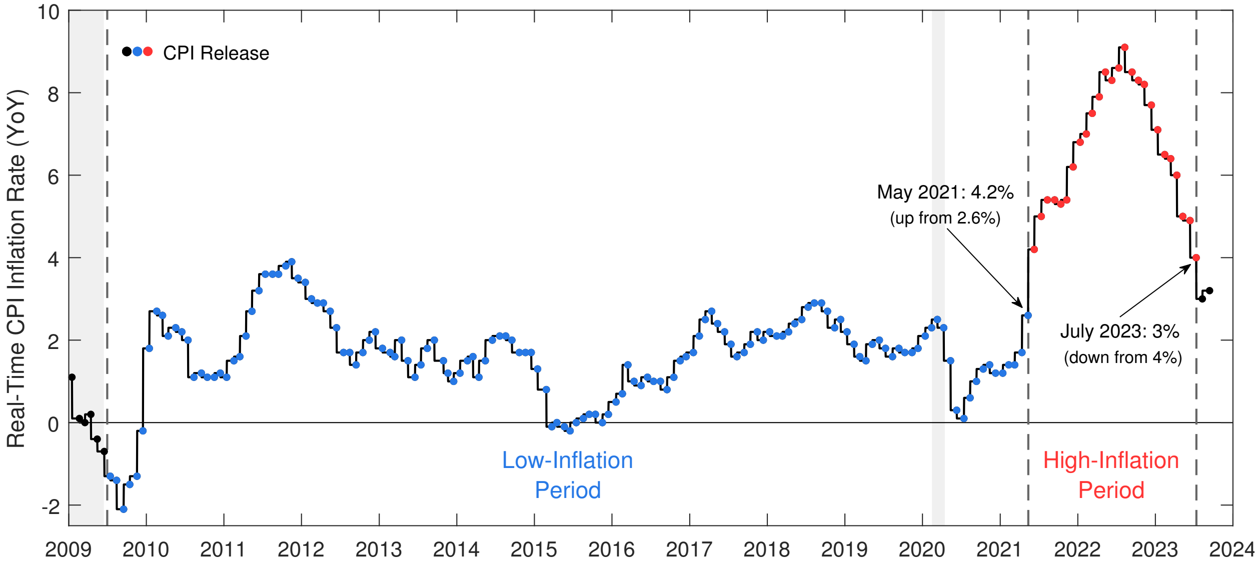
Overall, one way to think about these other, non-inflation news release $s^{\neg\pi}$ is as a "control group." There are many other things potentially changing between a low-inflation and high-inflation environment. So comparing $\beta_L^{x|k}$ and $\beta_H^{x|k}$ for inflation surprises is not necessarily informative about testing the hypotheses of increased attention to inflation. For example, the zero-lower-bound period should affect the interest rate sensitivity of all macro news. Any transmission mechanism which affect all news releases can be tested and potentially ruled out this way.

**Interpretation of $\beta_L^{x|k}$ and $\beta_H^{x|k}$** Coefficients $\beta_L^{x|k}$ and $\beta_H^{x|k}$ capture the effect of surprise $s_t^k$ on asset price $x$. First, note that $\beta_L^{x|k}$ and $\beta_H^{x|k}$ capture the effect of the same amount of news, i.e., the same unit of surprise. For example, in the case of the CPI a one standard deviation surprise maps to a 0.11 percent forecast error in the month-over-month (MoM) CPI inflation across both inflation periods. Hence, it is not the size of the surprise that is driving any differences across both periods. Second, both coefficients can be consistently estimated by Ordinary Least Squares (OLS) if the error term $\varepsilon_t^k$ is uncorrelated with the surprise. In a narrow window event window, as used in my analysis, this is likely to hold. Hence, I assume that this assumption holds throughout the paper. As a consequence, $\beta_L^{x|k}$ and $\beta_H^{x|k}$ measure the causal effects of information about release $k$ on asset price $x$. That is, the estimates can unambiguously attribute systematic changes in the asset price to the surprises. In this context, it should be also mentioned that the surprises are forecast errors and not structural shocks. Rather, they are a combination of the underlying structural shocks. See Boehm and Kroner (2023) for more discussion on this. It is important to understand that while $\beta_L^{x|k}$ and $\beta_H^{x|k}$ are informative about how the same amount of new information of $k$ leads to changes in asset price $x$ during a low and high inflation environment, the difference in coefficient size cannot be necessarily attributed to the changes in inflation and attention.

**Linking it back to attention** In addition to using the asset price sensitivity to test increased attentiveness, I will also look at patterns of attention proxies around releases. Similar to DellaVigna and Pollet (2009), I will look at trading volume as a measure of attention. As they point out, one indirect implication of the model with inattentive investors is potentially that trading volume should be positively related with the number of attentive investors as "trading is the mechanism that causes prices to adjust" (DellaVigna and Pollet, 2009, p.738–739).[9] I also employ Google searches for announcement-specific topics such as "Consumer Price Index." The extent to which people are more interested in these data releases should be reflected in the Google searches for the corresponding topic.

[9] As in DellaVigna and Pollet (2009), my model has no natural definition of trading volume.

Figure 2: Low- and High-Inflation Period based on CPI Inflation




Notes: This figure shows the real-time CPI inflation rate, measured in year-over-year (YoY) percentage change, at the beginning of each day from January 2009 until September 2023. Dots depict days of CPI releases, where blue dots indicate observations during the low-inflation period, while red dots during the high-inflation period. Shaded areas indicate NBER recession periods.

# 3 Data

In this section, I provide an overview of the data used for the main empirical analysis.

## 3.1 Low- and High-Inflation Period

The baseline sample starts on July 1, 2009, i.e., after the Great Recession, and ends on July 12, 2023 when inflation falls below 4 percent. The starting point is chosen both to avoid the documented anomalies in financial markets during Great Recession and to ensure sufficient liquidity in the inflation swap market, which I will use to measure inflation expectations in the analysis. As shown by Figure 2, my sample choice also allows me to cleanly split the sample into a period of low inflation and of high inflation. In particular, the figure shows the real-time CPI inflation rate, measured in year-over-year percentage change, at the beginning of each day from January 2009 until September 2023. The dots depict the days of CPI releases. Since the inflation rate at the beginning of each day is reported, the dots are not located at the new announced inflation rate but rather at the rate prevalent until the CPI release. This is the rate of interest for my analysis as it proxies the inflation environment at the time of the release.

As Figure 2 illustrates, the period following the Great Recession is characterized by low inflation. So, I define the period from July 1, 2009 until May 12, 2021 as the *low-inflation period*. That means macro releases starting from July 1, 2009 are included, even if the released data has an earlier reference month. To define the *high-inflation period*, I use a inflation threshold of 4 percent consistent with recent work by Korenok, Munro, and Chen (2022) and Pfäuti (2023).[10] Hence, the last day of the low-inflation period is May 12, 2021, which corresponds to the April CPI release of a 4.2 percent inflation rate, up from 2.6 percent in March. As noted in the press release, this represented "the largest 12-month increase since a 4.9-percent increase for the period ending September 2008."[11] Consequently, the high-inflation period starts on May 13, 2021, i.e., after the release of the April CPI numbers, and ends it on July 12, 2023 when the inflation rate drops to 3 percent, as shown in Figure 2.

### 3.2 Macroeconomic News

I use Bloomberg's U.S. Economic Calendar to obtain the data on the macroeconomic news releases. Bloomberg provides all required information for my analysis such as release date and time, released value, and the market expectations prior to the release. I consider 16 major macro releases throughout my analysis which are mostly chosen based on their importance documented in prior papers (e.g., Rigobon and Sack, 2008; Gürkaynak, Kısacıkoğlu, and Wright, 2020; Boehm and Kroner, 2023). For a succinct exposition, I often show results for only 8 of the 16 releases in the main text. Table 1 provides the summary statistics of these 8 releases and Appendix B1 shows the entire set of releases.

In this context, two things are worth mentioning. First, I combine the three GDP releases for given quarter to a single series so that I obtain a monthly series. This is done to have sufficient number of observations for the each both subperiods. Second, surprises in Core CPI and Core PPI are normally shown to have larger effects on average compared to the headline numbers. Despite this, I use the headline number as I conjecture that general attention will be centered on it. That being said, I will later show in Section 4 that the main findings are robust to choosing surprises about core measures instead of headline ones.

For as each release, I construct surprises based on equation (10). In particular, I use the average market expectation of the release as the measure of $\mathrm{E}\left[k_t|\mathcal{I}_{t-\Delta^-}\right]$. Bloomberg

[10] Korenok, Munro, and Chen (2022) and Pfäuti (2023) estimate inflation levels above which people pay attention to inflation. Korenok, Munro, and Chen (2022) and Pfäuti (2023) find thresholds for the U.S. of 3.55% and 4%, respectively. Thus, inflation rates above these values are perceived as high.

[11] https://www.bls.gov/news.release/archives/cpi_05122021.pdf (accessed on July 24, 2023).

Table 1: Overview of Macroeconomic News Announcements

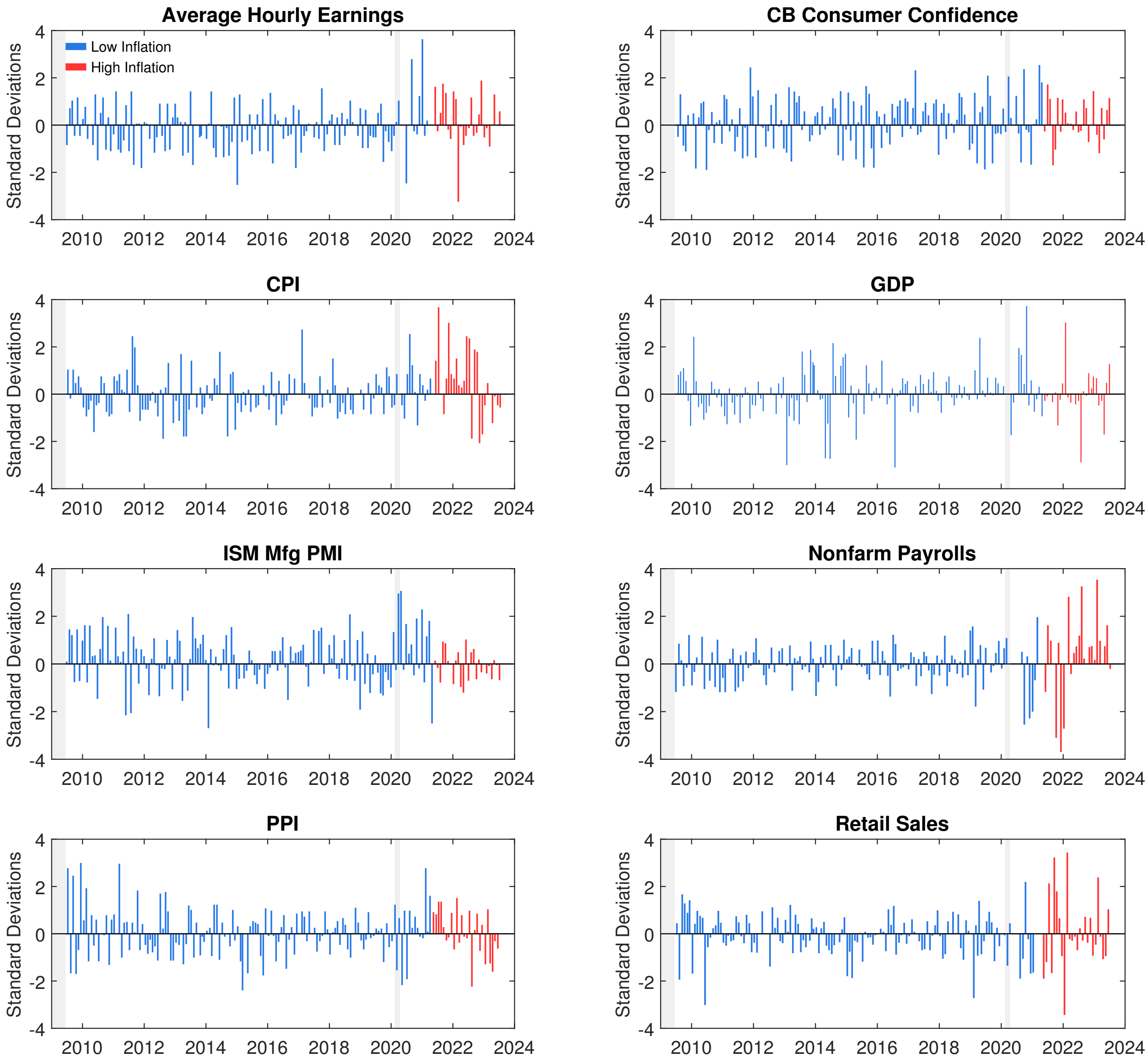
| Announcement | Release Time | Frequency | Observations | | | Unit | Surprise (+1 SD) |
|---|---|---|---|---|---|---|---|
| | | | Total | Low | High | | |
| Average Hourly Earnings | 8:30 | Monthly | 160 | 135 | 25 | % MoM | 0.15 |
| CB Consumer Confidence | 10:00 | Monthly | 168 | 142 | 26 | Index | 4.99 |
| CPI | 8:30 | Monthly | 166 | 140 | 26 | % MoM | 0.11 |
| GDP | 8:30 | Monthly | 164 | 140 | 24 | % QoQ ann. | 0.42 |
| ISM Mfg PMI | 10:00 | Monthly | 169 | 143 | 26 | Index | 1.75 |
| Nonfarm Payrolls | 8:30 | Monthly | 156 | 133 | 23 | Change | 90.15k |
| PPI | 8:30 | Monthly | 168 | 142 | 26 | % MoM | 0.32 |
| Retail Sales | 8:30 | Monthly | 161 | 135 | 26 | % MoM | 0.47 |

Notes: This table displays the 8 major macroeconomic series I focus on in most of the paper. Online Appendix Table B1 shows the full set of series considered in the paper. The sample ranges from July 2009 to July 2023. *Frequency* refers to the frequency of the data releases and *Observations* to the number of observations (surprises) of a macroeconomic series in my sample. *Unit* refers to the unit in which the data release and the survey is reported. *Surprise (+1 SD)* provides the mapping between a one standard positive surprise and the unit in which the release is originally reported. Abbreviations: Mfg—Manufacturing; CB—Chicago Board; ISM—Institute for Supply Management; PMI—Purchasing Managers' Index; MoM—month-over-month; QoQ—quarter-over-quarter; ann.—annualized.

allows forecasters to update their prediction up until the release time. Hence, these forecasts should reflect all publicly available information at the time. As noted above, surprises are also standardized so that the coefficients $\beta_L^{x|k}$ and $\beta_H^{x|k}$ measure the effects of a one standard deviation surprise for the entire sample. Notice that I use average rather median forecast to construct. While both are highly correlated (correlation between for the 16), the surprise based on average leads to more small surprises which allow me to have sufficient power when excluding larger surprises in robustness exercises. I compare both series for CPI in Appendix Figure B1 and also show that the main findings are robust to using both surprise series later in my analysis.

Figure 3 displays the resulting time series of each of the six macro releases. Consistent with my definition above, I color surprises during the low-inflation period blue and during the high-inflation period red. Note that I exclude observations which are larger then 4 standard deviations to avoid extreme observations, e.g., at the start of the pandemic. However, this does not affect the CPI and the PPI series. Moreover, both series look surprisingly good in terms of statistical properties considering the inflation surge. That being said, the volatility of the CPI series is slightly higher and has more positive observations during the high-inflation period. To mitigate concerns that both properties drive my results, I conduct robustness checks of the main analysis which I discuss below.

Figure 3: Time Series of Standardized Surprises




Notes: This figure shows the standardized surprises of the 8 major macroeconomic series over the sample. Blue and red observations indicate surprises which occurred during the low- and high-inflation period, respectively, as defined in Section 3.1. Shaded areas show NBER recession periods.

## 3.3 Financial Data

I employ intraday data on asset prices throughout my analysis which comes from the *Thomson Reuters Tick History* dataset and is obtained via *Refinitiv*. For my purposes, the key advantage of intraday data is that it leads to more precise estimates in the event study by

Table 2: Intraday Financial Data

| Name | Underlying Instrument | Tickers | Sample |
|---|---|---|---|
| *Interest Rates* | | | |
| ED1 | 1-Quarter Eurodollar/SOFR Futures | EDcm1/SRAcm2 | 2009–2023 |
| ED4 | 4-Quarter Eurodollar/SOFR Futures | EDcm4/SRAcm5 | 2009–2023 |
| 2-Year | 2-Year Treasury Futures | TUc1/TUc2 | 2009–2023 |
| 5-Year | 5-Year Treasury Futures | TUc1/TUc2 | 2009–2023 |
| 10-Year | 10-Year Treasury Futures | TYc1/TYc2 | 2009–2023 |
| 30-Year | 30-Year Treasury Futures | TYc1/TYc2 | 2009–2023 |
| *Inflation Expectations* | | | |
| 1-Year | 1-Year Inflation Swap Rate | USCPIZ1Y= | 2009–2023 |
| 2-Year | 2-Year Inflation Swap Rate | USCPIZ2Y= | 2009–2023 |
| 5-Year | 5-Year Inflation Swap Rate | USCPIZ5Y= | 2009–2023 |
| 10-Year | 10-Year Inflation Swap Rate | USCPIZ10Y= | 2009–2023 |
| 30-Year | 30-Year Inflation Swap Rate | USCPIZ30Y= | 2009–2023 |

Notes: The table shows the asset prices used in the main analysis. The data is from *Thomson Reuters Tick History*. For all series, the sample period ends in July 2023. *Ticker* refers to the Reuters Instrument Code (RIC). Abbreviations: SOFR—Secured Overnight Financing Rate.

mitigating noise in outcome variable. This allows me to investigate systematic differences in the financial markets responses, even in a small sample (in my case, the high-inflation sample with less 30 observations). Table 2 provides an overview of the employed asset prices which I go through in the following.

**Interest Rates** Similar to various other papers, I employ interest rates futures. To capture shorter horizons, I employ Eurodollar futures. With the cessation of the LIBOR, I use from April 2022 onwards the Secured Overnight Financing Rate (SOFR) futures which are successor futures contracts at the Chicago Mercantile Exchange (CME).[12] Following Gürkaynak, Kısacıkoğlu, and Wright (2020), I construct yield changes from Treasury futures by dividing the price changes by the approximate modified duration and taking the negative of it. Throughout the analysis, price changes are based on a window ranging from 5 minutes before to 60 minutes after the given release, which I simply refer to as *60-minute window* or *60-minute change* hereafter. The window size is chosen so that I have consistent window across asset prices. This will be clear talk about the inflation swap rates in the paragraph. The impulse responses to CPI news in Appendix Figure B4 show that the precise window size does not matter for interest rate futures. This is consistent with prior work and the fact that interest rates futures are highly liquid. In addition, they are also traded via a

[12] April 2022 is the first month in which the trading volumes of the SOFR futures contracts exceed the ones of the corresponding Eurodollar futures.

centralized exchange, i.e., the CME. So I also have access to trading volume which I will employ later in Section 5 as a proxy for attention.

**Inflation Expectations** To measure inflation expectations, I employ (zero-coupon) inflation swaps. These are based on the CPI. Broadly speaking, two counterparties agree at given point in time to exchange a fixed rate, the swap rate, in exchange for a floating payment based on the realized CPI over the maturity of the swap.[13] Appendix Figure B3 illustrates the timing of the payoffs. Hence, the $h$-year inflation swap rate measures the risk-neutral expectation of the annual CPI inflation over next $h$-years. Inflation swap rates are preferred to break-even rates from inflation-indexed Treasury bonds (TIPS) as they are less prone to liquidity issues (Fleckenstein, Longstaff, and Lustig, 2014; Cieslak and Pflueger, 2023). Table 2 provides on overview of the employed swap rates covering maturities from 1 to 30 years. For a given swap, the rate is constructed as the midpoint of the bid and ask prices. As the inflation swap measures the risk-neutral expectation, it captures the expected inflation rate adjusted for an inflation risk premium. In the subsequent analysis, I assume that inflation risk premia are not the dominant component driving changes in a narrow window around announcements. While non-innocuous, one would need a model to clean the rates from the premia, which does not come without its own problems.

In general, inflation swaps are less liquid and since they are not coming from centralized exchange, the data quality is lower. This has two consequences for my analysis. First, a too narrow will not capture the announcement effects. Based on the the impulse responses in Appendix Figure B5 around CPI releases, I use the same 60-minute window from 5 minutes before to 60 minutes after the given release. Second, I clean the inflation swap rates based on the procedure by Brownlees and Gallo (2006). I defer details to Appendix B.2.

**Others** I employ additional financial market data throughout the paper. Appendix B.2 provides information on all data used in the paper. If additional data is employed for given analysis, I note that and reference the appropriate information in the appendix.

## 4 The Effects of Macro News under Low and High Inflation

In this section, I implement the high-frequency event study and estimate the effects of U.S. macro releases on asset prices under low and high inflation. I start with yields and inflation expectations which, as discussed in the previous section, are both theoretically and

[13]Note that inflation swaps have an indexation lag of two to three months, i.e., realized inflation is constructed based on a period starting and ending two to three months prior to the start and end dates of the contract, respectively.

empirically preferable. I show that surprises about the CPI lead to much stronger effects under high inflation. This increase in market impact is unique among macro releases. Lastly, I show similar patterns for U.S. and international stocks, exchange rates and international yields

### 4.1 Interest Rates

Before I talk about the main analysis, note that I investigate in Appendix C.1 the average effects of the macro surprises on interest rates over my sample period. Across releases, I find that higher-than-expected news lead to increases in interest rates, which is in line with prior papers and confirms a Taylor-type rule interpretation. I defer details and discussion of the results to Appendix C.1.

I now turn to the main specification to estimate the effect of macro news during the low- and high-inflation period as defined in Section 3. In particular, I estimate, for each announcement series $k$, the following event study regression

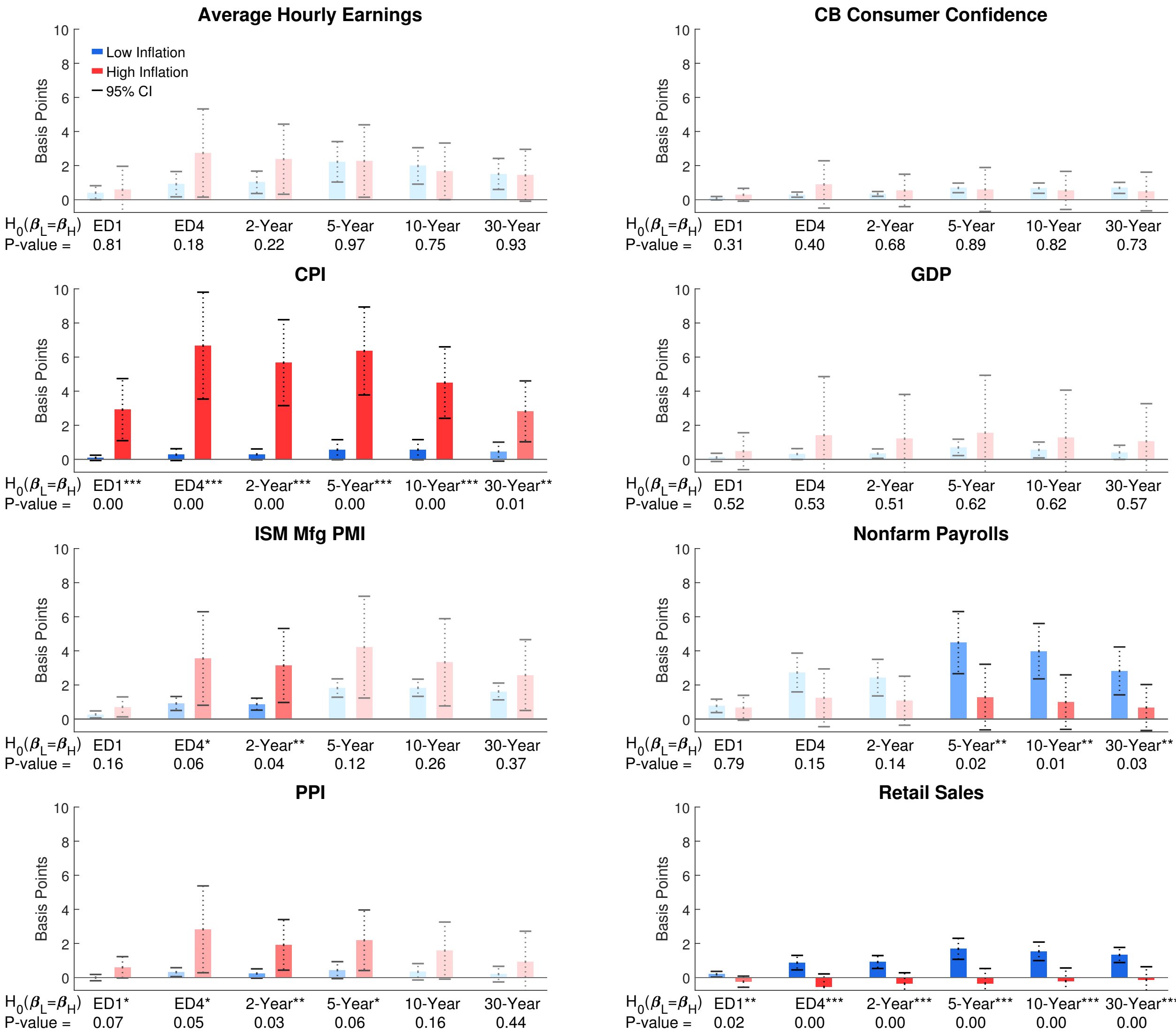
$$\Delta y_t = \alpha_L^k + \alpha_H^k + \beta_L^{y|k} s_t^k \mathbb{1}_{t\in L} + \beta_H^{y|k} s_t^k \mathbb{1}_{t\in H} + \varepsilon_t^k, \tag{12}$$

where $s_t^k$ is the announcement surprise of interest and $\Delta y_t$ is the 60-minute change in one of the 6 interest rates described in Table 2. $\mathbb{1}_{t\in L}$ is an indicator function, which equals one if the announcement $t$ is in during the low-inflation period and zero otherwise. $\mathbb{1}_{t\in H}$ is defined accordingly. Note that $\mathbb{1}_{t\in L} = 1 - \mathbb{1}_{t\in H}$. Further, I allow each period to have a separate intercept, $\alpha_L^k$ and $\alpha_H^k$.

Figure 4 shows the results for equation (12). The blue bars show the estimates of $\beta_L^{y|k}$ and the red bars display the estimates of $\beta_H^{y|k}$. Equation (12) also allows me to directly test the equivalence of $\beta_L^{y|k}$ and $\beta_H^{y|k}$. In other words, I test for a structural break in in the effect of the surprise.[14] For each left-hand side variable, the test's p-value is reported below the interest rate abbreviations in the figure. Based on the significance level of the test, more significant differences in the coefficients $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are reflected in darker shades of the bars.

[14]This is similar to a Chow-test, except that I do not test the equivalence of intercepts in the low- and high-inflation period as well.

Figure 4: Effects of Macro News on Interest Rates under Low and High Inflation




Notes: This figure shows the responses of interest rates under the low-inflation and the high-inflation period for each of the 8 main macro announcements. Interest rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given interest rate, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{y|k}$ of equation (12), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{y|k}$ of equation (12). The black error bands depict 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level of rejecting the null hypothesis that $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are equal. The p-value of this hypothesis test is reported below each interest rate. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests. The interest rate abbreviations are explained in Table 2. Appendix Figure C3 shows the results for the other 8 macro announcements.

The key findings of Figure 4 can be summarized as follows: First and foremost, positive

CPI news leads to much larger increases on the yield curve during high inflation. The effects are more than an order of magnitude larger, on average. The differences between $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are also highly statistically significant, where I can reject the equivalence across periods at the one or the five percent level in the case of the 30-year yield. For ISM Mfg PMI and PPI, I find a some evidence for an increase in sensitivity but it is much less pronounced and much more noisy. While I mostly focus on the CPI release in the rest of the paper, the results can be seen as consistent with attention to inflation. The PPI is a price index itself and ISM Mfg PMI is informative in supply chain issues which are seen as key driver of inflation surge.[15]

For Nonfarm Payrolls and Retail Sales, two releases which are among the most important macro releases, I actually find a significant reduction in the market impact on interest rates. While I do not emphasize this result much throughout the paper, one way to rationalize it is through the idea of attention substitution. If investors have some sort of capacity on information processing, more attention to inflation news could be accompanied with less attention to other, non-inflation releases. An alternative interpretation is that both releases became harder to interpret since the pandemic as Retail Sales is not adjusted for prices and the labor market seemed to have generally transformed.[16]

To better visualize the extraordinary increase in market sensitivity to the CPI news, I also plot the differences in coefficients across low- and high-inflation period for the broader set of releases. In particular, Figure 5 shows the estimates of $\delta_H^{y|k}$ from the following regressions

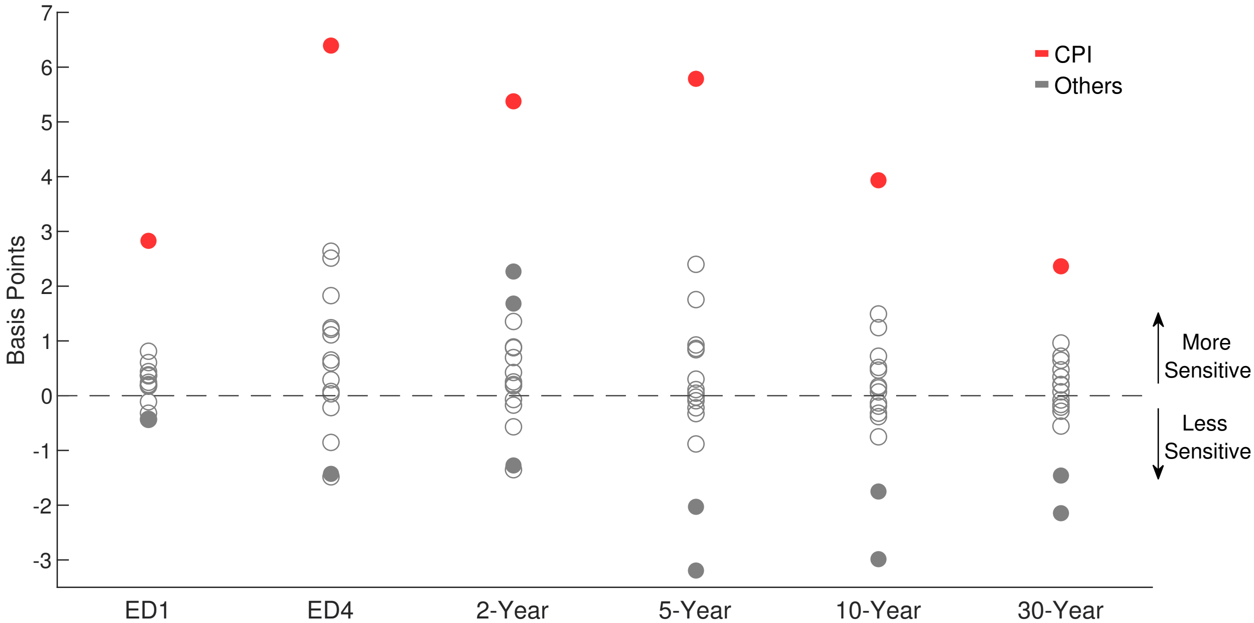
$$\Delta y_t = \alpha_L^k + \alpha_H^k + \beta_L^{y|k} s_t^k + \delta_H^{y|k} s_t^k \mathbb{1}_{t\in H} + \varepsilon_t^k, \tag{13}$$

where $\delta_H^{y|k} = \beta_H^{y|k} - \beta_L^{y|k}$. Note that testing the null $\delta^{y|k} = 0$ is equivalent to testing $\beta_L^{y|k} = \beta_H^{y|k}$ for equation (12). As Figure 5 illustrates, the CPI release is unique in how its impact on interest rates rose during the recent inflation surge. None of the other 15 macro releases experiences a comparable statistically and economically significant in effect size.

[15] For example, the following Bloomberg article talks about supply chain issues in the context of ISM Mfg PMI release: `https://www.bloomberg.com/news/articles/2022-06-01/us-manufacturing-growth-unexpectedly-firms-on-stronger-orders?sref=b88bZRaf` (accessed on January 17, 2014).

[16] See the following Bloomberg article for a mentioning of the difficulty on interpreting Retail Sales due to inflation: `https://www.bloomberg.com/news/articles/2023-06-15/us-retail-sales-unexpectedly-rise-in-sign-of-consumer-resilience?sref=b88bZRaf` (accessed on January 17, 2024). See the following Bloomberg article for an example of the difficulty of interpreting the employment report please see: `https://www.bloomberg.com/news/articles/2023-06-02/us-payrolls-surge-while-jobless-rate-rises-wages-decelerate?sref=b88bZRaf` (accessed on January 17, 2024).

Figure 5: Change in Interest Rate Sensitivity to Macro News under High Inflation




Notes: The figure displays differential responses of the interest rates for the high-inflation period. For a given interest rate, a circle indicates the estimate of coefficient $\delta_H^{y|k} = \beta_H^{y|k} - \beta_L^{y|k}$ of equation (13). Filled circles indicate significance at the 5 percent level while an empty circle indicates an insignificant effect. Heteroskedasticity-robust standard errors are employed. *Others* includes the following 15 other releases: Average Hourly Earnings, Capacity Utilization, CB Consumer Confidence, Durable Goods Orders, GDP, Initial Jobless Claims, ISM Mfg PMI, New Home Sales, Nonfarm Payrolls, PCE Price Index, Philadelphia Fed Index, PPI, Retail Sales, UM Consumer Sentiment P, and Unemployment Rate. See Appendix Table B1 for details on the releases.

**Robustness** I now discuss how the documented change in interest rate sensitivity to CPI releases is a robust feature of the data. This is based on an extensive sensitivity analysis which is detailed in Appendix C.3 and which I summarize in the following. First, the top row of Appendix Figure C5 shows that the results are essentially unchanged when using surprises about the core CPI (*Core*) or the year-over-year CPI (*YoY*) instead of month-over-month CPI in the baseline. In the second row, I also show that the results are almost identical when I use surprises based on the median instead of the mean forecast (*Median Forecast Surprise*).

Further, I investigate how sensitive the results are with respect to two statistical properties of CPI surprises which are potentially of concern. First, there are a couple of large surprises in the sample, in particular during the high-inflation period. The second row of Appendix Figure C5 shows that the results are robust of excluding these large surprises (*Excluding Large Surprises*). In fact, the effect of CPI news during the high-inflation period becomes actually stronger compared to the baseline. There, it is also shown that the main findings are essentially unchanged when taking out any autocorrelation in the CPI surprise series (*Residualized Surprises*). In addition, I check a couple of other specifications such as starting the low-inflation sample in 1996 instead of 2009. I refer the interested reader to Appendix C.3 for details.

Lastly, in Appendix Figure C7, I investigate the robustness of my analysis with respect to the break date between low- and high-inflation period. As the figure shows, the main findings are robust to choosing different break months around the baseline one. To sum up, the key finding of the increased impact of CPI news on yields is robust across a wide variety of specifications and not driven by particular choices in the baseline analysis.

### 4.2 Inflation Expectations

In the previous section, I established that interest rates are significantly more sensitive to CPI news under high inflation, consistent with the theoretical prediction of higher attention. The model also predicts that inflation expectations should be more responsive, which I investigate in this section. Ultimately, the goal of this section is to connect the increased interest rate sensitivity to CPI news to a rise in sensitivity of inflation expectations.

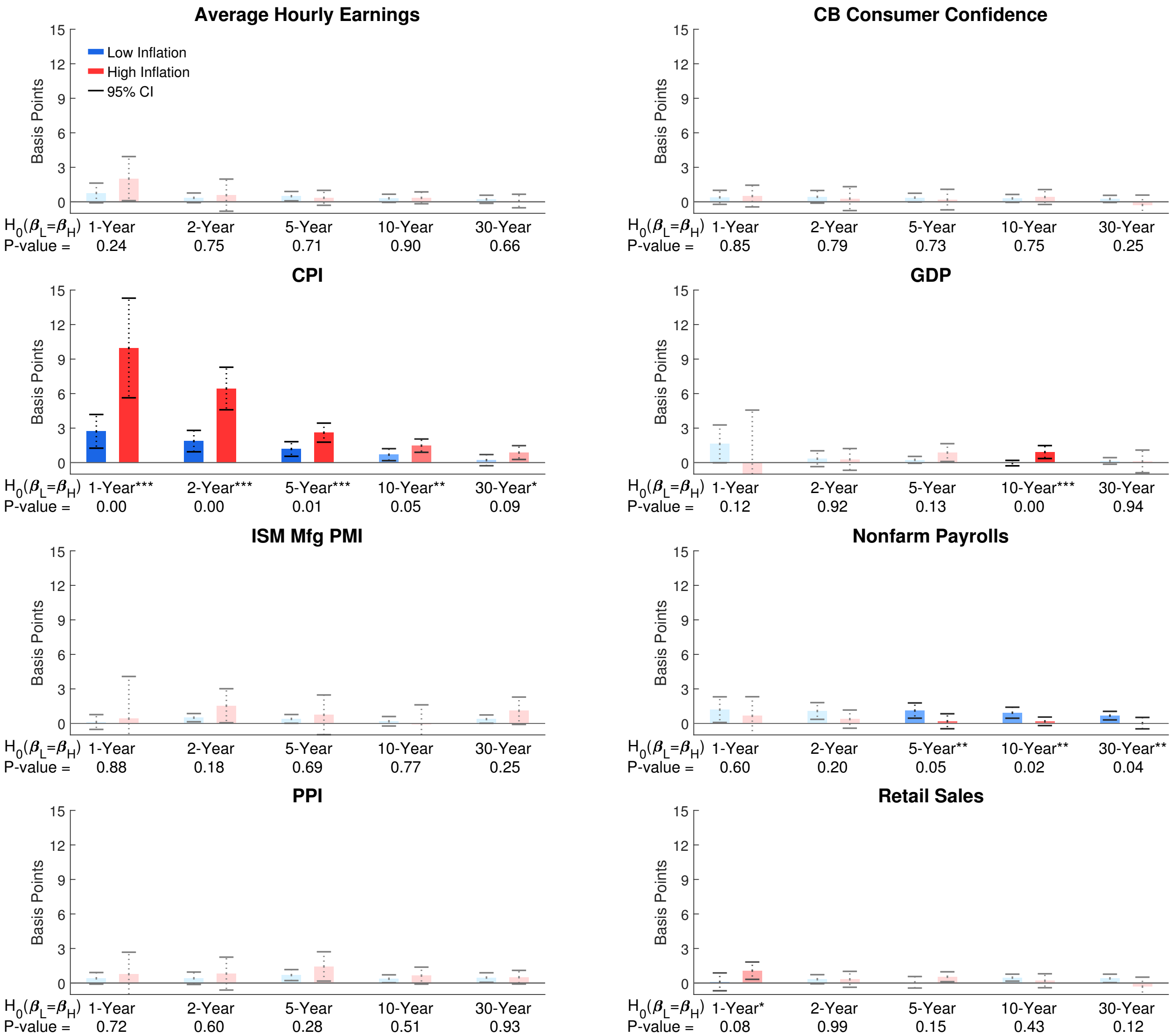
As with the interest rates, I begin by studying in Appendix C.1 the average of the macro news on inflation expectations over my sample releases. Consistent with the argument laid out in Section 2, a higher-than-expected CPI release leads by far to the largest increases in inflation expectations. That being said, a handful of other releases are also associated with significant effects where a higher-than-expected news causes inflation swap rates to increase. In sum, the results do not indicate any red flags with respect to the main specification.

I now turn to estimating the effects of macro news on the inflation swap rates under low and high inflation. To do so, I estimate, for each announcement series $k$, the following event study regression

$$\Delta\pi_t = \alpha_L^k + \alpha_H^k + \beta_L^{\pi|k} s_t^k \mathbb{1}_{t\in L} + \beta_H^{\pi|k} s_t^k \mathbb{1}_{t\in H} + \varepsilon_t^k, \tag{14}$$

where $s_t^k$ is the announcement surprise of interest, and $\Delta\pi_t$ is the 60-minute change in one of the five inflation swap rates described in Table 2. $\mathbb{1}_{t\in L}$ is an indicator function, which equals one if the announcement $t$ is during the low-inflation period and zero otherwise. $\mathbb{1}_{t\in H}$ is defined accordingly. Note that $\mathbb{1}_{t\in L} = 1 - \mathbb{1}_{t\in H}$. Further, I allow each period to have a separate intercept, $\alpha_L^k$ and $\alpha_H^k$.

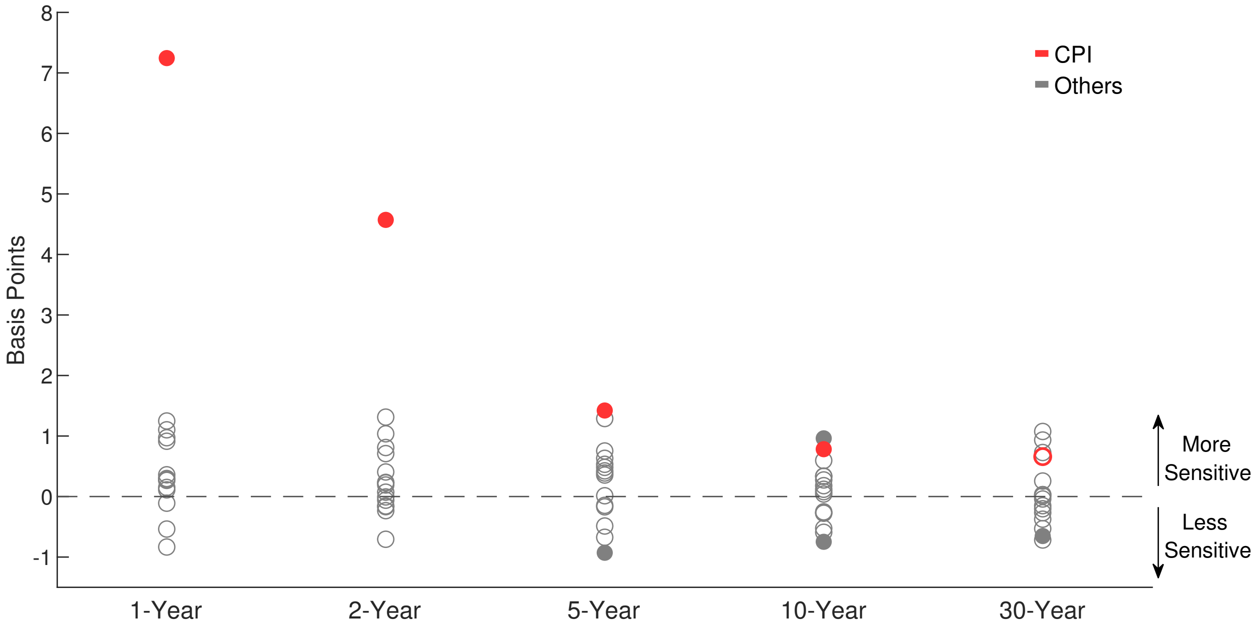
Figure 6: Effects of Macro News on Inflation Expectations under Low and High Inflation




Notes: This figure shows the responses of inflation swap rates under the low-inflation and the high-inflation period for each of the 8 main macro announcements. Inflation swap rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given inflation swap rate, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{\pi|k}$ of equation (14), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{\pi|k}$ of equation (14). The black error bands depict 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level of rejecting the null hypothesis that $\beta_L^{\pi|k}$ and $\beta_H^{\pi|k}$ are equal. The p-value of this hypothesis test is reported below each inflation swap rate. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests. Appendix Figure C4 shows the results for the other 8 macro announcements.

Figure 6 displays the results for equation (14). A couple of things stand out: First and foremost, CPI news has substantially stronger effects on inflation swap rates during the high

Figure 7: Change in Inflation Expectation Sensitivity to Macro News under High Inflation




Notes: The figure displays differential responses of inflation expectations for the high-inflation period. For a given interest rate, a circle indicates the estimate of coefficient $\delta_H^{\pi|k} = \beta_H^{\pi|k} - \beta_L^{\pi|k}$ of equation (13). Filled circles indicate significance at the 5 percent level while an empty circle indicates an insignificant effect. Heteroskedasticity-robust standard errors are employed. *Others* includes the following 15 other releases: Average Hourly Earnings, Capacity Utilization, CB Consumer Confidence, Durable Goods Orders, GDP, Initial Jobless Claims, ISM Mfg PMI, New Home Sales, Nonfarm Payrolls, PCE Price Index, Philadelphia Fed Index, PPI, Retail Sales, UM Consumer Sentiment P, and Unemployment Rate. See Appendix Table B1 for details on the releases.

inflation period. This is in particular prevalent for swap rates of shorter maturities, where differences are both economically and statistically most significant. The downward shaped responsiveness of the inflation swap rates also suggests that market beliefs that the Federal Reserve will be bring down inflation medium- to long-run. Put differently, long-run inflation expectations seemed to be anchored. Second, none of the other releases display much of a change in the effect sizes across periods. We observe a slight increase in the impact on the 10-year rate for the GDP release and a somewhat decline in sensitivity to Nonfarm Payrolls which echoes the interest rates results.

To better visualize the extraordinary increase in market sensitivity to the CPI news, I also plot the differences in coefficients across low- and high-inflation period for the broader set of releases. In particular, Figure 7 shows the estimates of $\delta_H^{\pi|k}$ from the following regressions

$$\Delta\pi_t = \alpha_L^k + \alpha_H^k + \beta_L^{\pi|k} s_t^k + \delta_H^{\pi|k} s_t^k \mathbb{1}_{t \in H} + \varepsilon_t^k, \tag{15}$$

where $\delta_H^{\pi|k} = \beta_H^{\pi|k} - \beta_L^{\pi|k}$. Note that testing the null $\delta^{\pi|k} = 0$ is equivalent to testing $\beta_L^{\pi|k} = \beta_H^{\pi|k}$ for equation (14). As Figure 7 illustrates, the CPI release is unique in how its impact on interest rates rose during the recent inflation surge. None of the other 15 macro releases experiences a comparable statistically and economically significant in effect size.

**Robustness** As for the results on interest rates, I also conduct an extensive sensitivity analysis to show that the change in inflation swap rate sensitivity to CPI releases is a robust feature of the data. This analysis is detailed in Appendix C.3. In the following, I summarize the key takeaways. First, Appendix Figure C6 shows that the results are robust to the same battery of robustness checks as conducted for interest rates. See the discussion in that robustness or the Appendix for details. Second, instead of extending the low-inflation period as for interest rates, which is not possible to the data availability on the inflation swaps, I conduct an analysis based on the breakeven inflation rates from Treasury Inflation-Protected Securities (TIPS). While these securities are only available for maturities larger than 5-years, Appendix Figure C6 illustrates in the bottom right panel (*Breakeven Inflation*) the results are very much consistent with the ones from swap rates.

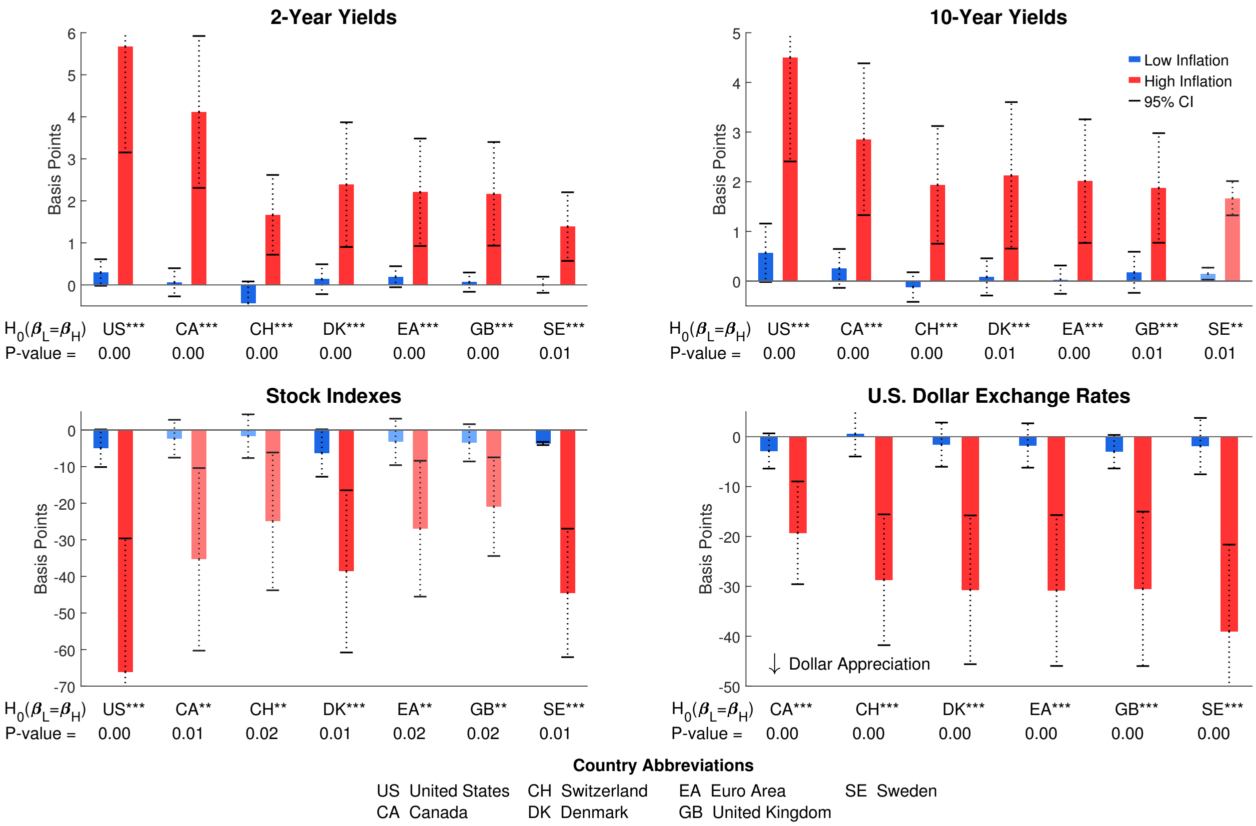
Lastly, in Appendix Figure C8, I investigate the robustness of my analysis with respect to the break date between low- and high-inflation period. As the figure shows, the main findings are robust to choosing different break months around the baseline one. To sum up, the key finding of the increased impact of CPI news on inflation expectations is robust across a wide variety of specifications and not driven by particular choices in the baseline analysis.

### 4.3 Stocks, Exchange Rates and International Spillovers

After documenting the results for interest rates and inflation swap rates, I now turn to other asset prices; in particular, stock prices, exchange rates, and foreign interest rates. For a clearer presentation, I now exclusively focus on CPI news. The goal of this section is to show that the stronger effects of CPI releases are a broad phenomenon across asset classes. To do so, I rerun equation (12) with a variety of different asset prices on the left-hand side. Figure 8 illustrates the results of this analysis.

The top-left and top-right panel of Figure 8 displays estimates of equation (12) for various countries' 2-year and 10-year government yields, respectively. For comparison, I also plot the earlier results for the U.S. Across countries, we see an increase in yield sensitivity to CPI news, which is both economically and statistically significant. Compared to the U.S., the effect sizes are smaller and similar across countries except for Canadian yields, which display a somewhat stronger response. The findings are consistent with market participants believing that U.S. inflation spills over to other countries leading the central banks to increase their policy rates in the near- and medium-term future.

Figure 8: Effects of CPI News on International Asset Prices




Notes: This figure shows the effects of CPI news on a variety of asset prices under the low-inflation and the high-inflation period. The top-left and top-right panels display the results for countries' 2-year and 10-year yields, while the bottom-left and bottom-right panels shows the estimates for stock returns and U.S. dollar exchange rates. Each panel shows the results of estimating $\beta_L^{x|k}$ and $\beta_H^{x|k}$ of equation (11) after replacing the left-hand side with the 60-minute change or (log-change) of the corresponding asset prices. For a given asset, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{x|k}$, while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{x|k}$. The black error bands depict 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level of rejecting the null hypothesis that $\beta_L^{x|k}$ and $\beta_H^{x|k}$ are equal. The p-value of this hypothesis test is reported below each announcement. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests. Appendix Table B2 provides an overview of the employed asset prices.

Moving on to stocks, the bottom-left panel of Figure 8 displays estimates of equation (12) for various countries' major stock indexes.[17] Consistent with a dominant interest rate

[17]To be precise, I use log-changes for stocks and exchange rates on the left-hand side.

channel, stock prices decline both during the low- and high-inflation period. The increase in sensitivity during the high-inflation period is substantial and statistically significant. In terms of magnitudes, the largest effect is observed for the U.S. which is qualitatively in line with findings for interest rates.

Lastly, I report in the bottom-right panel of Figure 8 results for the U.S. dollar vis-a-vis other major currencies. Similar to the other results so far, I find a stark increase in sensitivity to CPI news during the high-inflation period. Further, consistent with larger increase U.S. interest rates, I find an appreciation of the U.S. dollar for the high-inflation period. The smaller appreciation against the Canadian dollar and the larger appreciation against the Swedish krona are both in line with the relative interest rate responses. To sum up, all four panels show that the sensitivity of asset prices increased significantly to the CPI release, both in an economic and statistical sense.

### 4.4 Time-Varying Coefficient Approach

So far, I employed a "discrete approach" in my empirical analysis. That is, I defined a low- and a high-inflation period and compared the estimated coefficients across. While I show that main findings are robust to varying the beak date, one might be still concerned about the underlying time-variation in the market impact of CPI news. To address this point, I employ in this section the nonparametric estimation approach based on Robinson (1989) and Cai (2007).[18] which allows one to estimate for time-varying effects in a flexible way, i.e., without taking a stand on the underlying source. In particular, I estimate the following specification

$$\Delta x_t = \alpha^k + \beta_t^{x|k} s_t^k + \varepsilon_t^k, \tag{16}$$

for $k \in$ CPI, and $\Delta x_t$ is the 60-minute change in the asset price of interest. Broadly speaking, the estimation idea is to view $\beta$ as a smooth function of time, i.e., $\beta_t^{x|k} = \beta^{x|k}\left(\frac{t}{T}\right)$, for $t = 1, 2, ..., T$. Hence, $\tau = \frac{t}{T}$ can be seen as the smoothing variable with $\tau \in [0, 1]$.

I use the local constant method to estimate $\beta_t^{x|k}$, where I employ a Gaussian kernel of bandwidth $b = \frac{12}{T}$. In simple words, the estimation does a series of weighted least squares regressions around each point $\frac{t}{T}$, where points further away are less weighted based on the Gaussian density function with a standard deviation of 12 months (12 observations), determined by the chosen bandwidth. Confidence intervals are constructed following the

[18]This methodology has been recently used, for example, by Farmer, Schmidt, and Timmermann (2023) to understand stock return predictability.

bootstrap procedure by Fan and Zhang (2000) and Chen et al. (2018).[19]

Figure 9: Time-Varying Effects of CPI News on Asset Prices


Notes: This figure shows the time-varying high-frequency effects of CPI news on asset prices over the sample period. Each panel displays the estimates $\beta_t^{x|k}$ of equation (16) for three different left-hand side variables. These are the 2-year interest rate, 2-year inflation swap rate, and the S&P 500. The blue and red color indicate if estimates are during the low- or high-inflation period, respectively. Shaded areas show 95 percent bootstrap confidence intervals. See text for details on the estimation.

For my analysis, I focus on the 2-year interest rate and inflation swap rate, as well at S&P 500. For the stock market, it is well documented that the effects of some macro news announcements on the stock market are not stable across time (e.g., Boyd, Hu, and Jagannathan, 2005; Gürkaynak, Kısacıkoğlu, and Wright, 2020). The intuition is that cash flows and equity premia, in addition to discount rates, make the transmission of macro news more complicated and potentially unstable over time.

[19] I use the R package by Casas and Fernández-Casal (2022) to implement the estimation procedure.

Figure 9 shows the estimates for each of the three variables. Overall, the figure paints a cohesive picture. As the sensitivity of the swap rate and interest rate increases from 2021, so does the sensitivity of the S&P 500. The results in Figure 9 are consistent with the fidings so far and imply that the increase in market impact aligns well with the rise in inflation. My findings also echo the recent evidence by Gil de Rubio Cruz et al. (2022), who show that the stock market and interest rate sensitivity to inflation surprises is increasing over the recent years.

# 5 Additional Analyses

## 5.1 Trading Volume

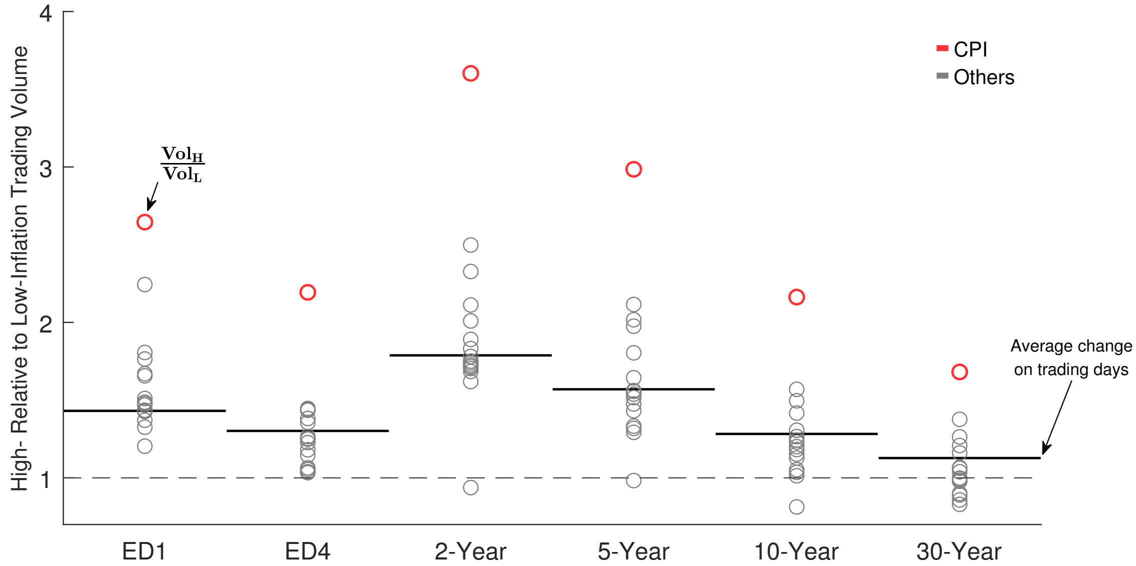
Based on the findings in the previous section, I now seek to provide direct evidence that the increased sensitivity to CPI releases is driven by investors attention. While attention is generally difficult to measure, I begin by studying the trading volume around macro releases in this subsection. Trading volume has been a widely used as a proxy for investor attention (e.g., Huberman and Regev, 2001; Barber and Odean, 2008). Following the argument by DellaVigna and Pollet (2009), one would expect a much higher trading volume around CPI releases if the increased market impact is indeed due to a large amount of attentive investors.

To test this prediction, I construct trading volumes for the interest rate futures around a given release and compare the average during the high-inflation with one during the low-inflation period. In particular, the trading volume around a release is measured as the number of contracts traded in the 60-minute window around it, where the window ranges from 5 minutes prior to 60 minutes after matching the length of the return window used so far. The data is coming directly from *Refinitiv*.[20]

Figure 10 displays the results. For a given interest rate, each circle corresponds to macro release and shows the ratio of the average trading volume during high inflation to the one during low inflation. I also plot the same ratio for the average trading volume across both subsamples as benchmark. So circles above (below) the line can be interpreted as abnormally increases (decreases) in trading volume around macro releases. First, notice how almost each circle and all lines are above the one line indicating that trading volume generally increased during the high inflation period. Second and more importantly, the figure shows the large increase in trading around CPI releases during the high-inflation period (red circles), which

[20]Unfortunately, I do not observe trades for inflation swap rates and hence trading volume is not available to me.

Figure 10: Change in Trading Volume around Macro News




Notes: This figure displays the changes in trading volumes of interest rate futures around macro releases. For a given interest rate, each dot corresponds to a specific macro release and shows the ratio of the average trading volume around that release during the high-inflation period ($Vol_H$) to the one during the low-inflation period ($Vol_L$), where volumes are constructed based on 60-minute windows around releases. Horizontal lines show the ratio of the average trading volumes across both periods. *Others* includes the following 15 other releases: Average Hourly Earnings, Capacity Utilization, CB Consumer Confidence, Durable Goods Orders, GDP, Initial Jobless Claims, ISM Mfg PMI, New Home Sales, Nonfarm Payrolls, PCE Price Index, Philadelphia Fed Index, PPI, Retail Sales, UM Consumer Sentiment P, and Unemployment Rate. See Appendix Table B1 for details on the releases.

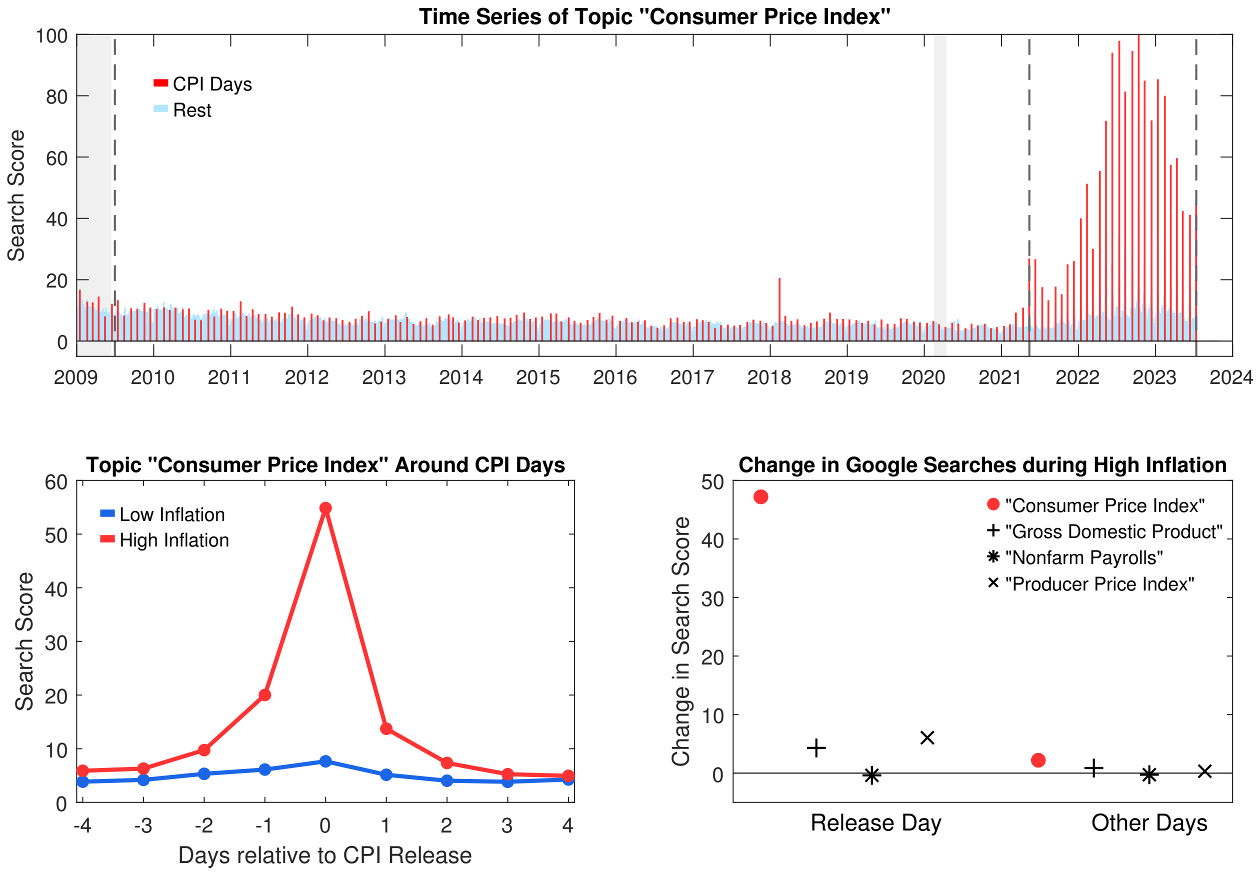
is exceptional both compared to other releases (grey circles) and compared to how much trading in general increased (black lines).

In Appendix Figure D1, I also plot the average minute-by-minute trading volumes. They reveal that the abnormal increase around CPI announcements is indeed driven by trading on the release itself. In summary, the evidence on trading volume is consistent with a rise in attentive investors to inflation news and thus supports an attention-based explanation for the increased market impact of CPI releases.

## 5.2 Google Searches

In this section, I turn to Google searches as another proxy for attention (e.g., Da, Engelberg, and Gao, 2011; Ben-Rephael, Da, and Israelsen, 2017). Google provides data on search interest over time via its platform *Google Trends.* Over the employed sample period, from January 2009 until July 2023, 84 percent of all search queries in the United States have been performed through Google.[21] In the following, I focus on search topics which can be closely related to specific data releases. Note that a "topic" is defined by Google and summarizes a group of search terms that share the same concept in any language (Google, 2023). For this analysis, I focus on searches within the United States.

Figure 11: Results from Google Searches




Notes: The **top panel** shows the daily Google searches for the topic "Consumer Price Index" in the United States. Red bars show searches for days of CPI releases, while blue bars show searches for the other days. The dotted, vertical lines illustrate the splits into the low- and high-inflation periods as defined in Section 3.1. *CPI Days* refers to days with a CPI release, while *Rest* to the rest of the days in the sample. Shaded areas indicate NBER recession periods. The **bottom-left panel** displays the average Google Searches around CPI releases under the low-inflation period (blue) and the high-inflation period (red). The **bottom-right panel** displays the average change in search score from the low- to the high-inflation period for four release-specific topics. In all three panels, *Search Score* is normalized such that 100 corresponds to the largest observation for the topic "Consumer Price Index" over the sample period.

Based on the previous results, my primary focus is on the topic "Consumer Price Index", but I also look at other topics which can be directly related to macroeconomic releases.

[21] https://gs.statcounter.com/search-engine-market-share/all/united-states-of-america/#monthly-200901-202307 (accessed on January 20, 2024).

My analysis differs in two aspects from other recent work, e.g., Korenok, Munro, and Chen (2022), which employs Google searches to measure attention to inflation. First, I do not focus on the topic "Inflation" which is not specific enough for my analysis. Second, I construct a daily search score series for each topic. As Google trends provides historical daily data only for short time intervals, various steps are needed to construct an internally consistent daily series over the entire sample period. Appendix B.3 provides the details of this construction.

The top panel of Figure 11 shows the resulting daily series for topic "Consumer Price Index." As the figure shows, the searches on days with no CPI release (Rest) are relatively constant throughout the sample. In contrast, for days with a CPI release, the amount of searches rises drastically during the high-inflation period. While during low inflation, the search interest is very similar across days, the search interest on release days spikes up with the start of the high-inflation period.

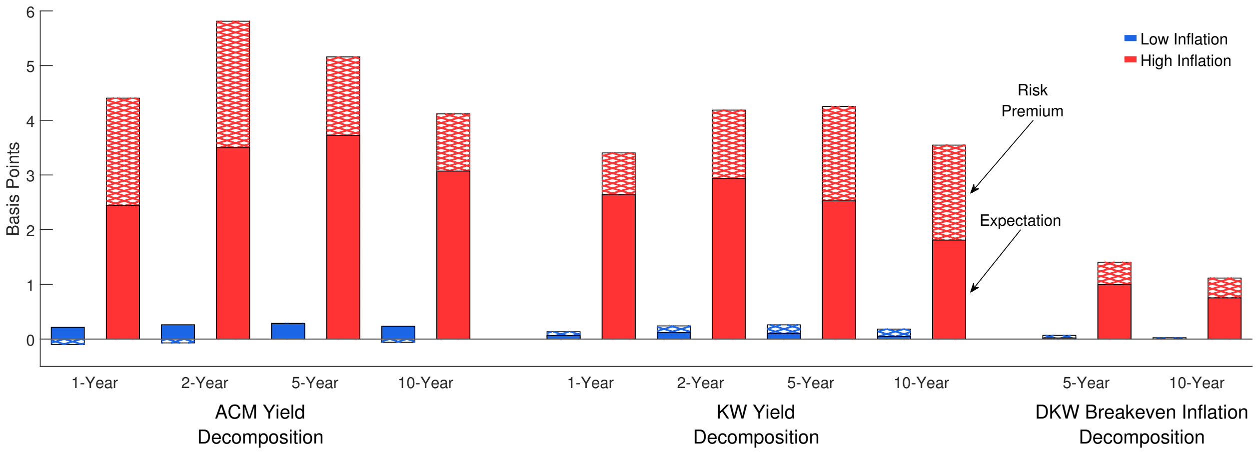
The bottom-left panel of Figure 11 plots the average Google searches around CPI releases, both during the low-inflation period (blue) and the high-inflation period (red). Consistent with the time series, the figure shows a large upward spike on the day of the release during the recent sample. Importantly, searches start rising even prior to the release. As I cannot observe the specific timing of searches on the release day, the increase prior to the release rules out that the Google searches solely capture ex-post instead of ex-ante attention to the release. Reassuringly, the averages across both periods are almost identical when moving away from the release.

To further connect the Google search data to my earlier findings, I also look at other topics that are linked to macro releases. In particular, I construct daily series for topics "Producer Price Index," "Nonfarm Payrolls," and "Gross Domestic Product," which map directly to the corresponding data release. The bottom-right panel of Figure 11 shows how the average search score changed on the days of the corresponding release and other days during the high-inflation period. As figure illustrates the increase for the topic "Consumer Price Index" on CPI release days is exceptional compared to other releases. In summary, the evidence based on Google searches further strengthens the case that attention plays a key part in the increased sensitivity of financial markets to CPI releases.

### 5.3 Expectations vs. Risk Premia

One aspect I mostly ignored so far in my analysis is that asset prices contain generally a risk premium, i.e., a compensation investors demand for the uncertainty of the asset's payoff. With respect to my analysis, the concern is that the increased sensitivity to CPI

Figure 12: Daily Effects of CPI news on Expectations and Risk Premia




Notes: This figure shows the daily effects of CPI news on expectations and risk premia of yields and breakeven inflation rates under the low-inflation and the high-inflation period. The figure shows estimates for three decompositions: the yield decompositions by Adrian, Crump, and Moench (2013) (ACM) and Kim and Wright (2005) (KW), as well as the decomposition of breakeven inflation rates by d'Amico, Kim, and Wei (2018) (DKW). For a given maturity, the red filled and red hatched bars depict the effects on expectation and risk premium under high inflation, respectively, i.e., estimates of coefficient $\beta_H^{y|k}$ of equation (12), where the left-hand side is now either the change in the expectation or risk premium of the corresponding decomposition. Similarly, the blue bars depict the effects under low inflation, i.e., estimates of coefficient $\beta_L^{y|k}$ of equation (12).

news is actually not driven by policy rate and inflation expectations but rather by the premia components of the asset prices. To mitigate this concern, I employ in this section three popular decompositions of yields and inflation compensation into expectations and risk premia and study the effects of CPI news on them. Before I go into the details, it is important to note that risk premia are generally very hard to measure and that the following analysis will be based on daily changes due to the availability of the decompositions.

I start by looking at yield curve decompositions into expected short rates and term premia. To do so, I use the estimates by Adrian, Crump, and Moench (2013) (ACM) and Kim and Wright (2005) (KW), which are the two most widely used and readily available off-the-shelf. For a given maturity, I regress the daily changes in the expected short rates and risk premium on the CPI surprises. Figure 12 displays the estimates. The blue and red filled bars show the effects on expected short rates under low and high inflation, respectively. The hatched bars display the effects on risk premia.

As Figure 12 displays, the largest portion of the increase in sensitivity is driven by expectations. In fact, while both decompositions lead to slightly different estimates, the average relative importance of short rate expectations across maturities is almost identical, 66 percent under the ACM decomposition and 65 percent under the KW decomposition. In sum, while the sensitivity of risk premia also increases, it is not the dominant force.

Moving on to inflation compensation, I employ the decomposition by d'Amico, Kim, and Wei (2018) (DKW) which decomposes TIPS breakeven inflation for given maturity into the average expected inflation and the inflation risk premium. Unfortunately, to the best of knowledge, an off-the-shelf decomposition for inflation swap rates does not exist. Hence, I can only look at maturities of 5- and 10-years. As discussed in Section 4.2, the results for inflation swap rates and breakeven inflation are very similar for these maturities.

Figure 12 displays the estimate for the DKW decomposition. Consistent with the results on yields, the large increase in inflation compensation is also driven by inflation expectations. Across both maturities, 69 percent of the sensitivity under high inflation comes from inflation expectations. The fact that importance of expectations are similar across all three decompositions also indicates potentially a common mechanism consistent with the suggested in this paper. Lastly, while I do not have direct evidence on shorter maturities, evidence from other papers, as discussed Diercks et al. (2023), suggests that inflation risk premia are less crucial for short horizons.

### 5.4 More Results

**FOMC announcements** Besides inflation news, monetary models of "rational inattention" would also predict that attention to monetary policy increases during high-inflation periods. Employing Google searches for the topic "Federal Open Market Committee", I show in Appendix Figure D2 that attention to FOMC announcements increased similar to CPI releases.

**Lower Frequency Effects** In Appendix Figure D3, I show the effects of CPI news over the next trading days following the release. There a couple of things to note. Generally, the lack of statistical power, which is due to the surprises being small and the short high-inflation period, makes it difficult to draw many conclusion at lower frequencies. That being said, there are couple of things I want to emphasize: First, the effect over the first five trading days is qualitatively consistent with the intraday results. Second, in all cases, one cannot reject that the responses are different after 15 days. In other words, the effect differences do seem to fade. Unfortunately, it is hard to draw much conclusions with respect to delayed reactions. The arguably cleanest evidence is one the initial underreactions of the 1- and 2-year yield during the low-inflation period which is consistent with the model channel.

# 6 Conclusion

In this paper, I show that the inflation environment affects investors' attention to inflation and thereby changes how financial markets incorporate inflation news. I do this by studying the high-frequency effects of U.S. macroeconomic news announcements on asset prices during the 2021-2023 inflation surge. Consistent with a rise in investor attention to inflation, I find that surprises about the CPI have much larger effects on interest rates and on inflation expectations—as measured by inflation swap rates—in comparison to the prior low-inflation period. This increase in market sensitivity to CPI news can also be documented for a broad range of other asset prices. However, it is unique among macro releases. Overall, the evidence points towards a faster incorporation of inflation news into investors' inflation expectations due to increased attention. I further support this interpretation by a variety of evidence, from documenting an exceptional increase around CPI releases in trading volume and Google searches—two proxies of attention—to demonstrating that the results are not driven by changes in risk premia.

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# Online Appendix

for

# Inflation and Attention: Evidence from the Market Reaction to Macro Announcements[*]

T. Niklas Kroner

Federal Reserve Board

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[*]The views expressed are those of the author and do not necessarily reflect those of the Federal Reserve Board or the Federal Reserve System.

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# A Model Appendix

## A.1 Intertemporal Budget Constraint

The budget constraints at the four dates are given by

$$\begin{aligned}
\bar{W}_1^i &= \bar{W}_0^i - P_1\lambda_1^i, \\
\bar{W}_2^i &= \left(\lambda_1^i - \lambda_2^i\right) P_2 + \bar{W}_1^i, \\
\bar{W}_3^i &= \bar{W}_2^i \left(1 + R_f\right), \\
\bar{W}_4^i &= \lambda_2^i + \bar{W}_3^i \left(1 + R_f + \Delta R\right),
\end{aligned}$$

where $\bar{W}_t^i$ depicts investor $i$'s wealth from date $t$'s perspective. Hence, the intertemporal budget constraint is given by

$$\bar{W}_4^i = \lambda_2^i + \left(\left(\lambda_1^i - \lambda_2^i\right) P_2 + \bar{W}_0^i - P_1\lambda_1^i\right)\left(1 + R_f\right)\left(1 + R_f + \Delta R\right). \tag{A1}$$

Let $W_t^i$ be investor $i$'s wealth in terms of date 1's present value, then $W_0^i$ and $W_4^i$ can be written as

$$W_4^i = \frac{\bar{W}_4^i}{\left(1 + R_f\right)\left(1 + R_f + \Delta R\right)} \quad \text{and} \quad W_0^i = \bar{W}_0^i. \tag{A2}$$

Note date 1's present value is also date 2's present value as there is no discounting between date 1 and 2 in the model. Combining (A1) and (A2), yields the intertemporal budget constraint used in the main text

$$\begin{aligned}
W_4^i &= \frac{\lambda_2^i}{\left(1 + R_f\right)\left(1 + R_f + \Delta R\right)} + \left(\lambda_1^i - \lambda_2^i\right) P_2 + W_0^i - P_1\lambda_1^i \\
&= \lambda_2^i \left(\frac{1}{\left(1 + R_f\right)\left(1 + R_f + \Delta R\right)} - P_2\right) + \lambda_1^i \left(P_2 - P_1\right) + W_0^i \\
&= \lambda_2^i \left(V - P_2\right) + \lambda_1^i \left(P_2 - P_1\right) + W_0^i,
\end{aligned} \tag{A3}$$

where we define $V = \frac{1}{(1+R_f)(1+R_f+\Delta R)}$ as the value of the bond.

## A.2 Conditional Expectations and Variances of $W_4^i$

The expectation of $W_4^i$ conditional on date 1 and date 2 information are given by

$$\begin{aligned}
\mathrm{E}_1^i[W_4^i] &= \mathrm{E}_1^i[\lambda_2^i \left(V - P_2\right) + \lambda_1^i \left(P_2 - P_1\right) + W_0^i] \\
&= \lambda_2^i \left(\mathrm{E}_1^i[V] - \mathrm{E}_1^i[P_2]\right) + \lambda_1^i \left(\mathrm{E}_1^i[P_2] - P_1\right) + W_0^i,
\end{aligned} \tag{A4}$$

and

$$\begin{aligned}
\mathrm{E}_2^i[W_4^i] &= \mathrm{E}_2^i\left[\tilde{\lambda}_2^i \left(V - P_2\right) + \lambda_1^i \left(P_2 - P_1\right) + W_0^i\right] \\
&= \tilde{\lambda}_2^i \left(\mathrm{E}_2^i[V] - P_2\right) + \lambda_1^i \left(P_2 - P_1\right) + W_0^i.
\end{aligned} \tag{A5}$$

The variance of $W_4^i$ conditional on date 1 and date 2 information are given by

$$\begin{aligned}\mathrm{Var}_1^i[W_4^i] &= \mathrm{Var}_1^i\left[\lambda_2^i\,(V-P_2)+\lambda_1^i\,(P_2-P_1)+W_0^i\right] \\ &= \left(\lambda_2^i\right)^2\mathrm{Var}_1^i[V]+\left(\lambda_1^i\right)^2\mathrm{Var}_1^i[P_2]\,, \end{aligned} \tag{A6}$$

and

$$\begin{aligned}\mathrm{Var}_2^i[W_4^i] &= \mathrm{Var}_2^i\left[\tilde{\lambda}_2^i\,(V-P_2)+\lambda_1^i\,(P_2-P_1)+W_0^i\right] \\ &= \left(\tilde{\lambda}_2^i\right)^2\mathrm{Var}_2^i[V]\,. \end{aligned} \tag{A7}$$

### A.3 Treasury Bond Value $V$ and Its Conditional Moments

The Treasury bond value $V$ can be simplified as follows:

$$\begin{aligned} V &= \frac{1}{(1+R_f)\,(1+R_f+\Delta R)} \\ &= \frac{1}{1+R_f}\left(\frac{1}{1+R_f}-\frac{\Delta R}{1+R_f+\Delta R}\right) \\ &= 1-\frac{\Delta R}{1+\Delta R} \\ &\approx 1-\Delta R \\ &= 1-\phi\Delta\pi, \end{aligned}$$

where I impose $R_f=0$ in the second step, use a first order approximation around $\Delta R=0$ in the third step, and substitute in the Taylor rule $\Delta R=\phi\Delta\pi$ in the last step.

To talk about the conditional moments of $V$, let me introduce the following notation. Let $\mathrm{E}_t^{\mu^\pi}[\cdot]$ be the expectation of attentive investors at date $t$, and let $\mathrm{E}_t^{1-\mu^\pi}[\cdot]$ be the expectation of inattentive investors at date $t$. Similarly, I define $\mathrm{Var}_t^{\mu^\pi}[\cdot]$ and $\mathrm{Var}_t^{1-\mu^\pi}[\cdot]$ for the conditional variance. At date 1, all investors have the same expectations for $V$,

$$\mathrm{E}_1^i[V]=1,\ \forall i.$$

At date 2 after receiving the signal $s$, attentive investors' expectation is

$$\mathrm{E}_2^i[V]=\mathrm{E}_2^{\mu^\pi}[V]=1-\phi\xi s,\ \text{ for } i\in[0,\mu^\pi]. \tag{A8}$$

where $\xi$ is the signal-to-noise ratio, i.e.,

$$\xi=\frac{\sigma_\pi^2}{\sigma_\pi^2+\sigma_\eta^2}.$$

Inattentive investors have still the same expectation as at date 1

$$\mathrm{E}_2^i[V]=\mathrm{E}_2^{1-\mu^\pi}[V]=1,\ \text{ for } i\in(1-\mu^\pi,1]. \tag{A9}$$

The conditional variance of $V$ at date 1 is given by

$$\begin{aligned}\mathrm{Var}_1^i[V] &= \mathrm{E}_1^i\Big[\big(V - \mathrm{E}_1^i[V]\big)^2\Big] = \mathrm{E}_1^i\Big[(1-\phi\Delta\pi - 1)^2\Big] \\ &= \mathrm{E}_1^i\Big[(\phi\Delta\pi)^2\Big] = \phi^2\sigma_\pi^2,\ \forall i,\end{aligned}$$

and is also the conditional variance at date 2 for inattentive investors, i.e.,

$$\begin{aligned}\mathrm{Var}_2^{1-\mu^\pi}[V] &= \mathrm{Var}_1^i[V] \\ &= \phi^2\sigma_\pi^2. \end{aligned} \tag{A10}$$

The conditional variance of the attentive investors at date 2 can be written as

$$\begin{aligned}\mathrm{Var}_2^{\mu^\pi}[V] &= \mathrm{E}_2^{\mu^\pi}\left[\left(V - \mathrm{E}_2^{\mu^\pi}[V]\right)^2\right] = \mathrm{E}_2^{\mu^\pi}\left[(1-\phi\Delta\pi - (1-\phi\xi s))^2\right] \\ &= \mathrm{E}_2^{\mu^\pi}\left[(\phi\Delta\pi - \phi\xi s)^2\right] = \phi^2\mathrm{E}_2^{\mu^\pi}\left[(\Delta\pi - \xi\Delta\pi - \xi\eta)^2\right] = \phi^2\mathrm{E}_2^{\mu^\pi}\left[((1-\xi)\,\Delta\pi - \xi\eta)^2\right] \\ &= \phi^2\mathrm{E}_2^{\mu^\pi}\left[(1-\xi)^2\Delta\pi^2 - 2\,(1-\xi)\,\Delta\pi\xi\eta + \xi^2\eta^2\right] = \phi^2\left((1-\xi)^2\,\mathrm{E}_2^{\mu^\pi}\left[\Delta\pi^2\right] + \xi^2\mathrm{E}_2^{\mu^\pi}\left[\eta^2\right]\right) \\ &= \phi^2\left((1-\xi)^2\sigma_\pi^2 + \xi^2\sigma_\eta^2\right) = \phi^2\left(\sigma_\pi^2 - 2\xi\sigma_\pi^2 + \xi^2\sigma_\pi^2 + \xi^2\sigma_\eta^2\right) \\ &= \phi^2\left(\sigma_\pi^2 - 2\xi\sigma_\pi^2 + \xi\sigma_\pi^2\right) \\ &= (1-\xi)\,\phi^2\sigma_\pi^2, \end{aligned} \tag{A11}$$

where I used

$$\xi^2\sigma_\pi^2 + \xi^2\sigma_\eta^2 = \left(\frac{\sigma_\pi^2}{\sigma_\pi^2+\sigma_\eta^2}\right)^2\left(\sigma_\pi^2+\sigma_\eta^2\right) = \left(\frac{\sigma_\pi^2}{\sigma_\pi^2+\sigma_\eta^2}\right)\sigma_\pi^2 = \xi\sigma_\pi^2.$$

### A.4 Portfolio Choice

At date 1, investor $i$ solves

$$\begin{aligned}&\max_{\lambda_1^i,\lambda_2^i} \mathrm{E}_1^i[W_4^i] - \frac{\gamma}{2}\mathrm{Var}_1^i[W_4^i] \\ &\text{s.t. } W_4^i = \lambda_2^i\,(V-P_2) + \lambda_1^i\,(P_2 - P_1) + W_0^i.\end{aligned}$$

Using expressions (A4) and (A6), the problem can be rewritten as

$$\max_{\lambda_1^i,\lambda_2^i} \lambda_2^i\left(\mathrm{E}_1^i[V] - \mathrm{E}_1^i[P_2]\right) + \lambda_1^i\left(\mathrm{E}_1^i[P_2] - P_1\right) + W_0^i - \frac{\gamma}{2}\left(\left(\lambda_2^i\right)^2\mathrm{Var}_1^i[V] + \left(\lambda_1^i\right)^2\mathrm{Var}_1^i[P_2]\right).$$

The first-order condition with respect to $\lambda_1^i$ is then given by

$$\mathrm{E}_1^i[P_2] - P_1 - \gamma\lambda_1^i\mathrm{Var}_1^i[P_2] = 0,$$

which yields the optimal demand for the Treasury bond

$$\lambda_1^i = \frac{\mathrm{E}_1^i[P_2] - P_1}{\gamma \mathrm{Var}_1^i[P_2]}.$$

Similarly, the first-order condition with respect to $\lambda_2^i$ is given by

$$\mathrm{E}_1^i[V] - \mathrm{E}_1^i[P_2] - \gamma \lambda_2^i \mathrm{Var}_1^i[V] = 0,$$

and the optimal demand is then

$$\lambda_2^i = \frac{\mathrm{E}_1^i[V] - \mathrm{E}_1^i[P_2]}{\gamma \mathrm{Var}_1^i[V]}.$$

At date 2, investor $i$ solves

$$\max_{\tilde{\lambda}_2^i} \tilde{\lambda}_2^i \left(\mathrm{E}_2^i[V] - P_2\right) + \lambda_1^i \left(P_2 - P_1\right) + W_0^i - \frac{\gamma}{2} \left(\lambda_2^i\right)^2 \mathrm{Var}_2^i[V],$$

where I used expressions (A5) and (A7). The optimal demand is then given by

$$\tilde{\lambda}_2^i = \frac{\mathrm{E}_2^i[V] - P_2}{\gamma \mathrm{Var}_2^i[V]}.$$

## A.5 Equilibrium

### A.5.1 Price $P_1$

At date 1, the market clearing condition for $\lambda_1^i$ yields

$$\begin{aligned}
\int_0^1 \lambda_1^i di &= 0 \\
\int_0^1 \frac{\mathrm{E}_1^i[P_2] - P_1}{\gamma \mathrm{Var}_1^i[P_2]} di &= 0 \\
\frac{\mathrm{E}_1[P_2] - P_1}{\gamma \mathrm{Var}_1[P_2]} &= 0 \\
P_1 &= \mathrm{E}_1[P_2], \qquad \text{(A12)}
\end{aligned}$$

where I used the fact that $\mathrm{E}_1^i[\cdot] = \mathrm{E}_1[\cdot]$ and $\mathrm{Var}_1^i[\cdot] = \mathrm{Var}_1[\cdot]$ for all $i \in [0, 1]$. Here, $\mathrm{E}_t[\cdot]$ denotes the weighted average expectation across investors at date $t$ and is defined formally below.

Similarly, the market clearing for $\lambda_2^i$ yields

$$\begin{aligned}\int_0^1 \lambda_2^i di &= 0\\ \int_0^1 \frac{\mathrm{E}_1^i[V]-\mathrm{E}_1^i[P_2]}{\gamma \mathrm{Var}_1^i[V]} di &= 0\\ \frac{\mathrm{E}_1[V]-\mathrm{E}_1[P_2]}{\gamma \mathrm{Var}_1[V]} &= 0\\ \mathrm{E}_1[P_2] &= \mathrm{E}_1[V]\,. \end{aligned} \tag{A13}$$

Combining (A12) and (A13) gives the bond price at date 1

$$\begin{aligned} P_1 &= \mathrm{E}_1[V]\\ &= 1. \end{aligned} \tag{A14}$$

### A.5.2 Price $P_2$

For date 2, the market clearing condition for $\tilde{\lambda}_2^i$ can be written as

$$\begin{aligned}\int_0^1 \tilde{\lambda}_2^i di &= 0\\ \int_0^1 \frac{\mathrm{E}_2^i[V]-P_2}{\gamma \mathrm{Var}_2^i[V]} di &= 0\\ \frac{\mu^\pi}{\gamma \mathrm{Var}_2^{\mu^\pi}[V]}\mathrm{E}_2^{\mu^\pi}[V] + \frac{1-\mu^\pi}{\gamma \mathrm{Var}_2^{1-\mu^\pi}[V]}\mathrm{E}_2^{1-\mu^\pi}[V] - P_2\left(\frac{\mu^\pi}{\gamma \mathrm{Var}_2^{\mu^\pi}[V]} + \frac{1-\mu^\pi}{\gamma \mathrm{Var}_2^{1-\mu^\pi}[V]}\right) &= 0. \end{aligned} \tag{A15}$$

I can define $a_2 = \left(\frac{\mu^\pi}{\gamma \mathrm{Var}_2^{\mu^\pi}[V]} + \frac{1-\mu^\pi}{\gamma \mathrm{Var}_2^{1-\mu^\pi}[V]}\right)^{-1}$, which allows me to rewrite equation (A15) as

$$\begin{aligned}\frac{\mu^\pi a_2}{\gamma \mathrm{Var}_2^{\mu^\pi}[V]}\mathrm{E}_2^{\mu^\pi}[V] + \frac{(1-\mu^\pi)\,a_2}{\gamma \mathrm{Var}_2^{1-\mu^\pi}[V]}\mathrm{E}_2^{1-\mu^\pi}[V] &= P_2\\ \frac{\mu^\pi a_2}{\gamma \mathrm{Var}_2^{\mu^\pi}[V]}\mathrm{E}_2^{\mu^\pi}[V] + \left(1-\frac{\mu^\pi a_2}{\gamma \mathrm{Var}_2^{\mu^\pi}[V]}\right)\mathrm{E}_2^{1-\mu^\pi}[V] &= P_2, \end{aligned}$$

where I used

$$\frac{1-\mu^\pi}{\gamma \mathrm{Var}_2^{1-\mu^\pi}[V]} = \frac{\mu^\pi}{\gamma \mathrm{Var}_1^{\mu^\pi}[V]} + \frac{1-\mu^\pi}{\gamma \mathrm{Var}_2^{1-\mu^\pi}[V]} - \frac{\mu^\pi}{\gamma \mathrm{Var}_1^{\mu^\pi}[V]} = \frac{1}{a_2} - \frac{\mu^\pi}{\gamma \mathrm{Var}_1^{\mu^\pi}[V]}.$$

Defining $b_2 = \frac{\mu^\pi a_2}{\gamma \mathrm{Var}_2^{\mu^\pi}[V]}$ yields

$$\begin{aligned} b_2 \mathrm{E}_2^{\mu^\pi}[V] + (1-b_2)\,\mathrm{E}_2^{1-\mu^\pi}[V] &= P_2\\ \mathrm{E}_2[V] &= P_2, \end{aligned} \tag{A16}$$

where the weighted average expectation is defined as $\mathrm{E}_t[\cdot] = b_t \mathrm{E}_t^{\mu^\pi}[\cdot] + (1-b_t)\,\mathrm{E}_t^{1-\mu^\pi}[\cdot]$. The weight $b_t$ resembles the population share of attentive investors relative to their contribution to the conditional variance of $V$. Note that this definition of the expectation operator is internally consistent as

$$a_1 = \left(\frac{\mu^\pi}{\gamma \mathrm{Var}_1^{\mu^\pi}[V]} + \frac{1-\mu^\pi}{\gamma \mathrm{Var}_1^{1-\mu^\pi}[V]}\right)^{-1} = \gamma \mathrm{Var}_1^{\mu^\pi}[V] \quad \text{and} \quad b_1 = \frac{\mu^\pi a}{\gamma \mathrm{Var}_1^{\mu^\pi}[V]} = \mu^\pi,$$

and hence

$$\begin{aligned} \mathrm{E}_1[\cdot] &= b_1 \mathrm{E}_1^{\mu^\pi}[\cdot] + (1-b_1)\,\mathrm{E}_1^{1-\mu^\pi}[\cdot] \\ &= \mu^\pi \mathrm{E}_1^{\mu^\pi}[\cdot] + (1-\mu^\pi)\,\mathrm{E}_1^{1-\mu^\pi}[\cdot] \\ &= \mathrm{E}_1^i[\cdot]\,. \end{aligned}$$

Plugging in the expression for $\mathrm{Var}_2^{\mu^\pi}[V]$ and $\mathrm{Var}_2^{1-\mu^\pi}[V]$, i.e., (A11) and (A10), into the expression for $a_2$ yields

$$\begin{aligned} a_2 &= \left(\frac{\mu^\pi}{\gamma \mathrm{Var}_2^{\mu^\pi}[V]} + \frac{1-\mu^\pi}{\gamma \mathrm{Var}_2^{1-\mu^\pi}[V]}\right)^{-1} = \left(\frac{\mu^\pi}{\gamma(1-\xi)\,\phi^2\sigma_\pi^2} + \frac{1-\mu^\pi}{\gamma\phi^2\sigma_\pi^2}\right)^{-1} \\ &= \gamma\phi^2\sigma_\pi^2\left(\frac{\mu^\pi}{1-\xi} + \frac{(1-\mu^\pi)(1-\xi)}{1-\xi}\right)^{-1} = \gamma\phi^2\sigma_\pi^2\left(\frac{\mu^\pi + 1 - \xi - \mu^\pi + \mu^\pi\xi}{1-\xi}\right)^{-1} \\ &= \gamma\phi^2\sigma_\pi^2\left(\frac{1-\xi}{1-\xi(1-\mu^\pi)}\right). \end{aligned}$$

Subsequently, expression $b_2$ can be written as

$$\begin{aligned} b_2 &= \frac{\mu^\pi a_2}{\gamma \mathrm{Var}_2^{\mu^\pi}[V]} \\ &= \frac{\mu^\pi\gamma\phi^2\sigma_\pi^2\left(\frac{1-\xi}{1-\xi(1-\mu^\pi)}\right)}{\gamma(1-\xi)\,\phi^2\sigma_\pi^2} \\ &= \frac{\mu^\pi}{1-\xi}\frac{1-\xi}{1-\xi(1-\mu^\pi)} \\ &= \frac{\mu^\pi}{1-\xi(1-\mu^\pi)}. \end{aligned} \tag{A17}$$

Plugging in the expressions for $b_2$, $\mathrm{E}_2^{\mu^\pi}[V]$, and $\mathrm{E}_2^{1-\mu^\pi}[V]$, i.e., (A17), (A8) and (A9), into (A16) yields the solution for the equilibrium price at date 2

$$\begin{aligned}
P_2 &= b_2 \mathrm{E}_2^{\mu^\pi}[V] + (1-b_2)\,\mathrm{E}_2^{1-\mu^\pi}[V] \\
P_2 &= \frac{\mu^\pi}{1-\xi\,(1-\mu^\pi)}\,(1-\phi\xi s^\pi) + \left(1 - \frac{\mu^\pi}{1-\xi\,(1-\mu^\pi)}\right) \\
P_2 &= 1 - \frac{\mu^\pi \phi\xi}{1-\xi\,(1-\mu^\pi)} s^\pi. \qquad \text{(A18)}
\end{aligned}$$

### A.5.3 Inflation Expectations

At date 1, investors do not expect any changes in inflation, i.e.,

$$\mathrm{E}_1[\Delta\pi] = \mathrm{E}_1^i[\Delta\pi] = 0,$$

while at date 2, attentive investors expect changes based on signal $s^\pi$

$$\mathrm{E}_2^{\mu^\pi}[\Delta\pi] = \xi s^\pi,$$

and inattentive investors still do not expect any changes

$$\mathrm{E}_2^{\mu^\pi}[\Delta\pi] = 0.$$

The average inflation expectation at date 2 is given by

$$\begin{aligned}
\mathrm{E}_2[\Delta\pi] &= b_2 \mathrm{E}_2^{\mu^\pi}[\Delta\pi] + (1-b_2)\,\mathrm{E}_2^{\mu^\pi}[\Delta\pi] \\
&= \frac{\mu^\pi}{1-\xi\,(1-\mu^\pi)} \xi s^\pi,
\end{aligned}$$

which allows one to rewrite the equilibrium price as

$$P_t = 1 - \phi \mathrm{E}_t[\Delta\pi]\,.$$

## A.6 Marginal Effect of Attention on Asset Price Sensitivity to News

Note that coefficients $\beta^y_{\mu^\pi}$ and $\beta^\pi_{\mu^\pi}$, as defined in (8) and (9), can be written as

$$\begin{aligned}
\beta^{y|\pi}_{\mu^\pi} &= \frac{1}{\tau}\frac{\mu^\pi \phi\xi}{1-\xi\,(1-\mu^\pi)} \\
&= b_2 \frac{\phi\xi}{\tau},
\end{aligned}$$

and

$$\begin{aligned}
\beta^{\pi|\pi}_{\mu^\pi} &= \frac{\mu^\pi \xi}{1-\xi\,(1-\mu^\pi)} \\
&= b_2 \xi,
\end{aligned}$$

where I used expression (A17). As $0 \leq \xi, \mu^{\pi} \leq 1$, the partial derivative of $b_2$ with respect to $\mu^{\pi}$ is

$$\begin{aligned}
\frac{\partial b_2}{\partial \mu^{\pi}} = \frac{\partial \left( \frac{\mu^{\pi}}{1-\xi(1-\mu^{\pi})} \right)}{\partial \mu^{\pi}} &= \frac{1-\xi\left(1-\mu^{\pi}\right)-\mu^{\pi}\xi}{\left(1-\xi\left(1-\mu^{\pi}\right)\right)^2} \\
&= \frac{1-\xi+\mu^{\pi}\xi-\mu^{\pi}\xi}{\left(1-\xi\left(1-\mu^{\pi}\right)\right)^2} \\
&= \frac{1-\xi}{\left(1-\xi\left(1-\mu^{\pi}\right)\right)^2} > 0.
\end{aligned}$$

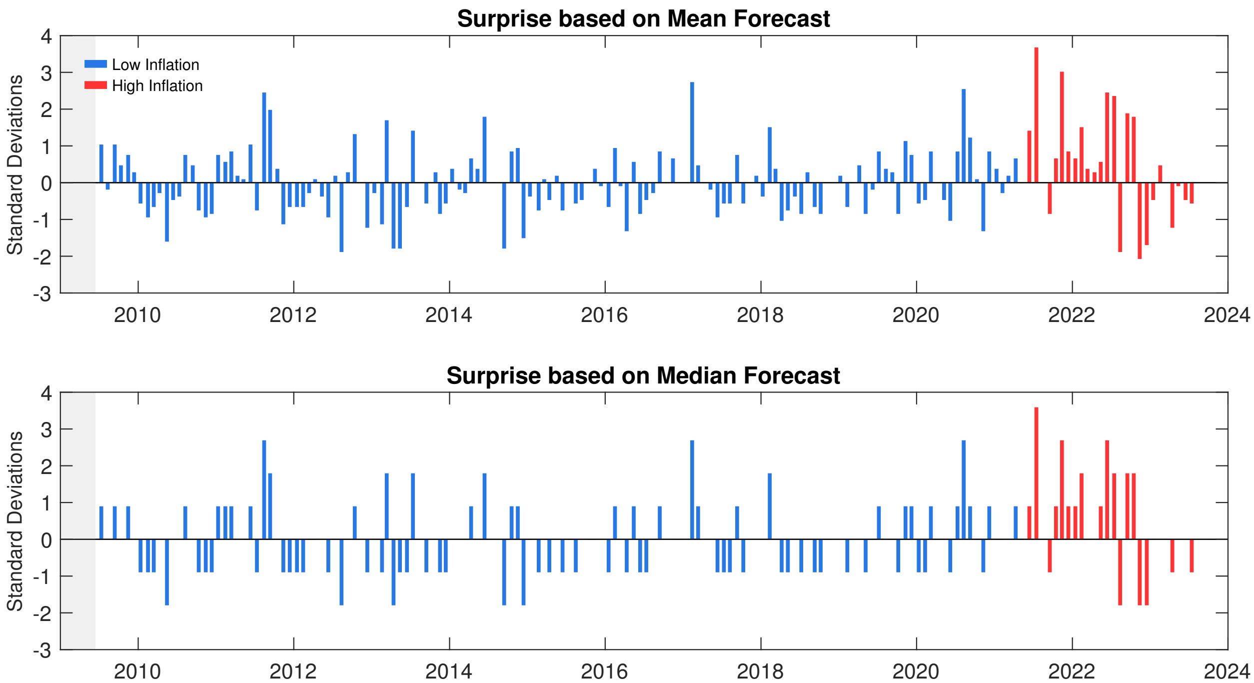
As $\phi$, $\xi$, and $\tau$ are independent of $\mu^{\pi}$, this implies that

$$\frac{\partial \beta_{\mu^{\pi}}^{y|\pi}}{\partial \mu^{\pi}} > 0 \text{ and } \frac{\partial \beta_{\mu^{\pi}}^{\pi|\pi}}{\partial \mu^{\pi}} > 0.$$

# B Data Appendix

## B.1 Macroeconomic News Releases

Figure B1: Time Series of CPI Surprises



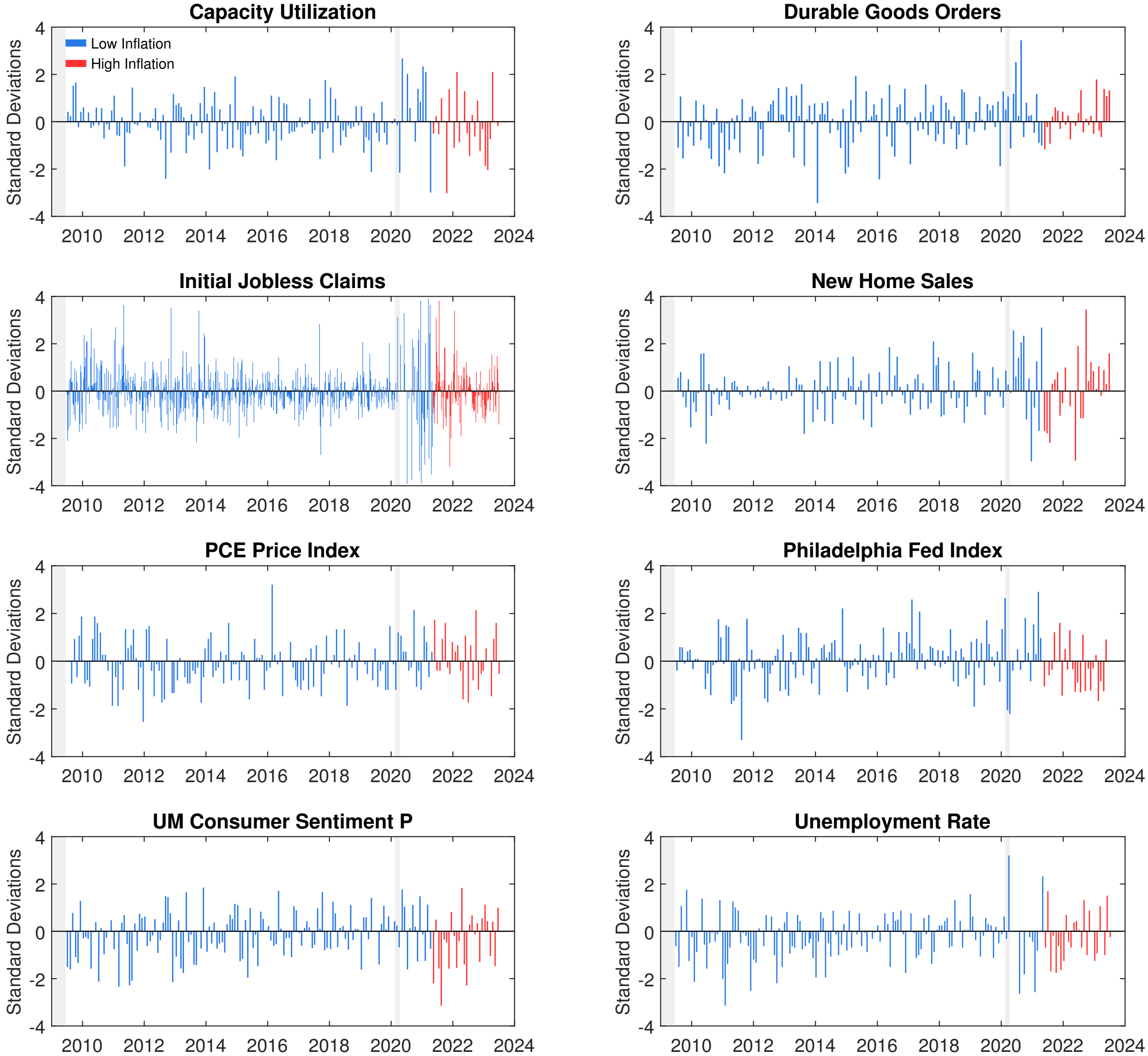

Notes: This figure shows in the top panel the baseline CPI surprises constructed from Bloomberg's mean forecast, and the CPI surprises constructed from Bloomberg's median forecast in the bottom panel.

Table B1: Overview of All Macroeconomic News Announcements

| Announcement | Release Time | Frequency | Observations | | | Unit | Surprise (+1 SD) |
|---|---|---|---|---|---|---|---|
| | | | Total | Low | High | | |
| Average Hourly Earnings | 8:30 | Monthly | 160 | 135 | 25 | % MoM | 0.15 |
| Capacity Utilization | 9:15 | Monthly | 165 | 140 | 25 | % | 0.38 |
| CB Consumer Confidence | 10:00 | Monthly | 168 | 142 | 26 | Index | 4.99 |
| Durable Goods Orders | 8:30 | Monthly | 166 | 140 | 26 | % MoM | 1.78 |
| CPI | | | | | | | |
| Headline (Baseline) | 8:30 | Monthly | 166 | 140 | 26 | % MoM | 0.11 |
| Core | 8:30 | Monthly | 164 | 139 | 25 | % MoM | 0.09 |
| Headline YoY | 8:30 | Monthly | 166 | 140 | 26 | % YoY | 0.12 |
| GDP | 8:30 | Monthly | 164 | 140 | 24 | % QoQ ann. | 0.42 |
| Initial Jobless Claims | 8:30 | Weekly | 708 | 595 | 113 | Level | 17.51k |
| ISM Mfg PMI | 10:00 | Monthly | 169 | 143 | 26 | Index | 1.75 |
| New Home Sales | 10:00 | Monthly | 167 | 141 | 26 | Level | 52.30k |
| Nonfarm Payrolls | 8:30 | Monthly | 156 | 133 | 23 | Change | 90.15k |
| PCE Price Index | 8:30 | Monthly | 162 | 137 | 25 | % YoY | 0.07 |
| Philadelphia Fed Index | 10:00 | Monthly | 167 | 141 | 26 | Index | 9.88 |
| PPI | 8:30 | Monthly | 168 | 142 | 26 | % MoM | 0.32 |
| Retail Sales | 8:30 | Monthly | 161 | 135 | 26 | % MoM | 0.47 |
| UM Consumer Sentiment P | 10:00 | Monthly | 168 | 142 | 26 | Index | 3.57 |
| Unemployment Rate | 8:30 | Monthly | 159 | 134 | 25 | % | 0.16 |

Notes: This table provides an overview of all macroeconomic announcement series used throughout the paper. Note that I flip the sign of Initial Jobless Claims surprises for ease of interpretation. A positive sign thus corresponds to positive news about real economic activity—consistent with the other releases.The sample ranges from July 2009 to July 2023. *Release Time* refers to the typical time of the release, referenced in am EST. *Frequency* refers to the frequency of the data releases and *Observations* to the number of observations (surprises) of a macroeconomic series in my sample. *Unit* refers to the unit in which the data release and the survey is reported. *Surprise (+1 SD)* provides the mapping between a one standard positive surprise and the unit in which the release is originally reported. Abbreviations: A—advanced; P—preliminary; Mfg—Manufacturing; CB—Chicago Board; UM—University of Michigan; ISM—Institute for Supply Management; PMI—Purchasing Managers' Index.

Figure B2: Time Series of Standardized Surprises




Notes: This figure shows the standardized surprises of the eight other macroeconomic series over the sample. *Low Inflation* and *High Inflation* indicates surprises which occurred during the low- and high-inflation period, respectively, as defined in Section 3.1. Shaded areas indicate NBER recession periods.

## B.2 Financial Data

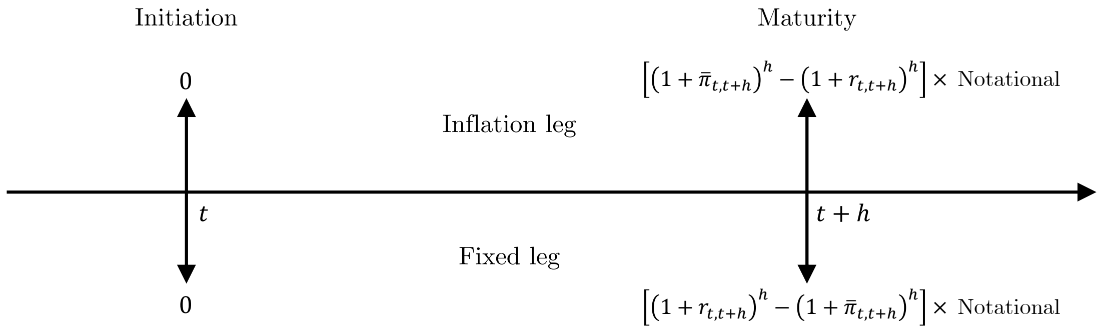
Table B2: Intraday Financial Data on International Markets

| Name | Underlying Instrument | Tickers | Sample |
|---|---|---|---|
| *2-Year Yields* | | | |
| United States | 2-Year Treasury Futures | TUc1/TUc2 | 2009–2023 |
| Canada | 2-Year Yield | CA2YT=RR | 2009–2023 |
| Switzerland | 2-Year Yield | CH2YT=RR | 2009–2023 |
| Denmark | 2-Year Yield | DK2YT=RR | 2009–2023 |
| Euro Area | 2-Year OIS Rate | EUREON2Y= | 2009–2023 |
| United Kingdom | 2-Year Yield | GB2YT=RR | 2009–2023 |
| Sweden | 2-Year Yield | SE2YT=RR | 2009–2023 |
| *10-Year Yields* | | | |
| United States | 10-Year Treasury Futures | TYc1/TYc2 | 2009–2023 |
| Canada | 10-Year Yield | CA10YT=RR | 2009–2023 |
| Switzerland | 10-Year Yield | CH10YT=RR | 2009–2023 |
| Denmark | 10-Year Yield | DK10YT=RR | 2009–2023 |
| Euro Area | 10-Year OIS Rate | EUREON10Y= | 2009–2023 |
| United Kingdom | 10-Year Yield | GB10YT=RR | 2009–2023 |
| Sweden | 10-Year Yield | SE10YT=RR | 2009–2023 |
| *Stock Indexes* | | | |
| United States/S&P 500 | E-mini S&P 500 futures | ESc1 | 2009–2023 |
| Canada | S&P/TSX index futures | SXFc1 | 2009–2023 |
| Switzerland | SMI | .SSMI | 2009–2023 |
| Denmark | OMX Copenhagen 20 | .OMXC20 | 2009–2023 |
| Euro Area | EURO STOXX 50 | .STOXX50 | 2009–2023 |
| United Kingdom | FTSE 100 | .FTSE | 2009–2023 |
| Sweden | OMX Stockholm 30 | .OMXS30 | 2009–2023 |

Notes: The table shows the asset prices used in Section 4.3. The data is from *Thomson Reuters Tick History*. For all series, the sample period ends in July 2023. *Ticker* refers to the Reuters Instrument Code (RIC). Abbreviations: OIS—Overnight Index Swap.

### Inflation Swaps

Figure B3: Net Cash Flows of $h$-Year Inflation Swap



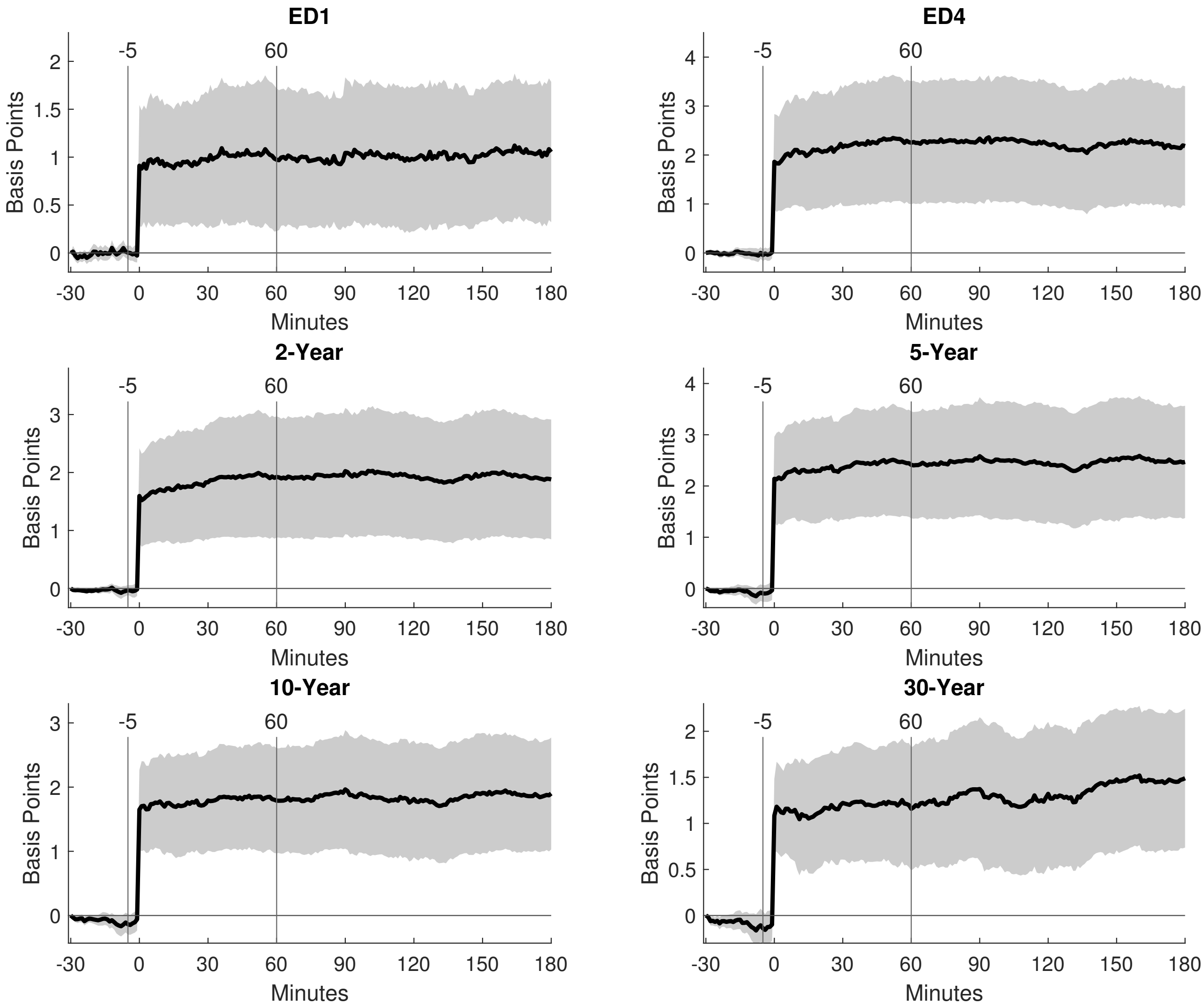

$r_{t,t+h}$: $h$-year inflation swap rate at $t$

$\bar{\pi}_{t,t+h}$: realized annual CPI inflation rate from $t$ to $t+h$

Notes: This figure illustrates the timing of net cash flows of an $h$-year zero-coupon inflation swap in the U.S. See, e.g., Kerkhof (2005) for a more detailed discussion of inflation swaps.

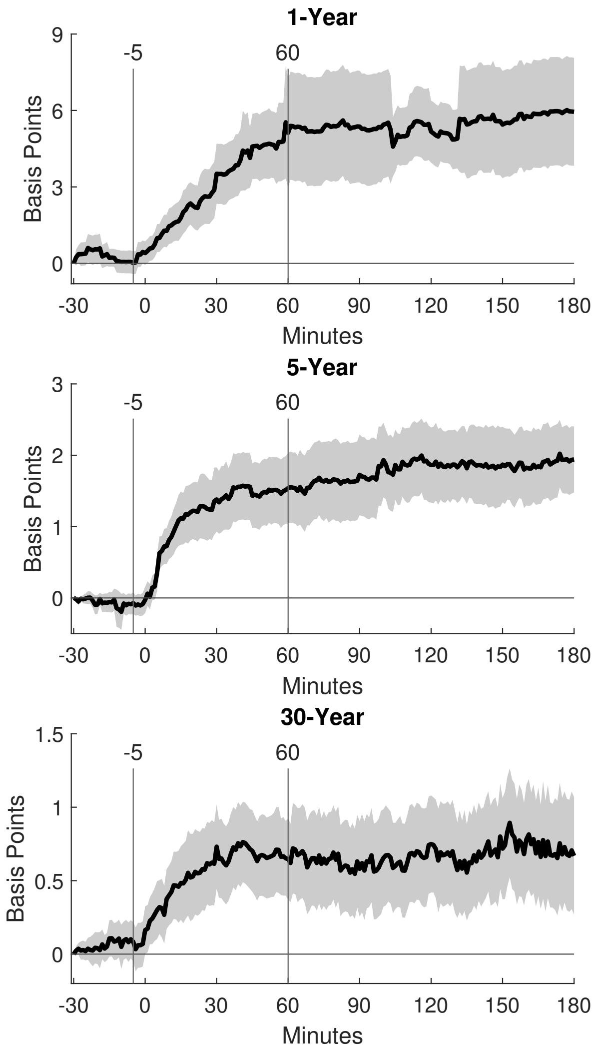
## Event Window

Figure B4: Impulse Responses of Interest Rates to CPI News




Notes: This figure shows the impulse responses of interest rates to CPI news. Grey bands display 95 percent confidence bands.

Figure B5: Impulse Responses of Inflation Expectations to CPI News




Notes: This figure shows the impulse responses of inflation swap rates to CPI news. Grey bands display 95 percent confidence bands.

## B.3 Google Trends

For a given topic, the construction of the daily search score series is done in the following steps:

1. For given topic in Google Trends, I download daily data from Google Trends in 90-day rolling window starting in January 1, 2009. 90 days is the maximum days for which Google Trends allows extraction of daily data. After each download the 90-day window is shifted by 60 days so that there is always an overlap of 30 days between two consecutive windows. Ending in October 2023, I obtain 91 subsamples for a given topic.

2. I merge the 91 subsamples into a continuous series by minimizing the Euclidean distance

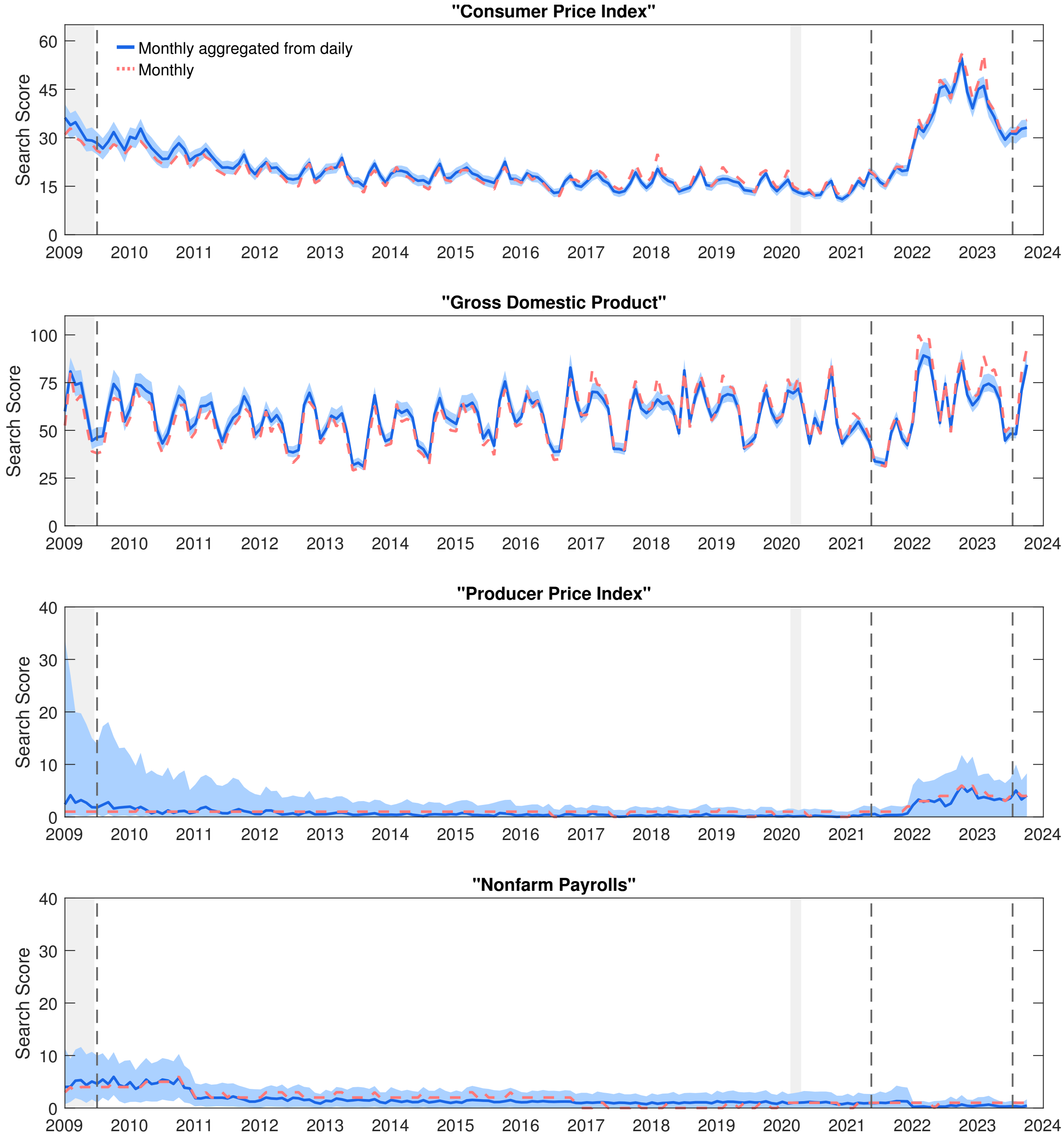
between the overlapping period of two consecutive subsamples.

3. To reduce sampling noise, steps 1 and 2 are repeated multiple times. For this current draft, this has been done 30 times. That is, for each topic I obtain 30 daily series of search scores. For my analysis, I use the median series, i.e., the median search score of a given day.

4. The Google Trends format makes it such that the daily series cannot be compared across topics. To make them comparable, I jointly download the search scores of all topics at the monthly frequency over the sample period. This allows me to rescale all daily series to a common unit by minimizing the Euclidean distance the monthly series and a aggregated version of the corresponding daily series to the month. Finally, I rescale all series such that 100 corresponds to the largest observation for topic "Consumer Price Inflation." As before, I repeat the joint monthly download n times and use the median of that series for the rescaling.

Figure B6 shows the monthly averages of the daily, constructed Google search scores. It also shows the monthly series used to rescale the daily ones. In essence, the figures shows how both series are very close to each other. The daily series match the monthly properties of the original data, thus validating the construction approach.

Figure B6: Time Series of Google Search Scores




Notes: This figure shows the monthly time series of the search scores for each of the 4 macroeconomic topics from January 2009 to October 2023. In particular, dark blue lines display the monthly sum of daily median scores, and the lighter blue bands show 68 confidence intervals based on the monthly sum of the daily 16 and 84 percentiles. The red dotted line shows the median of the monthly search scores series. The grey dotted, vertical lines illustrate the splits into the low- and high-inflation periods as defined in Section 3.1. Grey shaded areas indicate NBER recession periods.

# C Additional Results for Section 4

## C.1 Average Effects

I now demonstrate that both higher-than-expected news leads to increases in bond yields, on average. The rationale is to confirm prior research and show that the clear theoretical relationship holds over my sample period. To do so, I estimate regressions of the form

$$\Delta y_t = \alpha^k + \beta^{y|k} s_t^k + \varepsilon_t^k, \tag{C1}$$

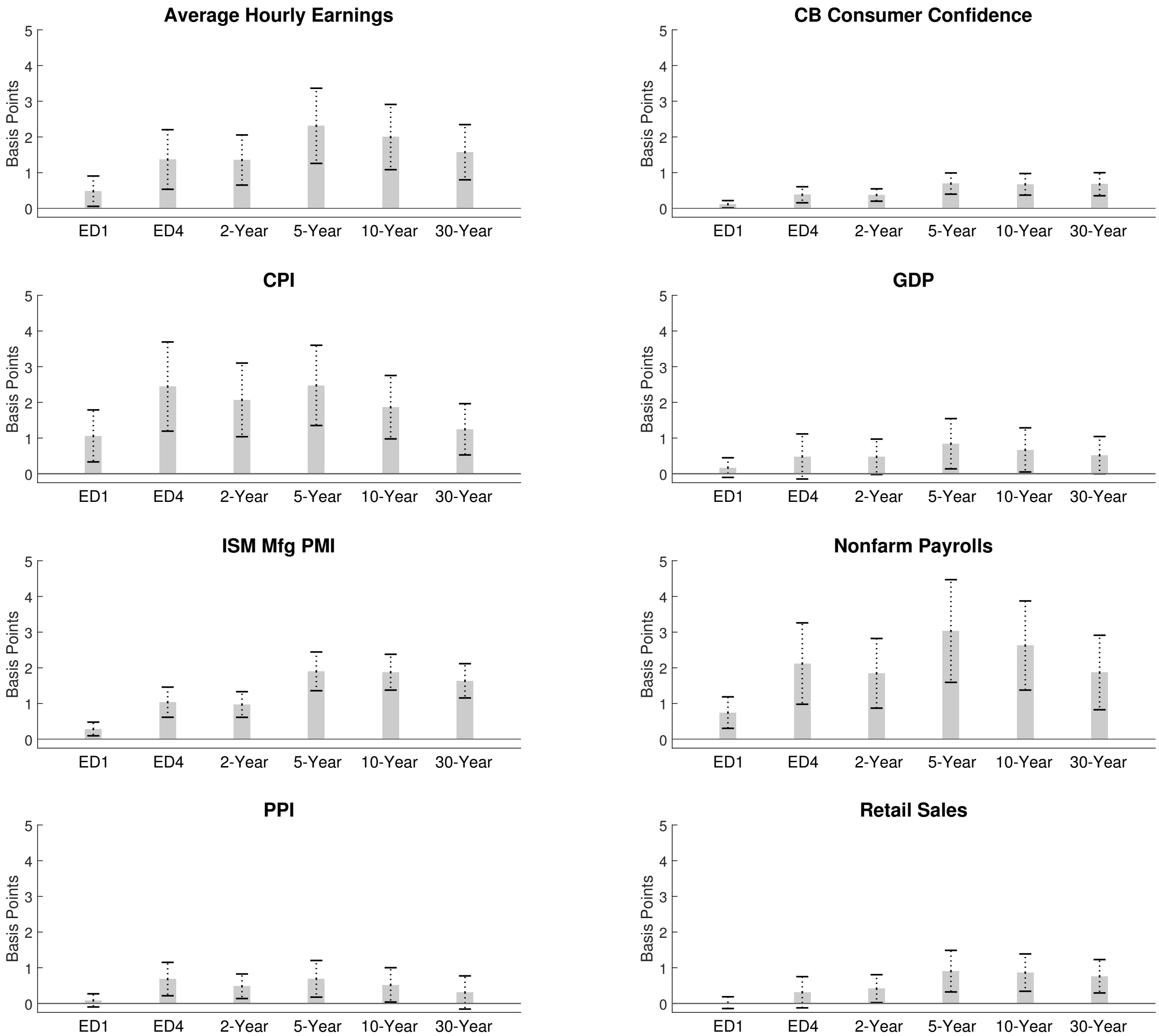
where $s_t^k$ is the announcement surprise of interest, and $\Delta y_t$ is the 60-minute change in one of the 6 interest rates described in Table 2.

As for interest rates, I also estimate the average effects on inflation swap rates over the sample period. In particular, I estimate regressions of the following form

$$\Delta \pi_t = \alpha^k + \beta^{\pi|k} s_t^k + \varepsilon_t^k, \tag{C2}$$

where $s_t^k$ is the announcement surprise of interest, and $\Delta \pi_t$ is the 60-minute change in one of the 5 inflation swap rates described in Table 2.

Figure C1: Effects of Macro News on Interest Rates

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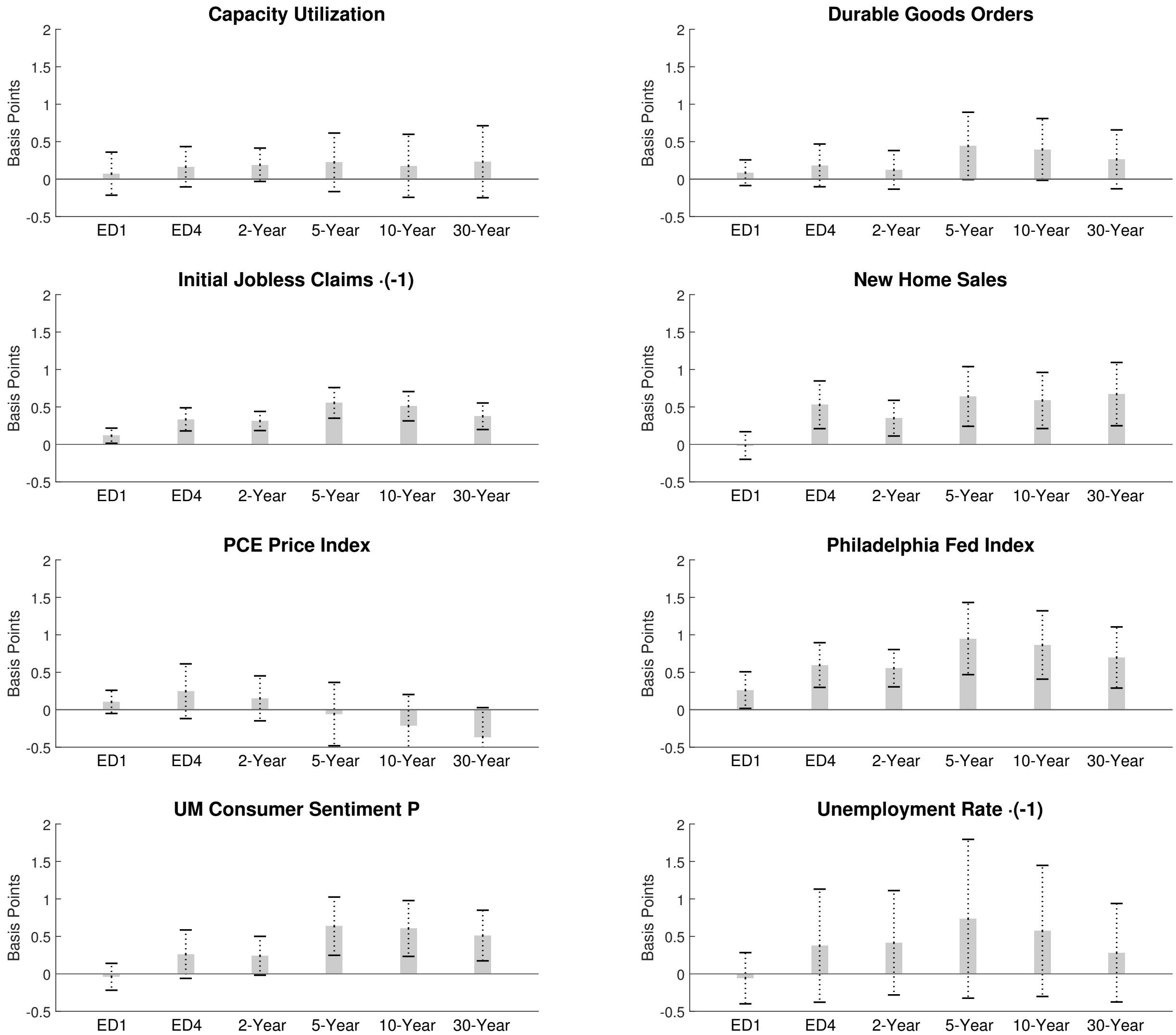
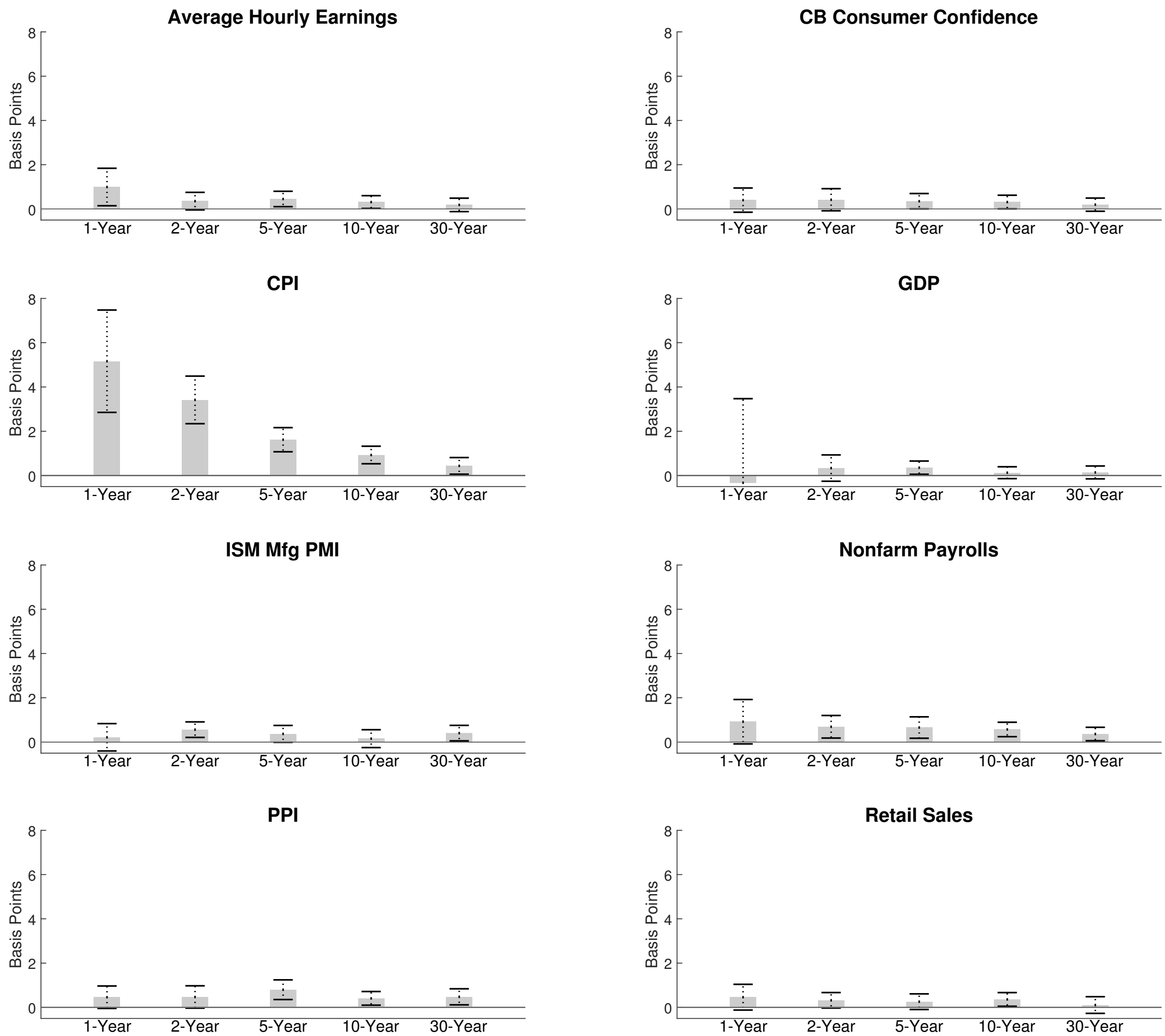



Notes: This figure shows the responses of interest rates for each of the 16 major macro announcements. Interest rate changes are expressed in basis points and announcement surprises are normalized to standard deviations. For a given interest rate, the grey bar shows the average effect, i.e., the estimate of coefficient $\beta^{y|k}$ of equation (C1). The black error bands depict 95 percent confidence intervals, where standard errors are heteroskedasticity-robust. The interest rate abbreviations are explained in Table 2.

Figure C2: Effects of Macro News on Inflation Expectations

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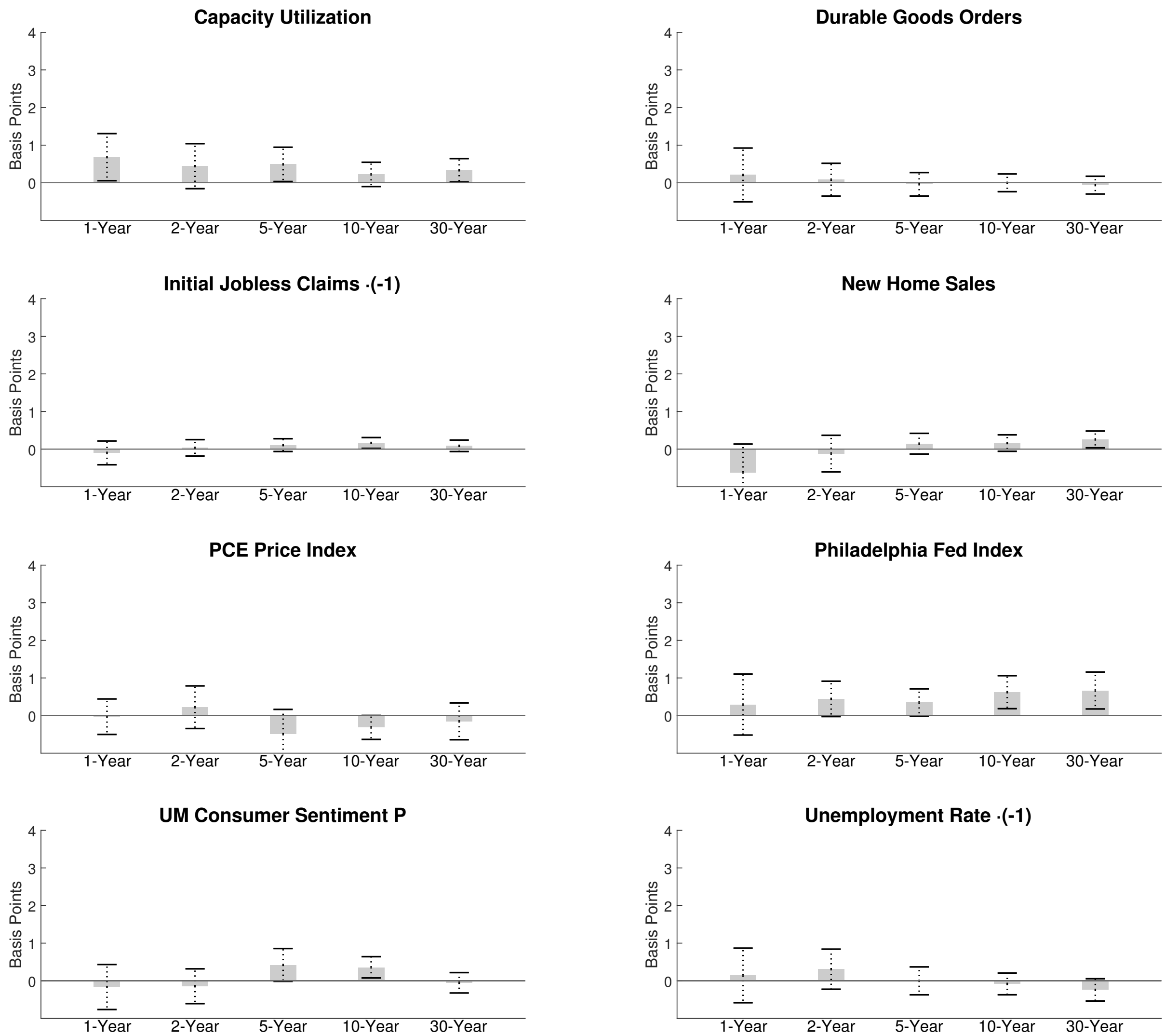
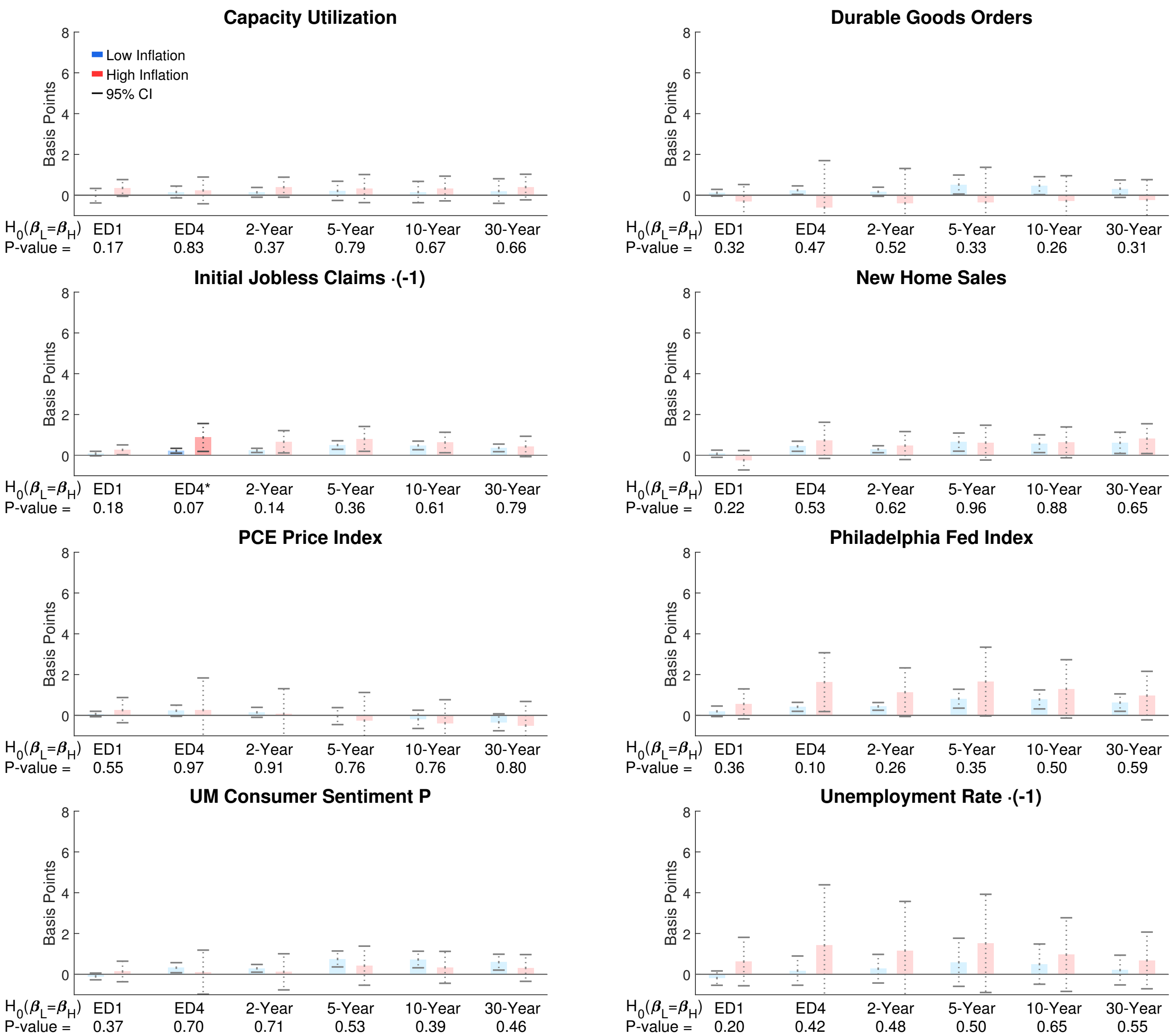



Notes: This figure shows the responses of inflation swap rates for each of the 16 macro announcements. Inflation swap rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given inflation swap rate, the grey bar shows the average effect, i.e., the estimate of coefficient $\beta^{\pi|k}$ of equation (C2). The black error bands depict 95 percent confidence intervals, where standard errors are heteroskedasticity-robust.

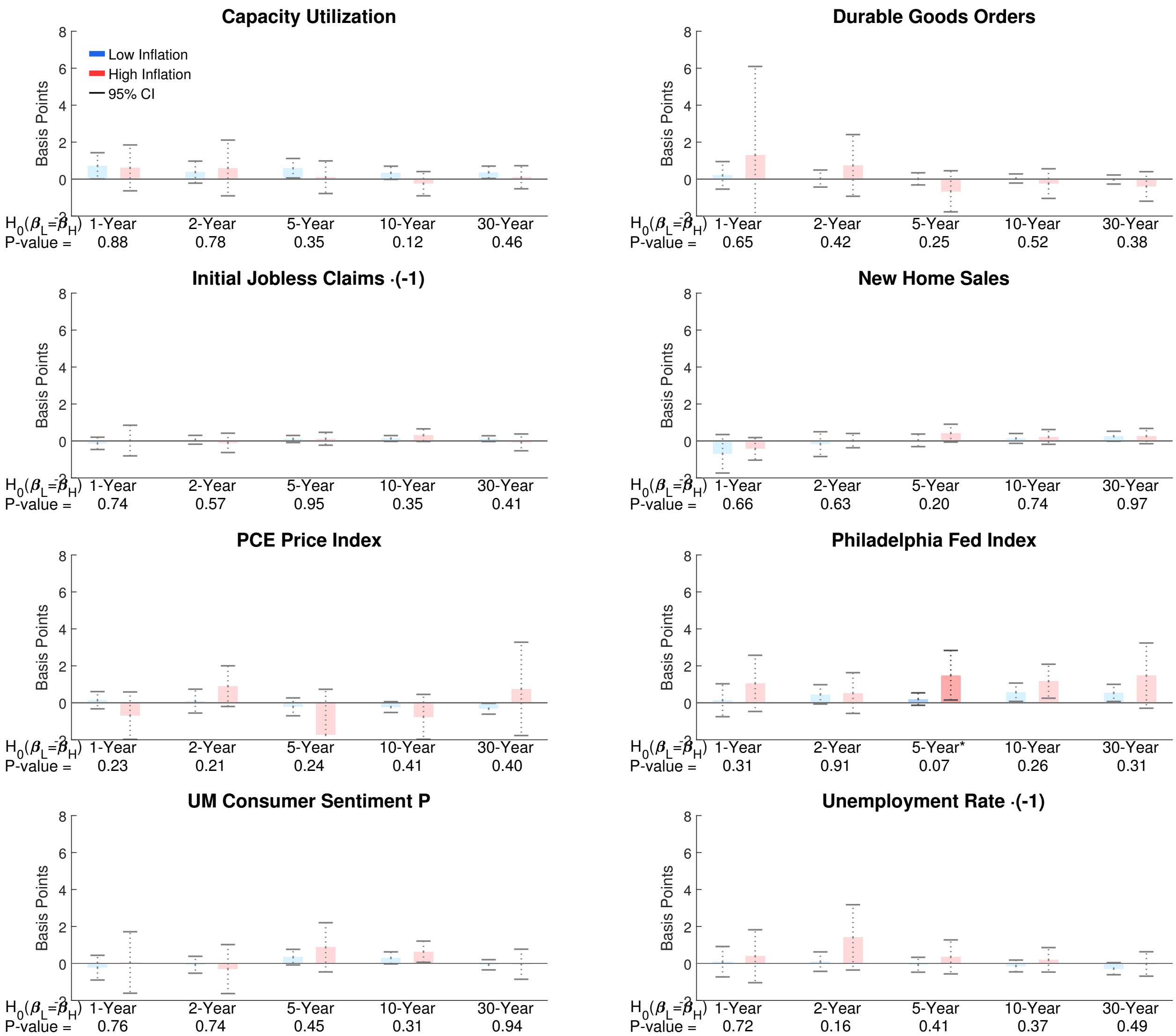
## C.2 Additional Macroeconomic Releases

Figure C3: Effects of Macro News on Interest Rates under Low and High Inflation




Notes: This figure shows the responses of interest rates under the low-inflation and high-inflation sample for each of the 8 other macroeconomic announcements. Interest rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given asset price, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{y|k}$ of equation (12), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{y|k}$ of equation (12). The black error bands depict 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level of rejecting the null hypothesis that $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are equal. The p-value of this hypothesis test is reported below each interest rate. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests. The interest rate abbreviations are explained in Table 2.

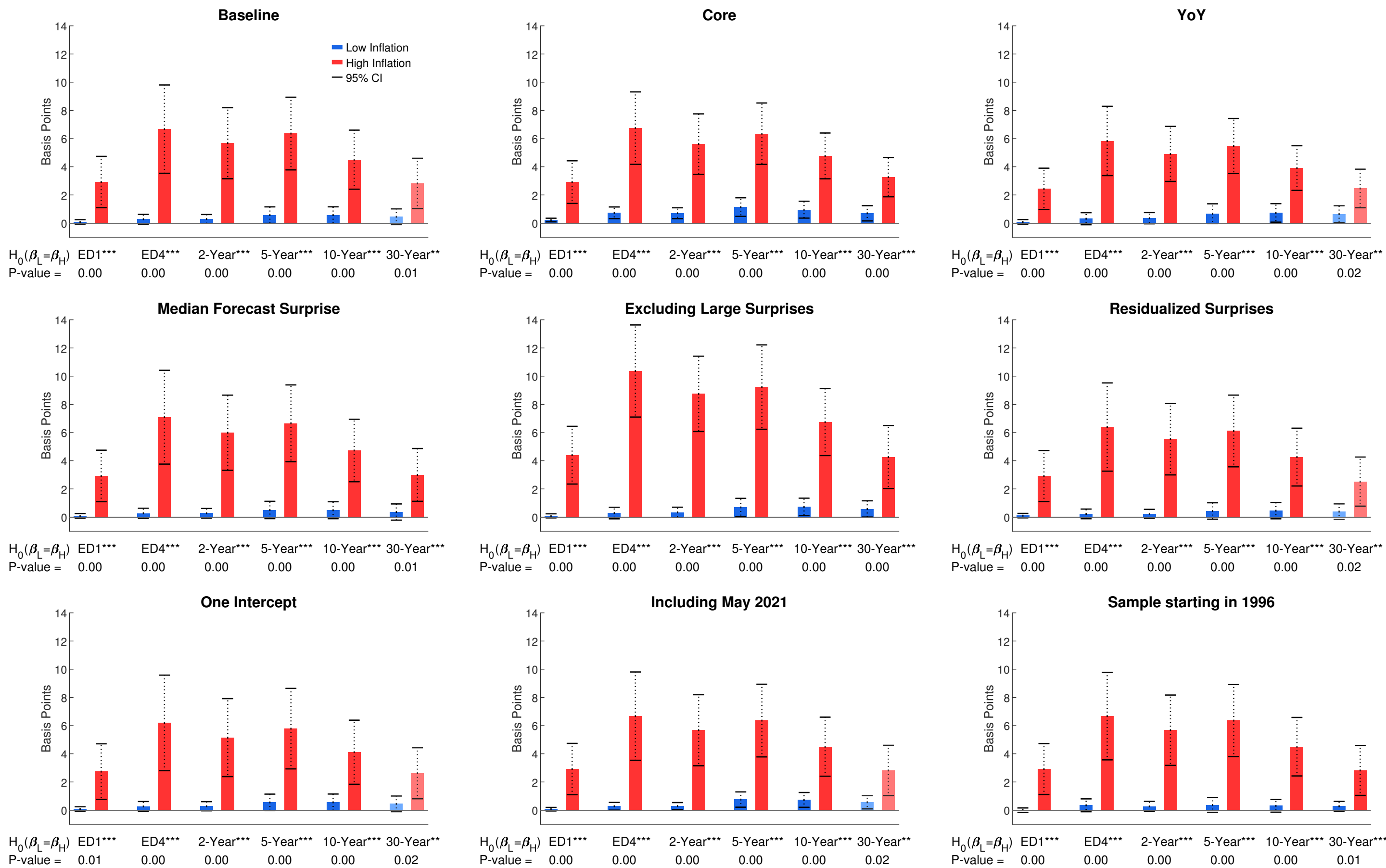
Figure C4: Effects of Macro News on Inflation Expectations under Low and High Inflation




Notes: This figure shows the responses of inflation swap rates under the low-inflation and high-inflation sample for each of the 8 other macroeconomic announcements. Inflation swap rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given asset price, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{y|k}$ of equation (12), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{y|k}$ of equation (12). The black error bands depict 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level of rejecting the null hypothesis that $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are equal. The p-value of this hypothesis test is reported below each interest rate. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests.

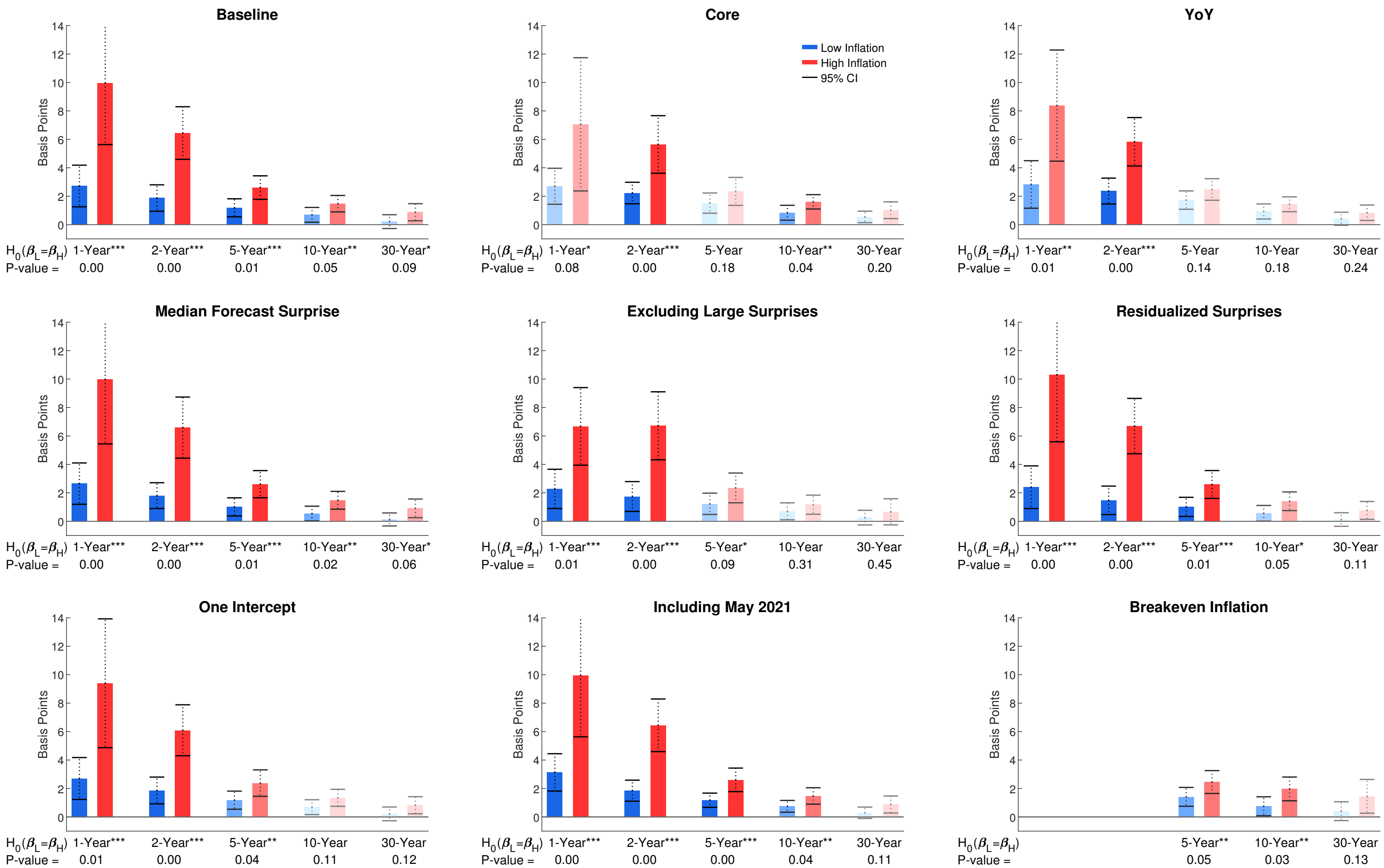
## C.3 Sensitivity Analysis

Figure C5: Effects of CPI News on Interest Rates under Low and High Inflation—Robustness



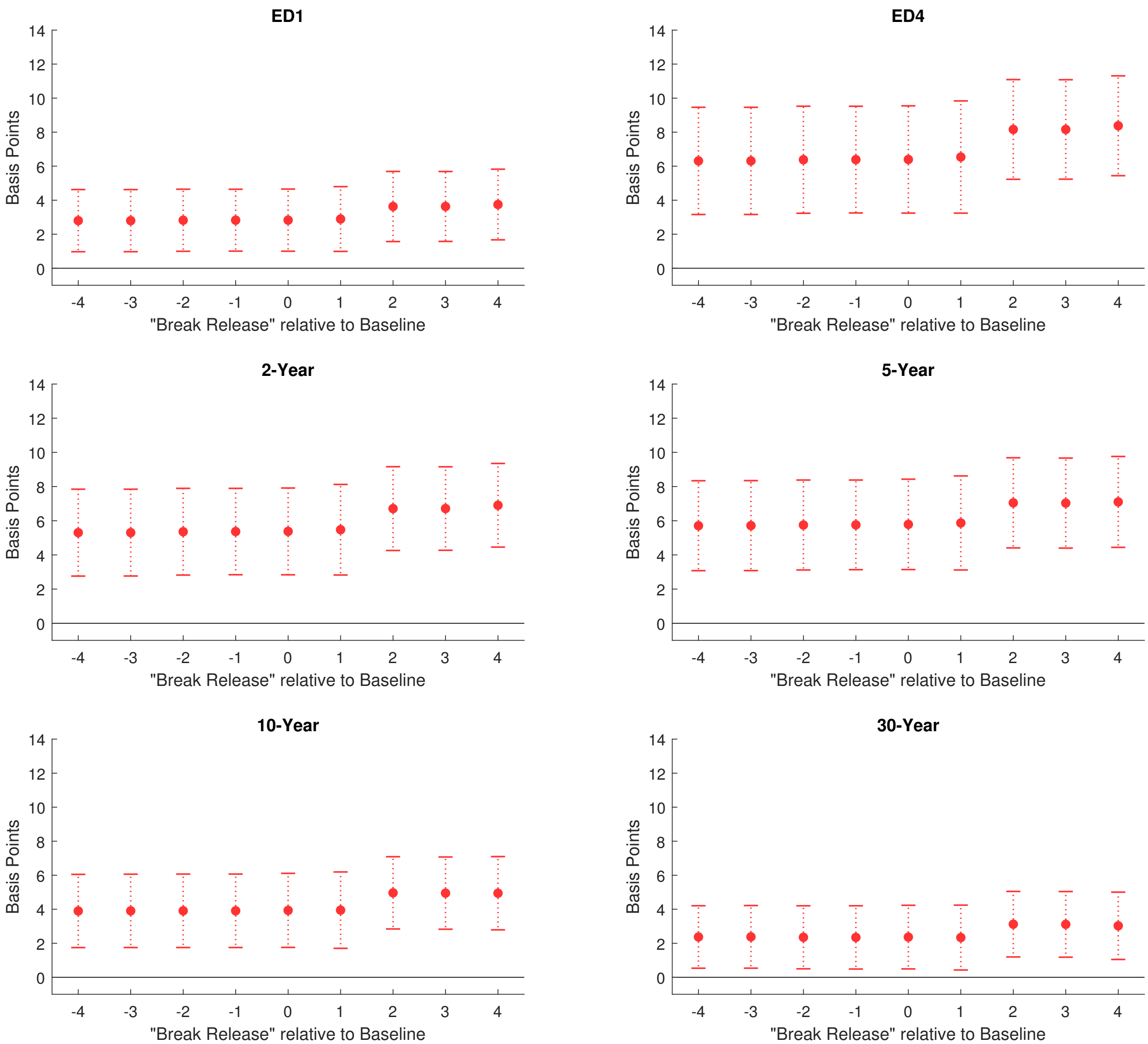

Notes: This figure shows the responses of interest rates to CPI news for different specifications. Each panel displays the results for a given specification and Appendix C.3 provides the details on each. Interest rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given interest rate, the blue bar depicts the effect under low inflation ($\beta_L^{y|k}$) while the red bar depicts the effect under high inflation ($\beta_H^{y|k}$). The black error bands depict 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level of rejecting the null hypothesis that $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are equal. The p-value of this hypothesis test is reported below each interest rate. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests.

Figure C6: Effects of CPI News on Inflation Expectations under Low and High Inflation—Robustness



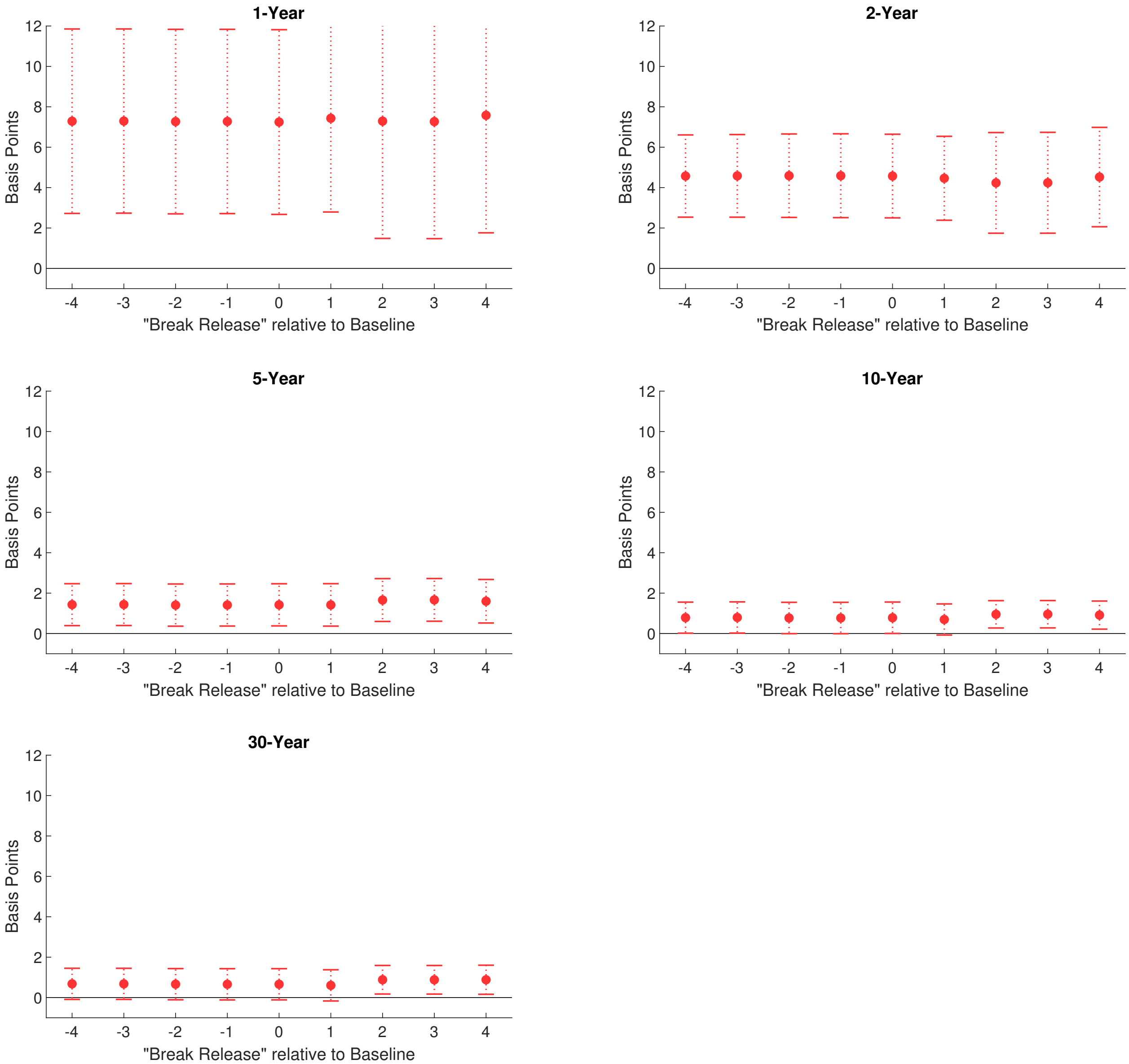

Notes: This figure shows the responses of inflation swap rates to CPI news for different specifications. Each panel displays the results for a given specification and Appendix C.3 provides the details on each. Inflation swap rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given interest rate, the blue bar depicts the effect under low inflation ($\beta_L^{\pi|k}$) while the red bar depicts the effect under high inflation ($\beta_H^{\pi|k}$). The black error bands depict 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level of rejecting the null hypothesis that $\beta_L^{\pi|k}$ and $\beta_H^{\pi|k}$ are equal. The p-value of this hypothesis test is reported below each inflation swap rate. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests.

Figure C7: Increased Sensitivity for CPI releases—Robustness




Notes: The figure displays estimates of the increased sensitivity of interest rates to CPI news under high inflation for alternative "break months". For a given asset price, each circle indicates the estimate of coefficient $\delta_H^{y|k}$ of a version of equation (13), for which only the "break month" between the low- and high-inflation sample is changed relative to the baseline. For each estimate, corresponding 95 percent confidence bands are plotted, where heteroskedasticity-robust standard errors are employed.

Figure C8: Increased Sensitivity of Inflation Swap Rates for CPI releases—Robustness

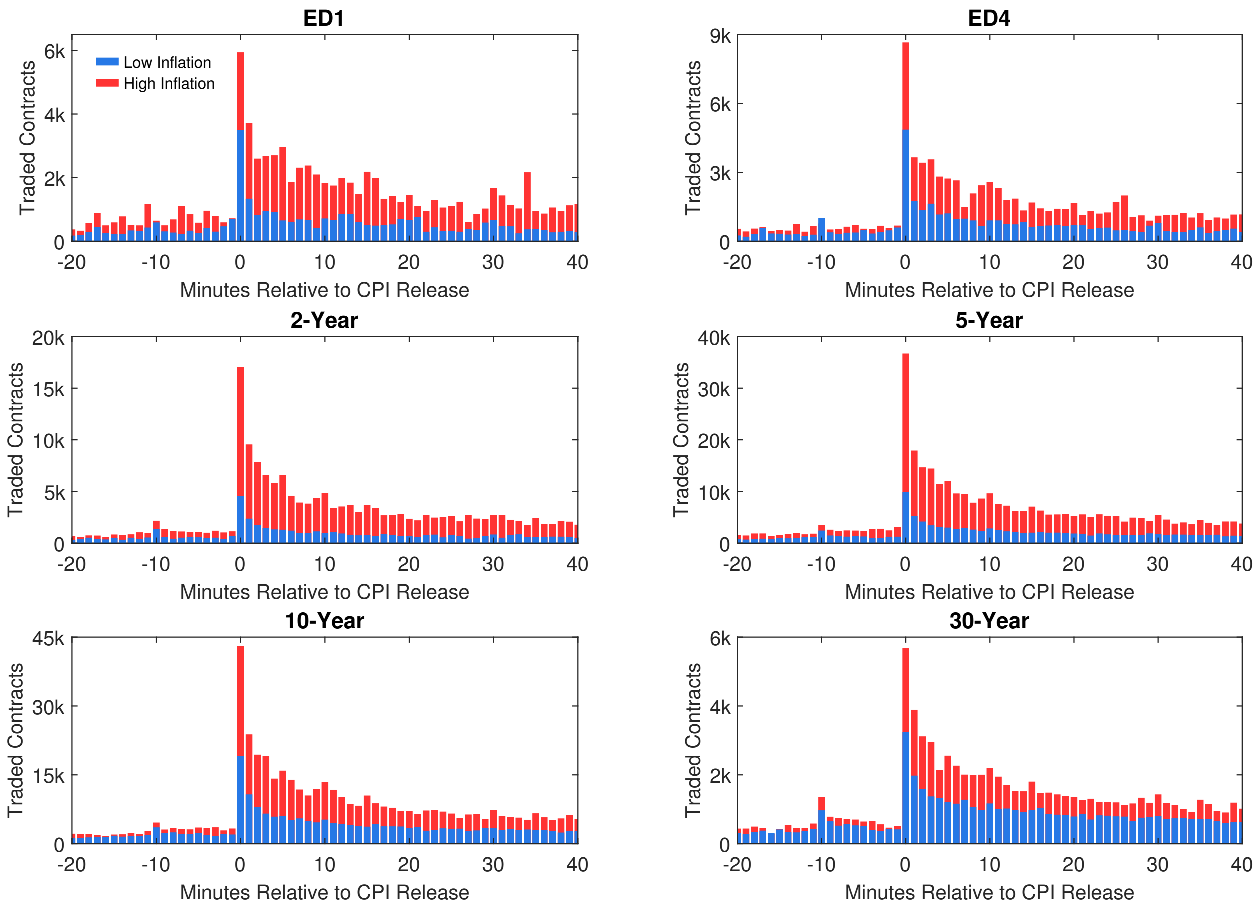



Notes: The figure displays estimates of the increased sensitivity of inflation swap rates to CPI news under high inflation for alternative "break months". For a given asset price, each circle indicates the estimate of coefficient $\delta_H^{\pi|k}$ of a version of equation (13), for which only the "break month" between low- and high-inflation sample is changed relative to the baseline. For each estimate, corresponding 95 percent confidence bands are plotted, where heteroskedasticity-robust standard errors are employed.

# D Additional Results for Section 5

## D.1 Trading Volume

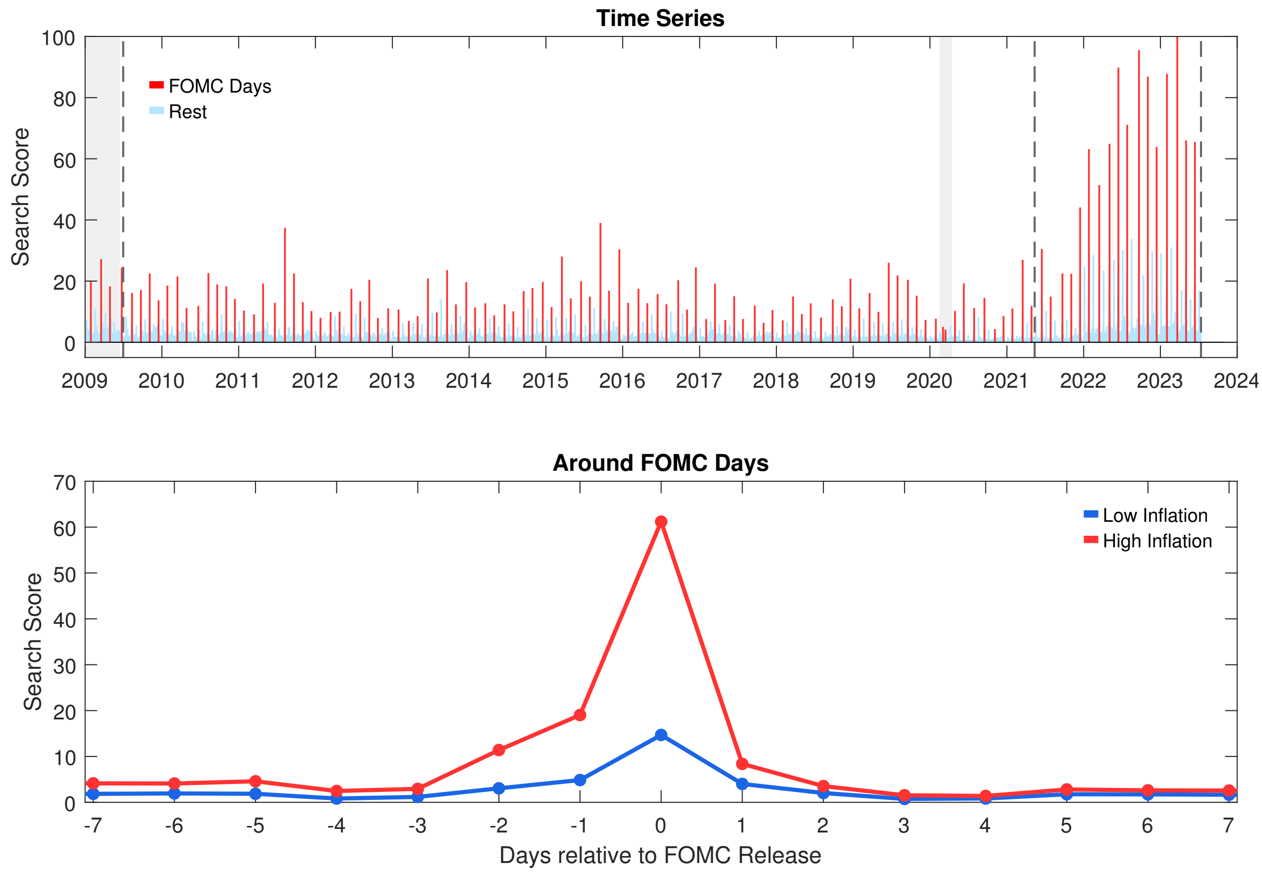
Figure D1: Trading Volume of Interest Rate Futures around CPI Releases




Notes: This figure displays the average trading volumes in interest rates futures around CPI releases during the low-inflation and high-inflation period. Each panel refers to the trading volume of a given interest rate futures contract.

## D.2 FOMC Announcements

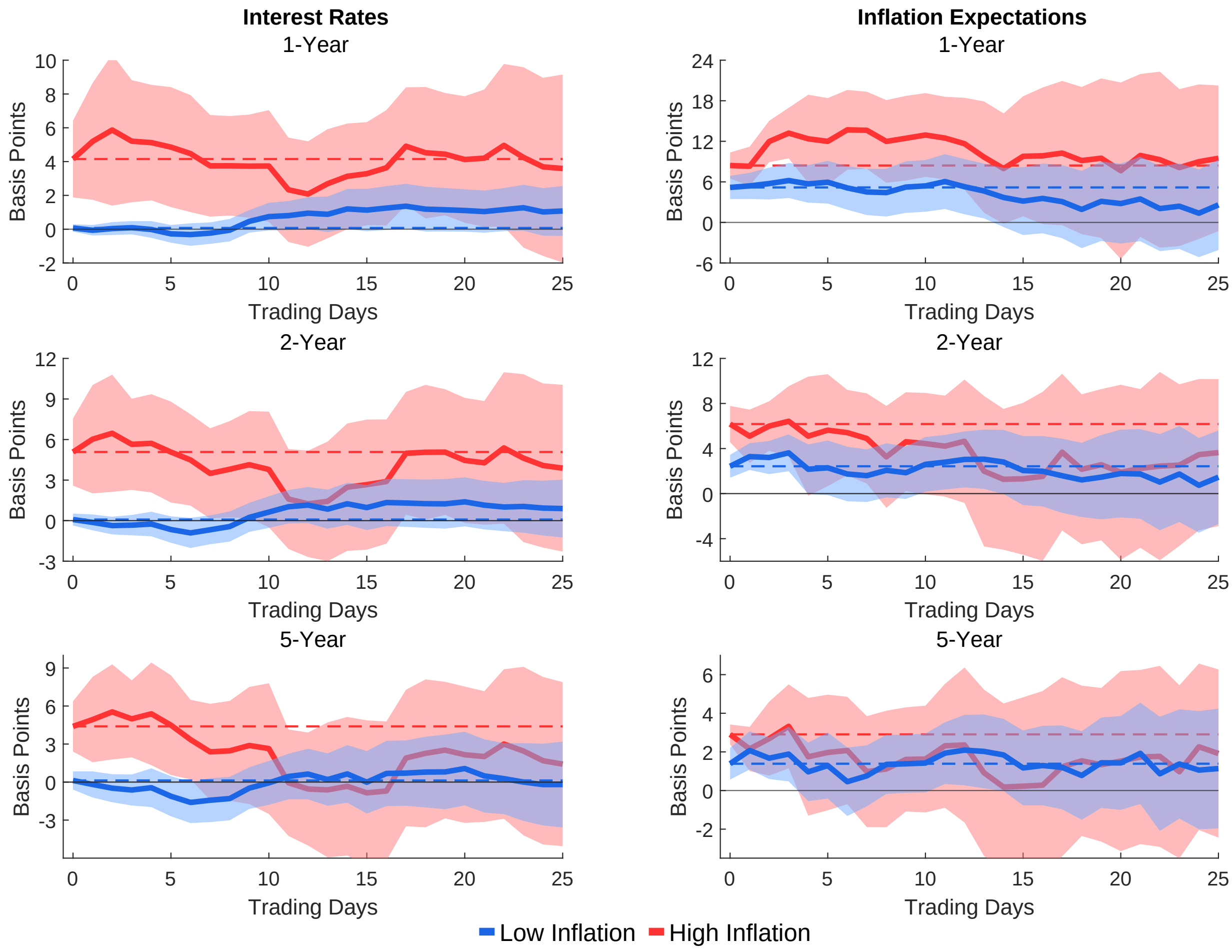
Figure D2: Google Searches for Topic "Federal Open Market Committee"




Notes: The **top panel** shows the daily Google searches for the topic "Federal Open Market Committee" in the United States. Red bars show searches for days of CPI releases, while blue bars show searches for the other days. The dotted, vertical lines illustrate the splits into the low- and high-inflation periods as defined in Section 3.1. *FOMC Days* refers to days with a FOMC meeting (day of press release), while *Rest* to the rest of the days in the sample. Shaded areas indicate NBER recession periods. The **bottom panel** displays the average Google Searches around FOMC days under the low-inflation period (blue) and the high-inflation period (red). *Search Score* is normalized such that 100 corresponds to the largest observation over the sample period. See text for details on the construction.

### D.3 Lower Frequency Effects

Figure D3: Daily Impulse Responses to CPI News




Notes:

$$\Delta^{(h)} x_d = \alpha^{(h)} + \beta_L^{(h)} s_d^{CPI} \mathbb{1}_{d \in L} + \beta_H^{(h)} s_d^{CPI} \mathbb{1}_{d \in H} + \sum_{j=1}^{20} \theta_j^{(h)} x_{d-j} + \theta_{ffr}^{(h)} ffr_{d-1} + \theta_{spx}^{(h)} spx_{d-1} + \varepsilon_d^{(h)}$$

This figure shows the impulse response to CPI surprises under low-inflation period (left column), and the high-inflation period (right column). Each of the four panels displays estimates of a local projection of a one standard deviation positive CPI surprise on the h-day change in the 2-year Treasury rate or the inflation swap rate. The impulse responses are estimated over the first 20 business days, i.e., month, following the release. Dotted lines show 90 percent confidence intervals based on Newey-West standard errors. Daily data on inflation swap rate comes from *Refinitiv*, and data on the Treasury rates comes from the updated Gürkaynak, Sack, and Wright (2007) database.

## References


Gürkaynak, Refet S, Brian Sack, and Jonathan H Wright. 2007. "The US Treasury yield curve: 1961 to the present." *Journal of monetary Economics* 54 (8):2291–2304.

Kerkhof, Jeroen. 2005. “Inflation derivatives explained.” *Fixed Income Quantitative Research, Lehman Brothers (July)* :1–80.