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

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This draft: July 31, 2023
First draft: July 31, 2023

Abstract

Do people pay more attention to inflation when it is high? A large class of behavioral models in macroeconomics would predict that. I test this prediction by studying the financial market impact of U.S. macroeconomic news announcements following the 2021 inflation surge. I show that the effect of inflation news on interest rates—measured in a 30-minute window around announcements—is much stronger since 2021. In particular, a surprise about Consumer Price Index (CPI) inflation, of the same magnitude, leads to a more than 10 times larger effect on yields compared to the prior, low-inflation period. I find similar evidence for other asset prices such as inflation swap rates, stocks, exchanges rates, and foreign interest rates. Importantly, the increased sensitivity of inflation swap rates indicates that the results are driven by a faster incorporation of inflation news into inflation expectations, consistent with higher levels of attention. In contrast, I do not find any evidence of systematic differences in sensitivity to other, non-price releases such as Nonfarm Payroll Employment. Finally, I show that around price releases, trading volume and Google searches, two proxies of attention, rose since 2021, further supporting an attention-based explanation. Overall, my findings support theories of rational information choice such as "rational inattention". The evidence also highlights the role of macroeconomic conditions for understanding the link between investor attention, macro news, and asset prices.

JEL Codes: E44, E71, G12, G14, G41

Keywords: Macroeconomic News Announcements, Investor Attention, Rational Inattention, Inflation, High-frequency data, Event study

*I thank Bastian von Beschwitz, Benjamin Knox, Mehrdad Samadi, Arsenios Skaperdas, and Emre Yoldas for helpful comments. I thank Jacob Williams for excellent research assistance. 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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1 Introduction

When inflation is persistently high, households and businesses must pay close attention and incorporate inflation into their economic decisions. When inflation is low and stable, they are freer to focus their attention elsewhere.

— Jerome Powell (2022)[1]

Inflation is costly to almost everyone: firms, households, and investors.[2] So the idea that people pay more attention to inflation when it is high sounds intuitive. It is also supported by theoretical models on inattention (Sims, 2003; Gabaix, 2014). Yet, the empirical evidence on this prediction is limited at best, as most empirical work on attention has focused on advanced economies and only started in recent decades, that is, during times of low inflation rates.[3]

In this paper, I provide novel evidence that the inflation environment is a key determinant of people's attention to inflation. I do so by studying the high-frequency effects of U.S. macroeconomic news releases on asset prices following the 2021 inflation surge. Consistent with increased attention to inflation, I find that price news releases, in particular the release of the Consumer Price Index (CPI), have much larger effects on interest rates and on inflation expectations, measured by inflation swap rates, during the recent high-inflation period. This increase in sensitivity compared to the previous, low-inflation environment is economically and statistically significant. It is also present for a broader range of asset prices such as stocks, exchange rates, and foreign interest rates. Importantly, other, not price-related macro news releases, such as Nonfarm Payroll Employment, do not show any significant changes in effect sizes during the high-inflation period. Additional evidence from trading volumes and Google searches, two proxies of attention, further corroborates the interpretation that attention to CPI releases increased starkly with the increase in inflation.

While recent papers have documented multiple empirical results in line with increased attention to inflation during high-inflation episodes (e.g., Weber et al., 2023), I complement these papers by directly showing that people pay more attention to the release of new information about inflation when inflation rates are high. My paper has also implications for asset pricing itself. While the importance of investors' attention for asset prices has been previously documented (e.g., Da, Engelberg, and Gao, 2011), the evidence I document in-

[1] `https://www.federalreserve.gov/newsevents/speech/powell20220826a.htm` (accessed on June 19, 2023).

[2] See, for example, Romer (2012, pp. 523-526) for a discussion and references on the costs of inflation. See Cieslak and Pflueger (2023) and references therein for details on the inflation costs to investors.

[3] I discuss the prior evidence on this question below when I talk about the related literature.

dicates that the interaction between attention and macroeconomic conditions might be of first-order importance. This might be especially relevant in understanding how asset prices respond to macroeconomic shocks which have been shown to be a key source of fluctuations in financial markets (e.g., Miranda-Agrippino and Rey, 2020; Boehm and Kroner, 2023).

Testing if people actually pay more attention to inflation news under rising inflation is empirically challenging. In this paper, I tackle this question by employing a high-frequency event-study analysis around macroeconomic announcements. For my purposes, this setting has two key properties. First, scheduled macroeconomic announcements provide unique variation to study a variety of economic questions (e.g., Faust et al., 2007). Specifically, the surprise about CPI inflation reflects an information treatment of "new information about inflation", even to the fully informed agent. Confronting people with truly new information about inflation is hard to achieve otherwise, even in more controlled settings (Cavallo, Cruces, and Perez-Truglia, 2017; Weber et al., 2023). Second, the fact that I employ intraday windows around releases is also crucial for my analysis. In essence, these narrow windows reduce noise and hence allow me to have sufficient statistical power to detect, if existent, statistical differences, even for a relatively short high-inflation period.

To motivate my empirical analysis, I start by setting up a simple investor model to illustrate that higher attention to inflation news leads to stronger effects on interest rates and on inflation expectations on impact. With these predictions at hand, I start my analysis by looking at high-frequency changes. I separate the sample into a low-inflation period, starting after the Great Recession until May 2021, and a subsequent high-inflation period ending in April 2023. Looking at the yield curve response, I find that CPI inflation surprises have more than an order of magnitude stronger effects in the high-inflation period. The differences across periods are highly significant at the 1 or 5 percent level. I find similar results but to a much lesser extent for the Producer Price Index (PPI). Consistent with the theoretical framework, inflation swap rates also respond much stronger to inflation surprises indicating that attention is indeed the underlying driver. Finally, I also find increased sensitivity for foreign yields, exchange rates, and stock market indicators.

Crucially, I also study other, non-price macro releases, such as Nonfarm Payroll employment, to rule out alternative explanations. 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 price news (treatment group) versus non-price news (control group). With no evidence of systematic differences for non-price news, I can rule out any alternative explanation which would imply changes in the sensitivity of asset prices to all macro announcements, e.g., muted sensitivity due to the zero-lower-bound period during the low-inflation sample. Finally, a careful robustness reveals, among other things, that the results are neither driven by large nor positive inflation surprises over the sample period.

While the asset price changes around macro news announcements yield findings consistent with increased attention to inflation news, I also corroborate my evidence by looking directly at two proxies of attention, trading volume and Google searches. Specifically, I use trading volumes of the interest rate futures which the yield changes are constructed from. Consistent with the results on the sensitivity of asset prices, trading volume within 30 minutes around CPI releases rose exceptionally since 2021. In addition, I study daily Google searches for topics such as "Consumer Price Index" or "Nonfarm Payrolls" which can be directly linked to specific releases. Consistent with my prior results, I find that searches around CPI releases for the topic "Consumer Price Index" increased dramatically since 2021, while very little on other days. Among other releases, I only find similar patterns for the topic "Producer Price Index" around PPI releases. In summary, the results based on both attention measures lend further support to an attention-based explanation of the asset price responses.

Related literature My paper relates to various topics in macroeconomics and finance. First, my paper relates to recent work providing empirical evidence on the relationship between inflation and attention consistent with "rational inattention" models (Sims, 2003).[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 rate and inflation-related Google searches. 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). Providing information treatments about inflation, they show that individuals in Argentina put less weight on the treatment and more weight on their priors, consistent with the idea that they are more informed about inflation. Building upon Cavallo, Cruces, and Perez-Truglia (2017), Weber et al. (2023) employs a set of randomized control trials across countries and over time, including the 2021 inflation surge. They also show that as inflation increases, survey participants are less responsive to exogenous information treatments about inflation. Exploiting variations across surveys and time, the authors can more directly link the responses to the treatment to the inflation environment.

[4] See Maćkowiak, Matějka, and Wiederholt (2023) for a recent survey.

Overall, my findings complement these papers by directly showing that when inflation is high people pay indeed more attention when new information about the inflation rate arrives. Here, it is important to understand that the treatments by Cavallo, Cruces, and Perez-Truglia (2017) and Weber et al. (2023) are publicly available information which are easily available prior to the treatment. Hence, more attentive people should have already incorporated this information and as a consequence be less responsive. In contrast, in my study the "information treatment" is new information about inflation which was not publicly available prior to the release. Thus, more attentive people should be more responsive as I show in my analysis.

My paper also relates to a literature documenting 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; Andrei and Hasler, 2015; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016, among many others). On the more empirical side, Huberman and Regev (2001) provide a early example of the importance of attention by documenting a stock price reaction to old public information once investors paid attention to it. Barber and Odean (2008) show that investor attention to a specific stock leads to buying pressure of it. Da, Engelberg, and Gao (2011) show that an investor attention measure based on Google searches can predict stock prices. Closer related to my work, a variety of papers study scheduled information releases such 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) construct an attention measure for specific stocks using search and activity data from Bloomberg terminals. They show, among other things, that post-earnings-announcement drifts can be connected to an insufficient amount of investor attention. Benamar, Foucault, and Vega (2021) and Andrei, Friedman, and Ozel (2023) show that investor attention, as a result of economic uncertainty, leads to stronger reactions of asset prices to macro and earnings announcements.

My paper contributes to this line of work by showing that the inflation rate is a macroeconomic variable which plays a crucial role in how investors' attention is allocated and how inflation news is incorporated into asset prices. Further, the majority of prior studies is conducted during low levels of inflation. However, based on my results, it is not obvious to what extent previous findings can be applied to the recent, high-inflation period. For example, one could think of potential attention spillovers to earnings announcements as in

Hirshleifer and Sheng (2022).

A third strand of papers studies the interaction between inflation and asset prices, a classic topic which attracted more interest again following the 2021 inflation surge (see Cieslak and Pflueger, 2023, for a survey). Related to this paper, Beechey and Wright (2009) and Gürkaynak, Levin, and Swanson (2010) study the effects of macro news releases on interest rates and break-even inflation rates for the U.S. and other advanced economies. More recently, Fang, Liu, and Roussanov (2022) emphasize the distinction between core and energy inflation in understanding the pricing of inflation risks in "real" assets such as stocks. Gil de Rubio Cruz et al. (2022) and Knox and Timmer (2023) study the response of U.S. stocks to CPI inflation news over the last 35 years. Among other things, Gil de Rubio Cruz et al. (2022) find evidence for a varying sensitivity of stocks over time. Consistent with my findings, they also find a much stronger effect on stocks during the recent inflation surge. Knox and Timmer (2023) argue that stocks of firms with higher market power are less affected by inflation surprises.

Roadmap The remainder of the paper is structured as follows. In the next section, I talk about my empirical approach and introduce a simple, theoretical framework to guide it. Section 3 introduces the data, and Section 4 shows the baseline results for the high-frequency effects of macro news on asset prices. In Section 5, I provide evidence based on two proxies of attention which supports an attention-based explanation of my asset pricing results. In Section 6, I discuss and interpret my findings along several dimensions. Section 7 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' 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.

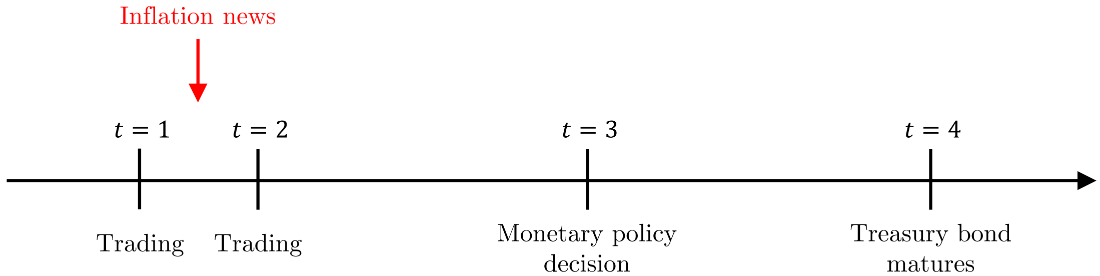
My framework is in the tradition of portfolio choice models under noisy information. Classic references are Grossman and Stiglitz (1980), Verrecchia (1982), Kim and Verrecchia (1991), Kandel and Pearson (1995), and Veronesi (2000). I model the news related to a macroeconomic announcement as a public, noisy signal, and 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 λ_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 ΔR 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 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

Figure 1: Model Timeline



Notes: This figure illustrates the timing of the four dates in the model including a summary headline for each date. Details are provided in text.

papers before which 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., $\Delta\pi \sim N(0, \sigma_\pi^2)$. Similarly 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 μ investors (attentive investors) incorporate the s^π into their expectations, while $1 - \mu$ inattentive investors ignore it.[5]

At date 2, each agent i face again a portfolio problem investing λ_2^i in the risky Treasury security in order to maximize her wealth at date 4. The difference to date 1 is that μ 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' entire 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 γ. Further, let $\mathrm{E}_t^i[\cdot]$ and $\mathrm{Var}_t^i[\cdot]$ denote investor i's expectation and variance conditional on

[5]Note that in DellaVigna and Pollet (2009) μ actually denotes the share of inattentive investors as opposed to the share of attentive investors.

date t information, respectively. At date 1, investor i solves

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

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

$$V = 1 - \phi\Delta\pi. \quad (2)$$

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.,

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

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

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

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

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

Here, $\mathrm{E}_t[\cdot]$ denotes the average expectation across investors.[6] Note that the inflation expectations in the model are given by

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

Hence, bond prices (5) can be rewritten in terms of the inflation expectations, i.e.,

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

[6] 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).

Predictions for empirical analysis I now talk about model predictions for the event study regression in the empirical part. First, note that the change in the bond price is given by

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

As mentioned earlier, the period from date 2 to 4 can be thought of being shorter or longer horizons depending on the maturity of the bond. In the empirical analysis, I will use *bond yields* rather than the bond prices as it is more commonly used. To be precise, let τ be the modified duration of the bond.[7] Following Gürkaynak, Kısacıkoğlu, and Wright (2020) and others, I approximate the bond's yield change by the change in its price divided by minus its modified duration, i.e.,

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

where bond prices are measured by the corresponding futures contracts. I will discuss this in more detail in Section 3 when I talk about the data.

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

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

As shown in Appendix A.6, the effect of inflation news on bond yields and inflation expectations is increasing in the share of attentive investors, i.e., $\frac{\partial\beta_\mu^{y|\pi}}{\partial\mu} > 0$ and $\frac{\partial\beta_\mu^{\pi|\pi}}{\partial\mu} > 0$, respectively. Hence, if we were to compare a period of higher attention versus one with lower attention, i.e., $\mu_H > \mu_L$, the model predicts that the sensitivity of interest rates and inflation expectations increases, i.e., $\beta_H^{y|\pi} > \beta_L^{y|\pi}$ and $\beta_H^{\pi|\pi} > \beta_L^{\pi|\pi}$.

To summarize, the theoretical framework has the following predictions for the empirical

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

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 response. 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 answer empirically this question, I first need a counterpart to inflation signal s^π which I construct based on unexpected information of macroeconomic data releases.

Consider the release of macroeconomic variable k at time t. For example, the Bureau of Labor Statistics publishes numbers on the Consumer Price Index at 8:30 am typically between the 10th and 15th of each month in recent years. 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, i.e., 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 and subperiods, 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 macro news at hand, I will center my analysis around the following specification. Let x denote the either an interest rate or inflation expectation, i.e., $x \in y, \pi$, then I estimate equations of the following form

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

where Δx_t is the change in the asset price of interest in a narrow window around the announcement time t, 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 β_L^k and β_H^k are the coefficients of interest. The error term ε_t^k includes the effects of unmeasured news and/or noise on the asset price of interest.

Equation (11) represents the key specification of the empirical analysis. Before I discuss in the next section the data which I will use to estimate it, I go through a couple of conceptual points in the following. These are important to understand how the empirical approach aims to answer the research questions and how the rest of the paper evolves.

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. This is very important to ensure that it is not the size of the news. Second, both coefficients can be consistently estimated by Ordinary Least Squares (OLS) if the error term ε_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.

Price and real-activity news 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 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.

In the empirical analysis, I will use price news, i.e., surprises about price releases, as the measure of inflation news s^{π} in the model, and real activity news, i.e., releases which are mostly concerning real economic activity, to measure $s^{\neg\pi}$. While this separation into both groups should not seen as structural, i.e., all releases are informative about inflation and real activity, releases within each group have qualitatively similar effects on many asset prices (e.g., Beechey and Wright, 2009; Boehm and Kroner, 2023).

One way to think about the real activity news with respect to my analysis 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 hypothesis. Many alternative explanations can be tested by studying the sensitivity to real activity news. 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.

Eventually, I will study real activity news mostly in the case of interest rates, i.e., $\beta_H^{y|\neg\pi} \approx \beta_L^{y|\neg\pi}$. Basically, real activity news have a clear and stable theoretical relationship with respect to yields. Better-than-expected news should lead to an increase in interest rates. Empirically, this relationship has been documented to be stable and strong (Andersen et al., 2007; Gürkaynak, Kısacıkoğlu, and Wright, 2020). In contrast, for inflation expectations, there is no clear theoretical relationship. Better-than-expected news could lead to an increase or decrease in inflation expectations depending on being interpreted as demand-side or supply-side shocks, respectively. So it is not clear that $\beta_H^{\pi|\neg\pi} \approx \beta_L^{\pi|\neg\pi}$ is not necessarily going hold due to other factors unrelated to 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 and show, 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).[8] Another measure I employ are Google searches for announcement-specific topics such as "Consumer Price Index". To extent that people are more interest in these data releases, this should be reflected in the Google Searches for the corresponding topic.

3 Data

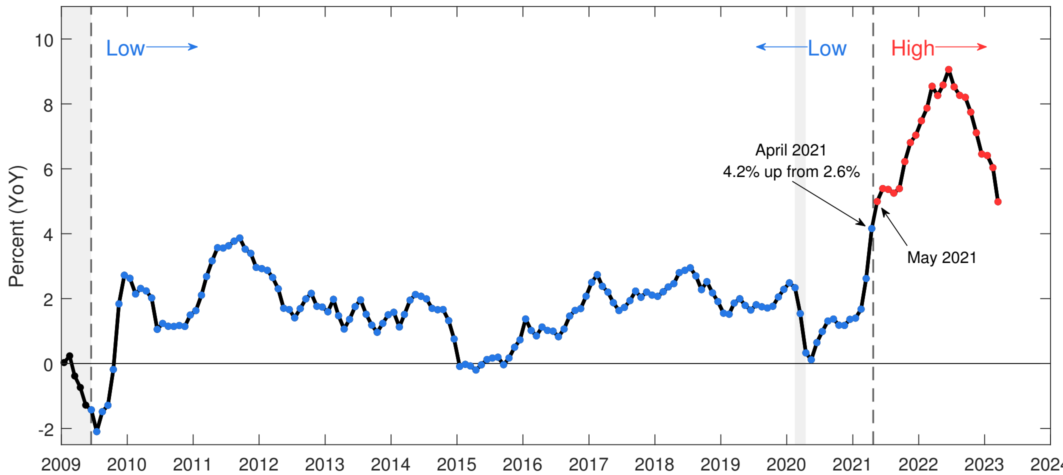
In this section, I provide a overview of the data used for my main analysis.

3.1 Low- and High-Inflation Period

For the majority of the paper, the sample starts on July 1, 2009, i.e., after the Great Recession, and ends on April 31, 2023. The starting point was chosen mostly due to availability of the inflation swap data as I will discuss more detail below, but also to avoid asset price

[8] 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 CPI inflation rate from January 2009 until March 2023, constructed as the year-over-year (YoY) percentage change. The blue dots indicate observations during the low-inflation period, while red dots during the high-inflation period as defined in the text. Shaded areas indicate NBER recession periods.

anomalies during Great Recession. In addition, this sample choice allows me to cleanly separate the sample into a period of low inflation and of high inflation. Figure 2 shows the year-over-year CPI inflation rate over the sample. Note that the since a CPI release in given month release numbers for the previous month, the figure plots the data till March 2023.

As Figure 2 shows, 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 their reference month of the released data might be prior to that. The last day of the subsample 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. This represented "the largest 12-month increase since a 4.9-percent increase for the period ending September 2008."[9] As I am interested in the effects of macro news conditional on the inflation environment, I start the *high-inflation period* on May 13, 2021, i.e., after the release of the April CPI numbers.

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

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

Table 1: Overview of Major US Macroeconomic News

Announcement	Release Time	Frequency	Category	Observations		
				Total	Low	High
CPI	8:30 am	Monthly	Price	164	141	23
PPI	8:30 am	Monthly	Price	166	142	24
CB Consumer Confidence	10:00 am	Monthly	Real Activity	166	142	24
ISM Mfg PMI	10:00 am	Monthly	Real Activity	166	143	23
Nonfarm Payrolls	8:30 am	Monthly	Real Activity	163	140	23
Retail Sales	8:30 am	Monthly	Real Activity	166	142	24

Notes: This table displays the 6 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 April 2023. *Frequency* refers to the frequency of the data releases and *Observations* to the number of observations (surprises) of a macroeconomic series in our sample. *Category* specifies if the news release is predominantly informative about real activity or prices. Abbreviations: Mfg—Manufacturing; CB—Chicago Board; ISM—Institute for Supply Management; PMI—Purchasing Managers' Index.

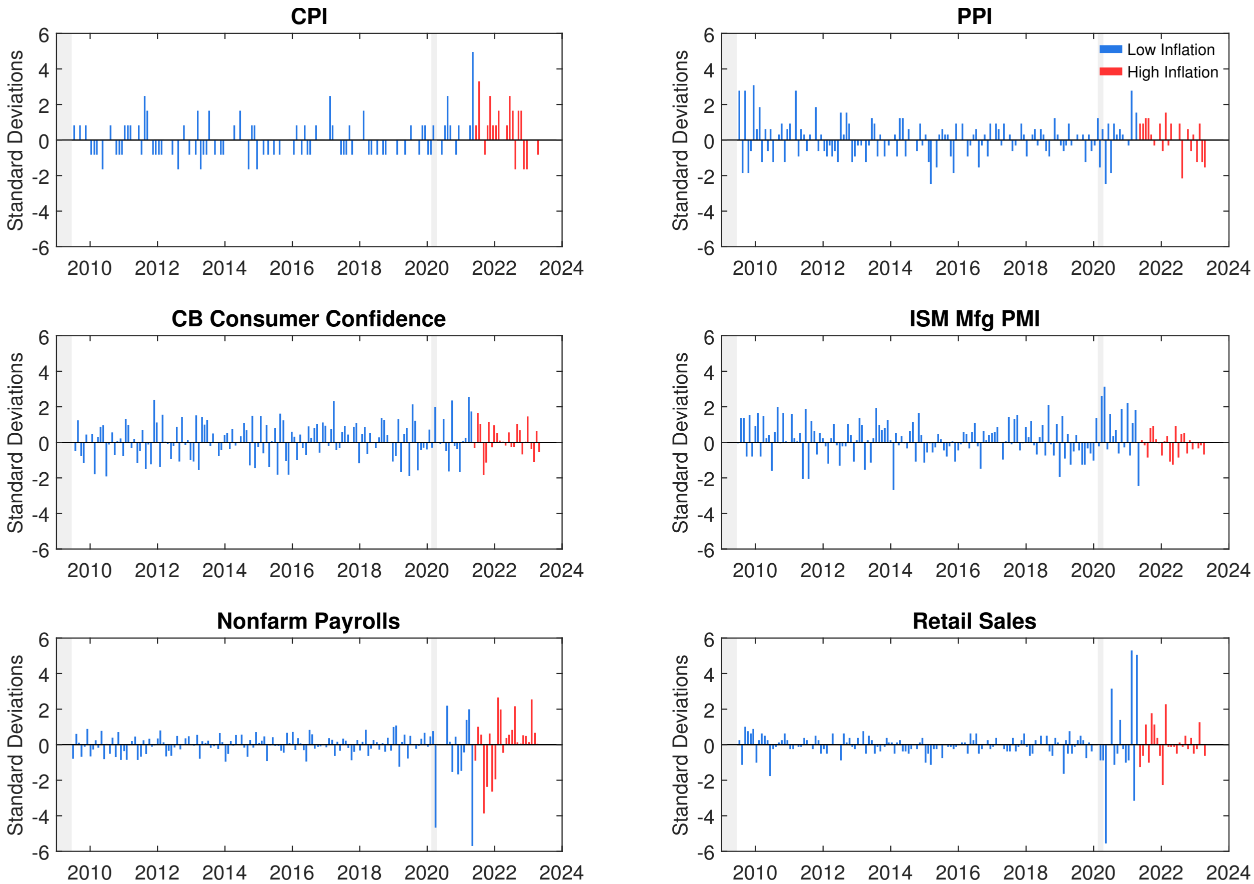
and time, released value, and the median market expectation prior to the release. I focus in most of my analysis on 6 major macroeconomic releases which Table 1 provides an overview of. The selection is based on two factors to ensure that I have enough statistical power for my analysis. First, prior papers have shown that these are closely watched and are able to move financial markets the most (e.g., Rigobon and Sack, 2008; Gürkaynak, Kısacıkoğlu, and Wright, 2020; Boehm and Kroner, 2023). Second, the announcements should have release monthly or higher. For example, the first release of Gross Domestic Product (GDP A) is normally shown to have sizable effects. However, as it is only a quarterly release, I have only a very small number of observations in the high-inflation period.

Further, surprises in Core CPI and Core PPI are normally shown to have larger effects on average compared to the headline numbers. Despite that, I use the headline number as I conjecture that general attention will be more linked to them. That being said, I will later show in 4 that the main findings are robust to choosing surprises about core measures instead of headline ones. Appendix Table B1 shows the broader set which encompasses the 14 releases.

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

Figure 3 displays the resulting time series of each of the six macro releases. Consistent

Figure 3: Time Series of Standardized Surprises



Notes: This figure shows the standardized surprises of the six major 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.

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 6 standard deviations to avoid extreme observations, e.g., at the start of the pandemic. However, the CPI and the PPI series are not affected by that. 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 later robustness checks of main analysis which I discuss below.

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 mitigating noise in outcome variable. This allows me to investigate systematic differences in the financial markets responses, even in a small sample as 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 As 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 contacts at the Chicago Mercantile Exchange (CME).[10] Following Gürkaynak, Kısacıkoğlu, and Wright (2020), I construct yield changes from Treasury futures by dividing the price changes by minus the approximate modified duration. Here, price changes are based on a 30-minute window ranging from 10 minutes before to 20 minutes after the given release. The interest rates futures are not only highly liquid, but as these are traded via a centralized exchange, i.e., the CME, I also have access to trading volume which I will employ later in Section 5 as proxy for attention.

Inflation Expectations To measure inflation expectations, I employ (zero-coupon) inflation swaps. These are based on which 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.[11] Appendix Figure B2 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 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,

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

[11] 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.

Table 2: Overview of 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
Others			
German 2-Year Govt. Yield		GB2YT=RR	2009–2023
U.K. 2-Year Govt. Yield		DE2YT=RR	2009–2023
Dollar-Euro Exchange Rate		EUR=	2009–2023
Dollar-Pound Exchange Rate		GBP=	2009–2023
S&P 500	E-mini S&P 500 Futures (front-month)	ESc1	2009–2023
VIX	VIX Futures (front-month)	VXc1:VE/VXc1	2011–2023

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 April 2023. *Ticker* refers to the Reuters Instrument Code (RIC). Abbreviations: SOFR—Secured Overnight Financing Rate.

I assume that inflation risk premia are not changing 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. As inflation swaps are less liquid than the other futures contracts employed, I will use a larger window of 90 minutes, 30 minutes before to 60 minutes after, to capture the impact effect of macro news releases.

Others To understand international spillovers, I will also employ German and U.K. government bond yields, as well as U.S. dollar exchanges rates with the Euro and Pound. To measure the response of the S&P 500 and VIX, I use the front-month contract of E-mini S&P 500 and VIX futures, respectively.

4 Effects of Macro News under High and Low 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 which, as discussed earlier, are both theoretically and empirically preferable. I show that price releases, especially the CPI release, lead to much stronger effects under high inflation. In contrast, I detect no difference for real activity news releases. Importantly, the amplification seems to be driven by inflation expectations which are also much more responsive to CPI news since 2021. Lastly, I show similar patterns for international spillovers, that is, exchange rates and international yields, as well as the U.S. stock market.

4.1 Interest Rates

Average effect I begin my empirical analysis by demonstrating that both higher-than-expected price and real activity news leads on average to increases in bond yields. The rationale here 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

$$\Delta y_t = \alpha^k + \beta^{y|k} s_t^k + \varepsilon_t^k, \tag{12}$$

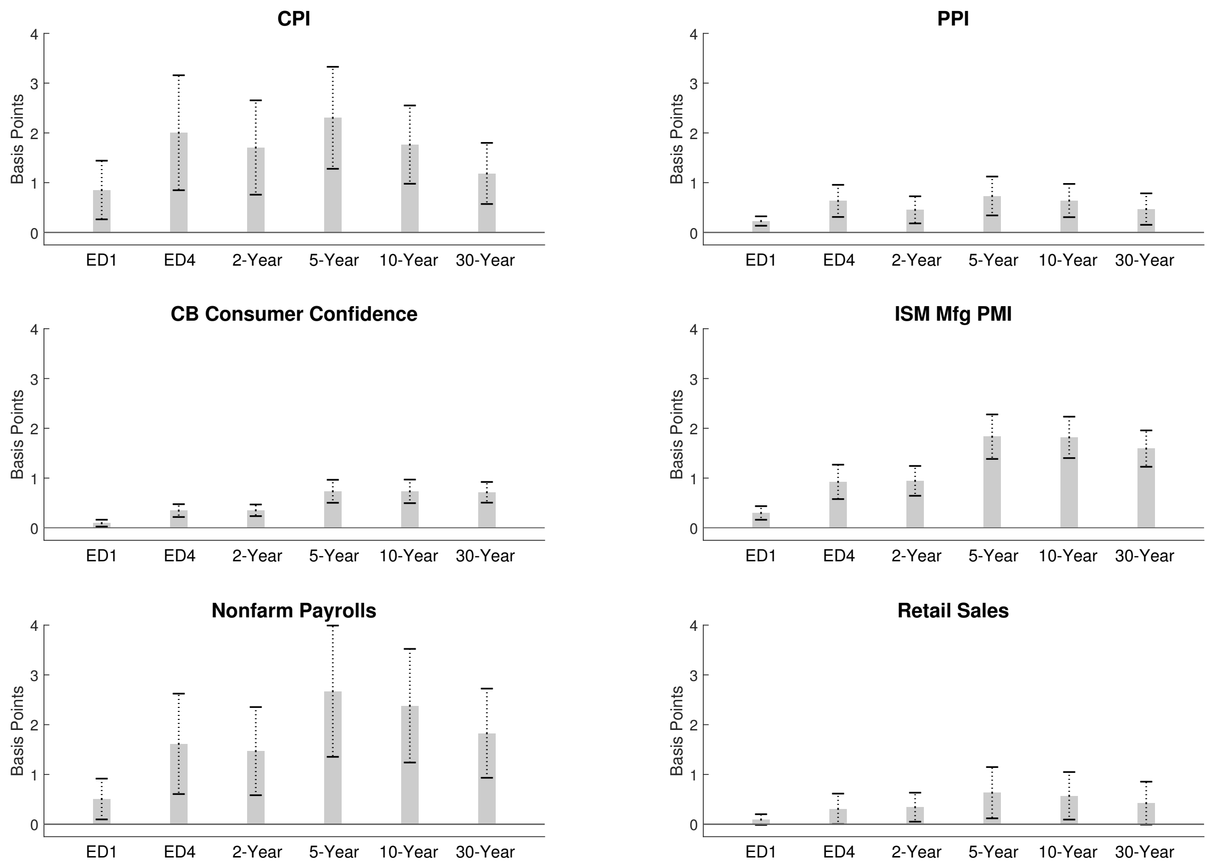
where s_t^k is the announcement surprise of interest, and Δy_t is the 30-minute change in one of the 6 interest rates described in Table 2.

Figure 4 shows the estimates of $\beta^{y|k}$ for each of the six macro releases. First of all, all releases have the expected effects on yields. Higher-than-expected price and real activity news leads to increases in interest rates. Second, all releases have significant effects at the 5 percent level except for Retail Sales, whose effects for the front-month Eurodollar contract (ED1) and the 30-year yield are somewhat more noisy. Third, the magnitudes for real activity news are qualitatively consistent with prior research. Among real activity news, Nonfarm Payrolls and ISM Mfg PMI have the two largest effects. In contrast, price releases have somewhat larger effects than in prior research. Overall, the average effects are very much consistent with the theoretical predictions discussed in Section 2. Appendix Figure C1 shows results for the other major macro releases.

Effect under low and high inflation After investigating the average effects, I now estimate the effect of macro news during the low- and high-inflation period as defined in Section 3. To do so, I estimate, for each announcement series k, the following event study regression

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

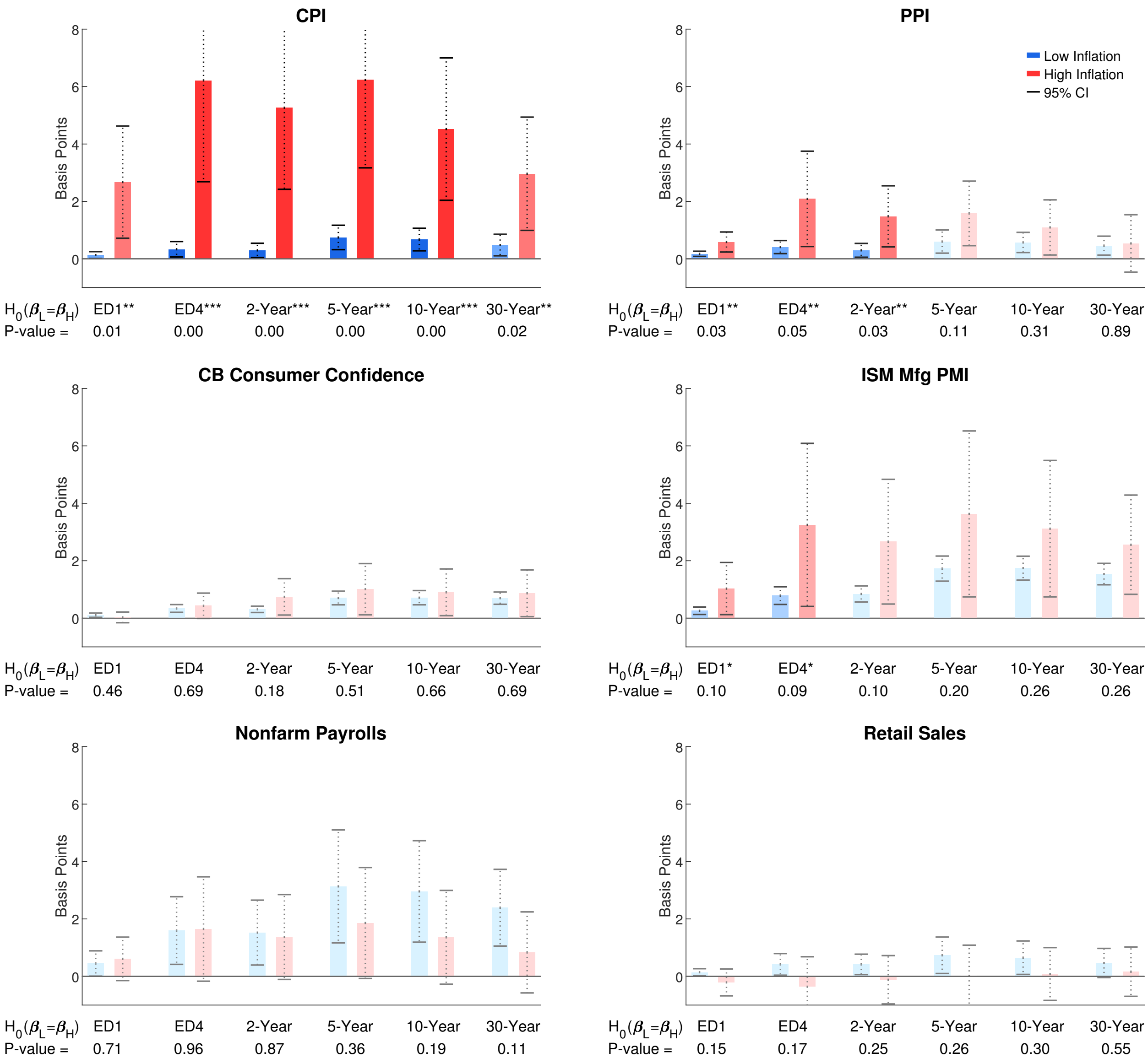
Figure 4: Effects of Macro News on Interest Rates



Notes: This figure shows the responses of the six interest rates for each of the six macroeconomic announcements. Interest rate changes are expressed in basis points and announcements 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 (12). The black error bands depict 95 percent confidence intervals, where standard errors are heteroskedasticity-robust. The interest rate abbreviations are explained in Table 2.

where s_t^k is the announcement surprise of interest, and Δy_t is the 30-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 $\mathbb{1}_{t \in L} = 1 - \mathbb{1}_{t \in H}$.

Figure 5: Effects of Macro News on Interest Rates under Low and High Inflation



Notes: This figure shows the responses of the six interest rates under the low-inflation and high-inflation period for each of the 6 macroeconomic 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 (13), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{y|k}$ of equation (13). 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 5 shows the results for equation (13). The blue bars show the estimates of $\beta_L^{y|k}$

and the red bars display the estimates of $\beta_H^{y|k}$. Equation (13) 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 coefficient $\beta^{y|k}$ of equation (12).[12] For each left-hand side variable, the test's p-value is reported below the interest rate abbreviations in the figure. Based on 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.

The key findings of Figure 5 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 on average more than an order of magnitude larger. The differences $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are also highly statistically significant, either at the one or five percent level. For PPI news, the results are somewhat similar but to a much lesser extent. Importantly, I do not find much evidence for a break in the coefficients for other macro news releases. This also confirmed by Appendix Figure C2, which shows results for the other real activity macro releases.

To better visualize these finding, I also plot the differences in coefficients across low- and high-inflation period for the broader set of releases. In particular, Figure 6 shows the estimates of $\delta_H^{y|k}$ from the following regressions

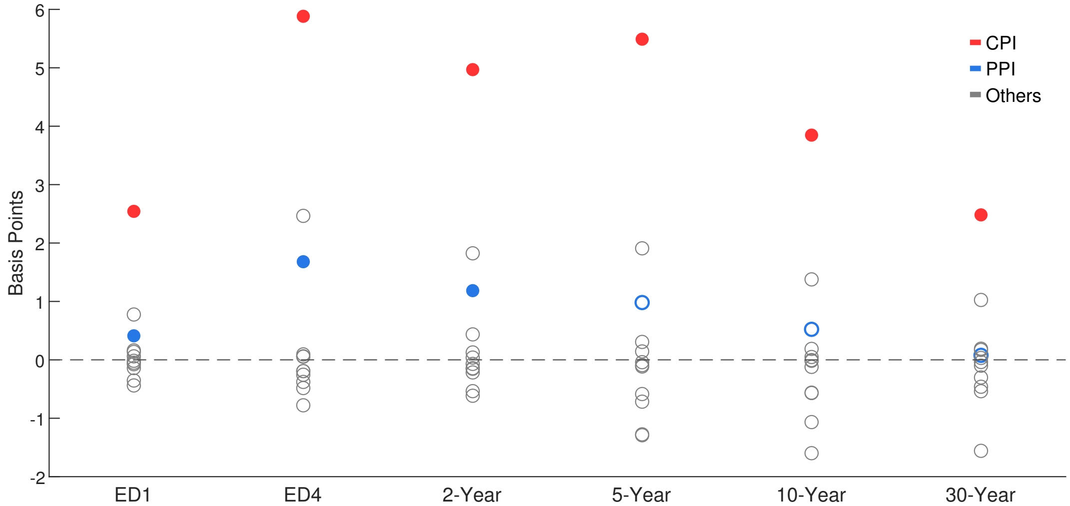
$$\Delta y_t = \alpha^k + \beta_L^{y|k} s_t^k + \delta_H^{y|k} s_t^k \mathbb{1}_{t \in H} + \varepsilon_t^k, \tag{14}$$

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 (13). As Figure 6 shows, the CPI release is the only one which shows large and significant increases in the yield sensitivity across the yield curve.

Robustness The key finding of so far can be summarized as follows: the sensitivity of interest rates to CPI news increased both statistically and economically significant during the recent inflation surge. As the high-inflation period is inevitable small, concerns about how robust this finding arise naturally. In the following, I seek to mitigate these concerns and show that the increased responsiveness is robust across a variety of exercises. First, I show in Appendix Figure C3 for the CPI and PPI *Core Measures*. In both cases, the effects of the core measures are stronger for the low inflation environment. For the PPI, the results for the core measure are somewhat weaker under high inflation. In contrast, effects for the Core CPI are almost identical with a slightly smaller increase in sensitivity for the core measure. The results are consistent with the idea that the headline measure is somewhat

[12] In essence, I am doing a Chow-test. However, I do not allow for separate intercepts in the low- and high-inflation period as it is not implied by the theoretical framework. That being said, I show in Appendix Figure C4 that having separate intercepts does not affect the findings.

Figure 6: Increased Sensitivity of Interest Rates to Macro News under High Inflation



Notes: The figure displays differential responses of the six interest rates for the high-inflation period. For a interest rate, a circle indicates the estimate of coefficient $\delta_H^{y|k}$ of equation (14). 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 releases: Capacity Utilization, CB Consumer Confidence, Durable Goods Orders, GDP A, Initial Jobless Claims, ISM Mfg PMI, New Home Sales, Nonfarm Payrolls, Retail Sales UM Consumer Sentiment P. See Appendix Table B1 for details on the releases.

more subject to an increase in attention as discussed in Section 2.

Second, Appendix Figure C4 displays the robustness of the CPI results to various alternative specifications. In the specification *Separate Intercepts*, I allow for a different intercept for the low-inflation and high-inflation period in equation (13). In the specification *No Positive Surprises*, I remove all positive CPI surprises from the sample. In the specification *No Large Surprises*, I remove all surprises with a standard deviation of more than two. In the specification *Winsorized*, I winsorize the left-hand side variables at the 1 and 99 percent level. In the specification *Sample from 1996*, I start the low-inflation sample in 1996 instead of 2009. As Appendix Figure C4 shows, the main finding is robust across all these specifications.

Lastly, in Appendix Figure C5, I investigate the robustness of my analysis with respect to the *break point* between low- and high-inflation period. Consistent with the argument laid out in Section 2, choosing an earlier break month relative to the baseline leads to slightly less significant differences. That being said, the figure shows that main findings are robust towards choosing different break months.

4.2 Inflation Expectations

Average effect 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 as well which I am going to investigate in this section. Eventually, the goal of this section is to connect the increased interest rate sensitivity to CPI news to a rise in sensitivity of inflation expectations.

To do so, I will study the effect of price news on inflation swap rates in this section. The focus on price news is due to the clear theoretical relationship between news and inflation expectations. Higher-than-expected inflation should lead to increases in expectations. This relationship should stable be relatively stable across time regardless of the underlying shocks, in particular for short-term expectations.[13] In contrast, real activity news should have unstable effects on inflation expectations depending if the underlying shocks are more from the demand or supply side.

As for interest rates, I start by estimating the average effects over the sample period. In particular, I estimate regressions of the following form

$$\Delta\pi_t = \alpha^k + \beta^{\pi|k} s_t^k + \varepsilon_t^k, \tag{15}$$

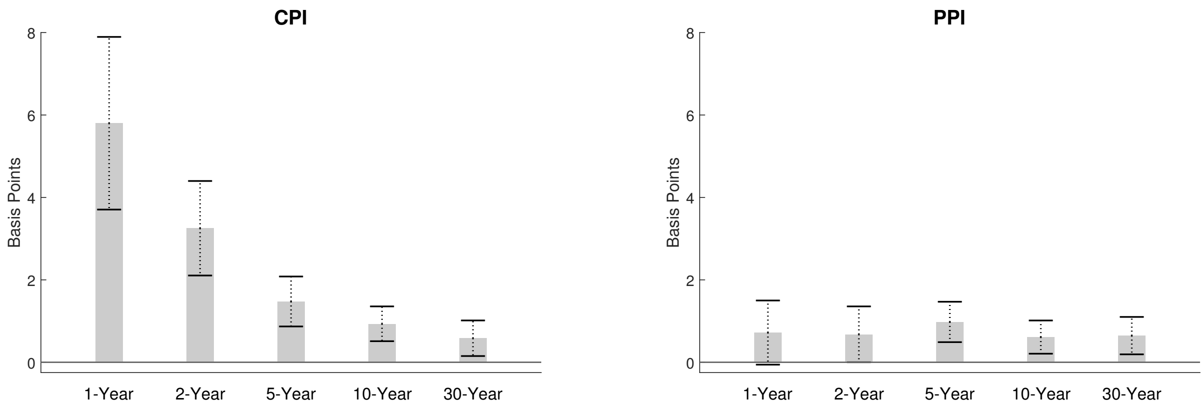
where s_t^k is the announcement surprise of interest, and $\Delta\pi_t$ is the 90-change change in one of the 5 inflation swap rates described in Table 2.

Figure 7 shows the estimates of $\beta^{\pi|k}$ of equation (15) for each of the two price releases. Let me emphasize a couple of things: First, for both price releases, the empirical relationship is consistent with the theoretical counterpart. Higher-than-expected price news leads to an increase in inflation expectations. Second, consistent with the interest rate responses, the effects on inflation expectations are substantially larger for the CPI surprises. Third, the downward sloping curve of inflation expectations suggests that market participants expect the Federal Reserve to bring down inflation in the medium to long-run, i.e., long-run inflation expectations are anchored over the sample period.

Appendix Figure C6 shows the responses of the inflation swap rates to a broader set of macro releases. As the results show, none of the real activity releases have statistically or economically significant effects. As both ISM Mfg PMI and CB Consumer Confidence

[13]For medium- and longer-term expectations, it might matter if the source of inflation is seen more as demand or supply driven.

Figure 7: Effects of Price News on Inflation Swap Rates



Notes: This figure shows the responses of the five interest rates for the two price 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 (15). The black error bands depict 95 percent confidence intervals, where standard errors are heteroskedasticity-robust.

lead to somewhat systematic responses, I also study the effects under low and high inflation for both of them. Consistent with the findings for interest rates, I find signs of increased sensitivity of inflation swap rates to ISM Mfg PMI, while none for CB Consumer Confidence. Overall, the findings support the idea that the increased sensitivity of interest rates is driven by the sensitivity of inflation expectations.

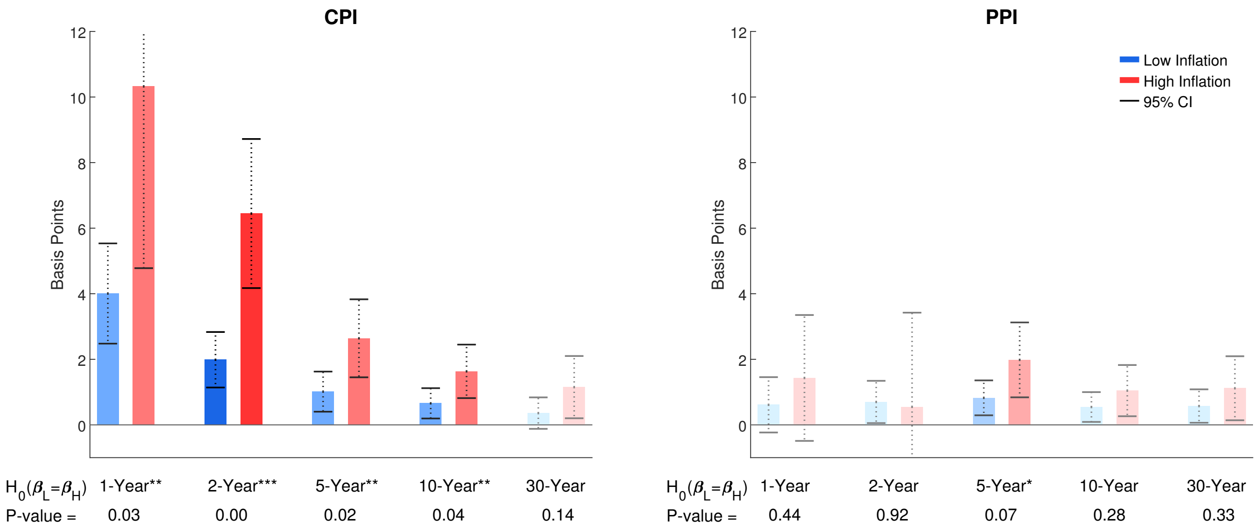
Effect under low and high inflation I now turn to the estimation of inflation swap rate responses under low and high inflation. To do so, I estimate for each price series k the following event study regression

$$\Delta \pi_t = \alpha^k + \beta_L^{\pi|k} s_t^k \mathbb{1}_{t \in L} + \beta_H^{\pi|k} s_t^k \mathbb{1}_{t \in H} + \varepsilon_t^k, \tag{16}$$

where s_t^k is the announcement surprise of interest, and $\Delta \pi_t$ is the 90-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 in during the low-inflation period and zero otherwise. $\mathbb{1}_{t \in H}$ is defined accordingly. Note that $\mathbb{1}_{t \in L} = 1 - \mathbb{1}_{t \in H}$.

Figure 8 displays the results for equation (16). A couple of things stand out: First, similar to the interest rates sensitivity, the inflation swap are become also substantially more responsive during the high inflation period. This is in particular prevalent for swap rates of shorter maturities, where differences are both economically and statistically significant.

Figure 8: Effects of Price News on Inflation Swap Rates under Low and High Inflation



Notes: This figure shows the responses of the five inflation swap rates under the low-inflation and high-inflation period for the two price 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 (16), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{\pi|k}$ of equation (16). 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 interest rate. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests.

Second, the response of the PPI shows much less increased sensitivity. This is somewhat consistent with the interest rates responses. Third, the sensitivity of short-term inflation swap rates to CPI surprises is sizable during the low inflation compared to the interest rate effects. This is consistent with the idea that the Federal Reserve allows inflation to rise when it is below target.

Robustness Appendix Figure C4 displays the robustness of the CPI results to various alternative specifications. In the specification *Separate Intercepts*, I allow for a different intercept for the low-inflation and high-inflation period in equation (13). In the specification *No Positive Surprises*, I remove all positive CPI surprises from the sample. In the specification *No Large Surprises*, I remove all surprises with a standard deviation of more than two. In the specification *Winsorized*, I winsorize the left-hand side variables at the 1 and 99 percent level. As Appendix Figure C4 shows, the main finding is robust across all these specifications. Lastly, I also show the results for Core CPI. Interestingly, the differences are less strong with the core measure since relative to headline inflation, the effects of core inflation are stronger during low-inflation and weaker during the high-inflation period.

Lastly, in Appendix Figure C5, I investigate the robustness of my analysis with respect to the *break point* between low- and high-inflation period. Consistent with the argument laid out in Section 2, choosing an earlier break month relative to the baseline leads to slightly less significant differences. That being said, the figure shows that main findings are robust towards choosing different break months.

4.3 International Spillovers

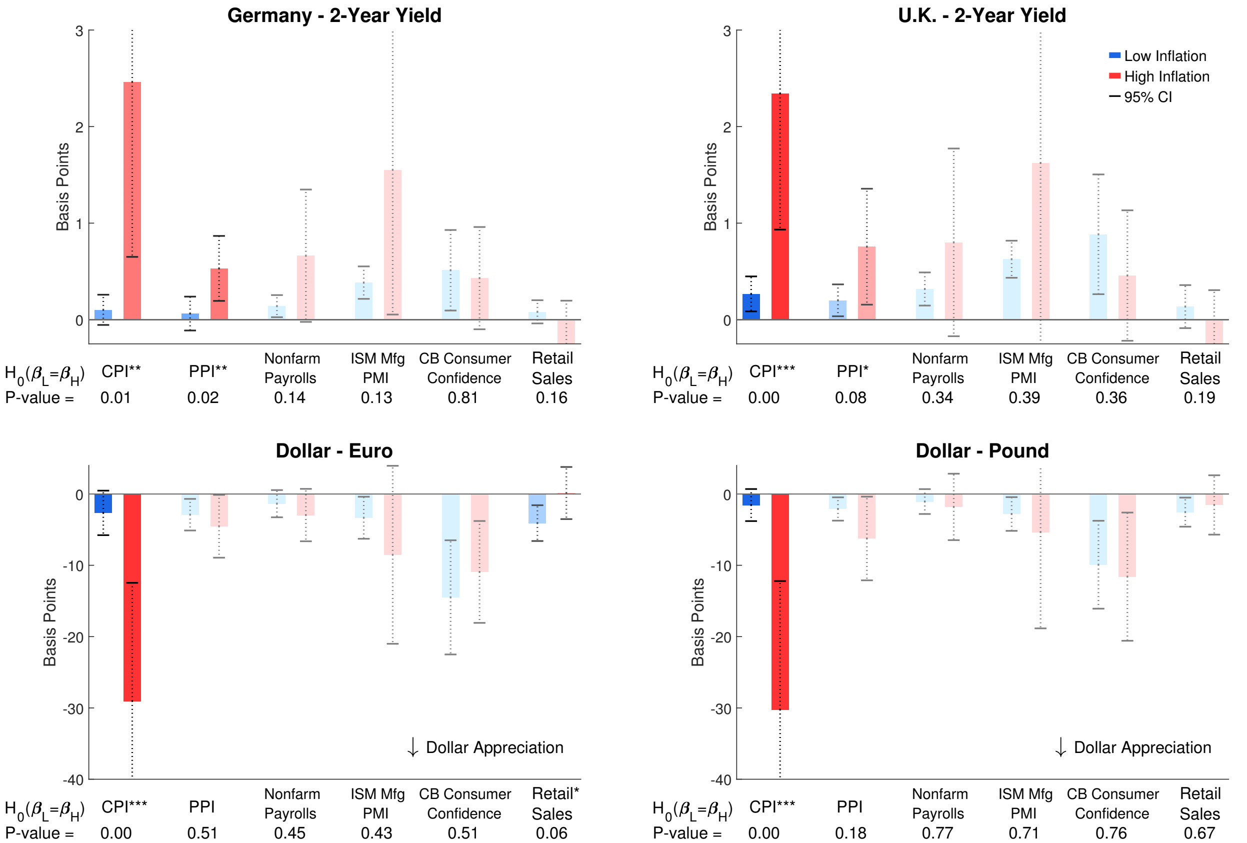
I now turn to the international transmission of U.S. macro news releases. Particularly, I want to show that the stronger effects of CPI releases are not only a phenomenon in the domestic context, but also in the international one. To do so, I rerun equation (13). However, instead of having domestic yields as the left-hand side variables, I employ 30-minute changes in the German and U.K. yield, as well as dollar-euro and dollar-pound exchange rate.

Figure 9 displays the results. In contrast to previous figure, each panel in Figure 9 keeps the left-hand variable fixed and shows the estimates of $\beta_L^{x|k}$ and $\beta_H^{x|k}$ for each of the six macro announcements. Let me point the following: first and foremost, all four panels show that the sensitivity of asset prices increased significantly, both in an economic and statistical sense. In comparison, none of the other releases show similar patterns. Second, the top two panels illustrate that the international yields respond stronger consistent the domestic response. Third. the bottom two panels show that the dollar appreciates under high inflation much more strongly. This can be rationalized by the interest rate differentials. Whereas the 2-year yields in Germany and U.K. increase by about 2.3 basis points, the U.S. yield (shown in Figure 5 above) responds by more than 6 basis points.

4.4 Stock Market

In this section, I am taking a look at the stock market. It is well known that the effects of macro news on the stock market are not stable as previous papers have shown (e.g., Boyd, Hu, and Jagannathan, 2005). The intuition is that discount rates and equity premia in addition to discount rates makes transmission of macro news over time more complicated and potentially unstable. Hence, I will focus in this section exclusively on the CPI news. As the cause of the unstable effect is still not entirely settled, I employ an estimation approach which allows for time-varying effects in a flexible way without taking a stand on the underlying source.

Figure 9: Effects of Macro News on International Asset Prices



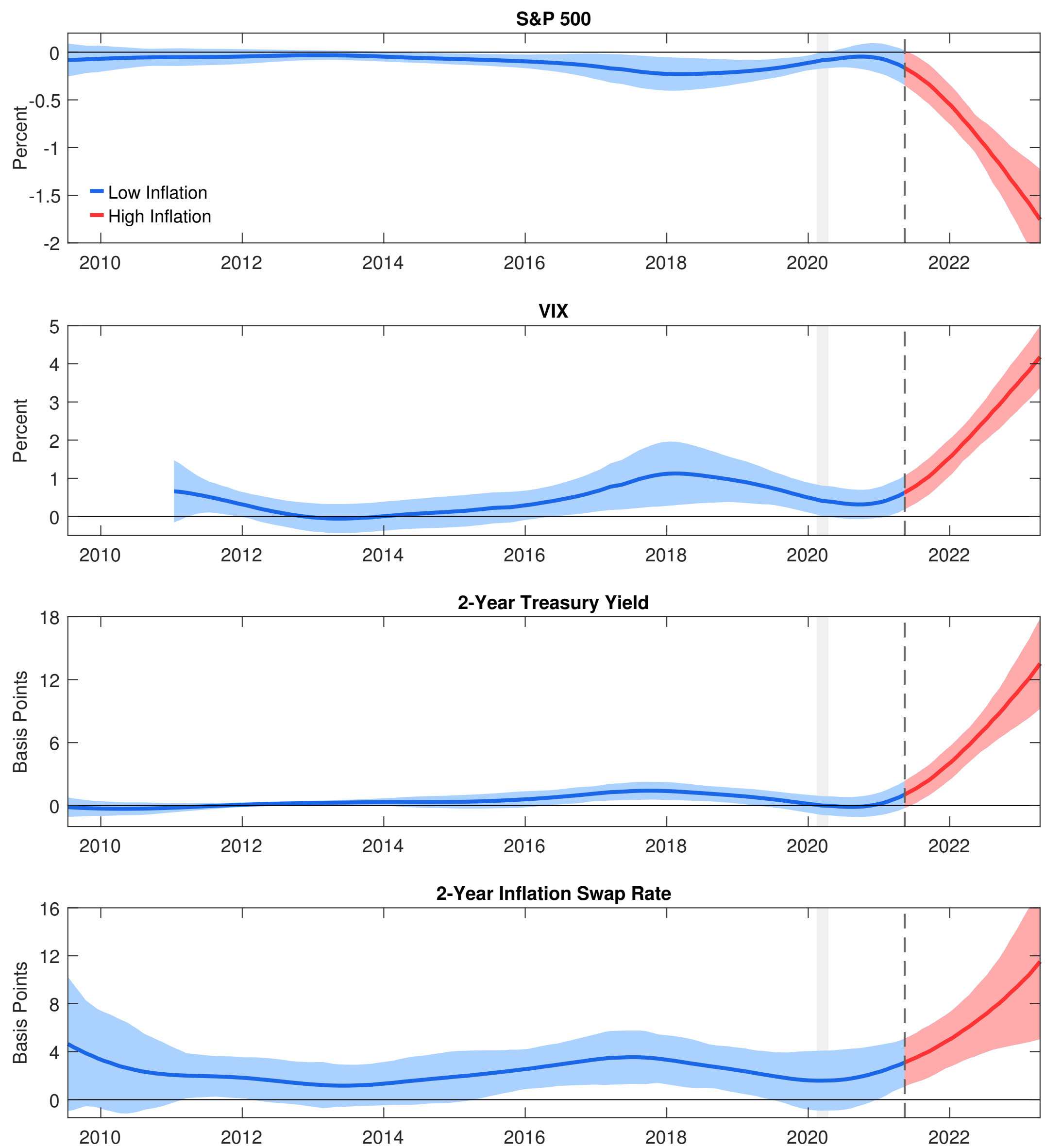
Notes: This figure shows the responses of four different international asset prices under the low-inflation and high-inflation period for the six macroeconomic announcements. Each panel shows results of estimating $\beta_L^{x|k}$ and $\beta_H^{x|k}$ of equation (11) after replacing the left-hand side with the 30-minute change of the corresponding asset prices. The top-left and top-right panels display the results for the German and U.K. 2-year yield, while the bottom-left and bottom-right panels shows the estimates for the dollar-euro and dollar-pound exchange rates. Interest rate and exchange rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. 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 interest rate. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests.

To do so, I employ the nonparametric estimation approach based on Robinson (1989) and Cai (2007), which, for example, has been recently used by Farmer, Schmidt, and Timmermann (2023) in a different context. For my purposes, I estimate the following regression

$$\Delta x_t = \alpha^k + \beta_t^{x|k} s_t^k + \varepsilon_t^k, \tag{17}$$

for $k \in$ CPI, and Δx_t is the 30-minute change in the asset price of interest. To measure the effect on the stock market, x will be the front-month E-mini S&P 500 or VIX futures contract.

Figure 10: 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 (17) for different dependent variables. The top two panels show results for the S&P 500 and the VIX based on the corresponding front-month futures contracts, while the bottom two for the 2-year Treasury rate and inflation swap rate. 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.

Broadly speaking, the estimation idea is to view β 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 simply 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 Gaussian density function with a standard deviation of 12 months (12 observations) which is determined by the chosen bandwidth. Confidence intervals are constructed following the bootstrap procedure by Fan and Zhang (2000) and Chen et al. (2018).[14]

Figure 10 shows the results. The four panels paint a cohesive picture. As the sensitivity of the swap rate and interest rate is increasing consistent with the findings in the previous sections, the sensitivities of the S&P 500 and VIX are also increasing consistent with a dominant effect of interest rates.

5 Attention to Macro News under High and Low Inflation

To do so, I employ two proxies of attention, trading volume and Google searches, to provide more direct evidence on the attention-based mechanism in the theoretical framework, which is consistent with the results on the sensitivity of asset prices shown Section 4.

5.1 Trading Volume

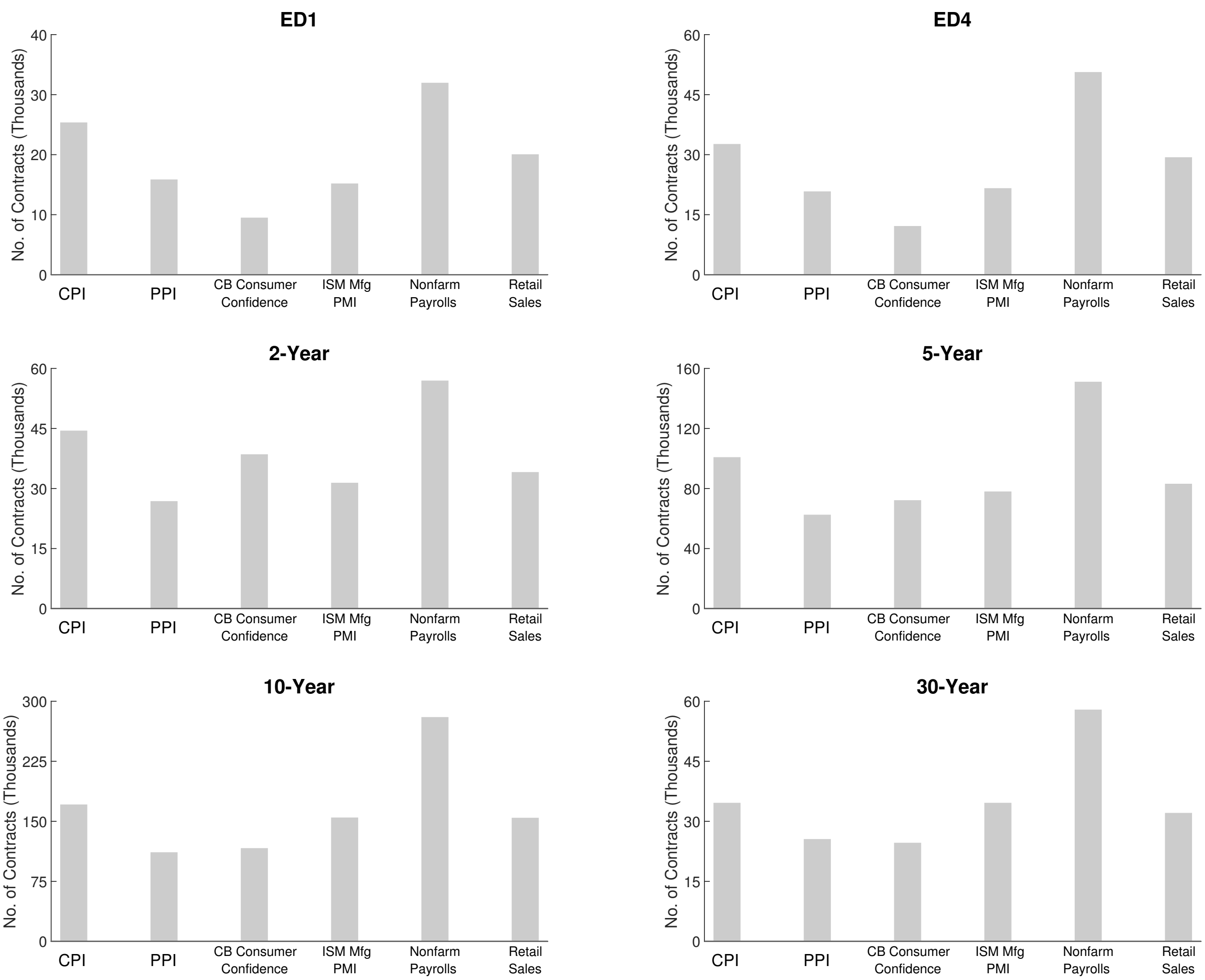
In this section, I look at the trading volume of the interest futures contracts employed in the previous sections. Trading volume has been used previously as a proxy of attention (e.g., Huberman and Regev, 2001; Barber and Odean, 2008). As mentioned in Section 2, trading volume has used by DellaVigna and Pollet (2009) to directly test the amount of attentive investors. In this section, trading volume will be measured as the number of contracts traded in a given time window. The data is coming directly from *Refinitiv*. Details on the construction are provided in Appendix B.2.

I start with the average trading volumes around each macro announcement which are constructed based on 30-minute windows and are shown in Figure 11. Let me point out the following things: First, there is quite a bit of heterogeneity across futures contracts as, for example, 5 and 10-year futures are much more traded than the other ones. Second and more importantly, there is heterogeneity across announcements with nonfarm payrolls announcements having the largest volume around its releases. This heterogeneity seems

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

stable across asset prices. It also shows that the trading volume around CPI releases is constantly higher compared to the PPI ones consistent with the idea of being more important.

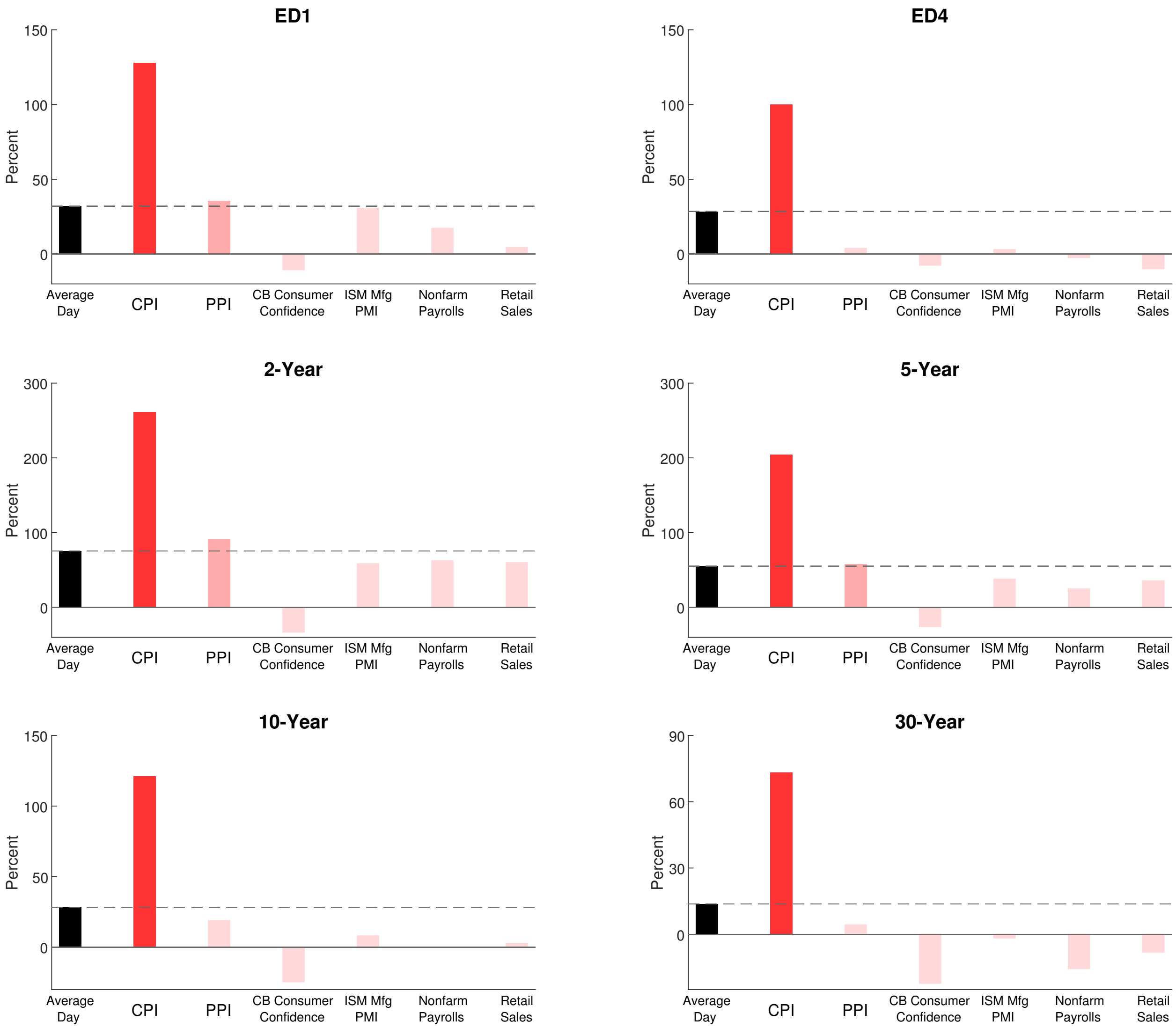
Figure 11: Average Trading Volume around Macro Announcements



Notes: This figure shows the average trading volumes around of each of the 6 macroeconomic announcements over the sample period. Each panel refers to the trading volume of a given interest rate futures contract. Trading volumes are based on 30-minute windows around releases.

More important for the analysis at hand is how the volume changed from the low-inflation to the high-inflation period. The percentage changes are shown in Figure 12. As the figure shows the percentage is starkly increasing for around releases. Since the trading volume have been generally increasing over the sample period, I also show in the with bar in each panel the average percentage increase from the low- to the high-inflation subperiod. Except for PPI, none over the other releases shows signs that trading volume increased during the recent high inflation period.

Figure 12: Changes in Trading Volume around Macro News under High Inflation



Notes: This figure displays the percent change in trading volumes around each of the 6 macroeconomic announcements from the low-inflation to the high-inflation period. Each panel refers to the trading volume of a given interest rate futures contract. Trading volumes are based on 30-minute windows around releases. *Average Day* is constructed based on daily volumes and serves as a reference point.

5.2 Google Searches

In this section, I turn to Google searches as another proxy for attention (e.g., Da, Engelberg, and Gao, 2011). As pointed out byBen-Rephael, Da, and Israelsen (2017), Google searches will most likely capture attention by retail investors, i.e., by the broader population. Google provides data on search interest over time via its platform *Google Trends*. Over the employed sample period, that is, from January 2009 until May 2023, 84 percent of all search queries in the United States have been performed through Google.[15] 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.

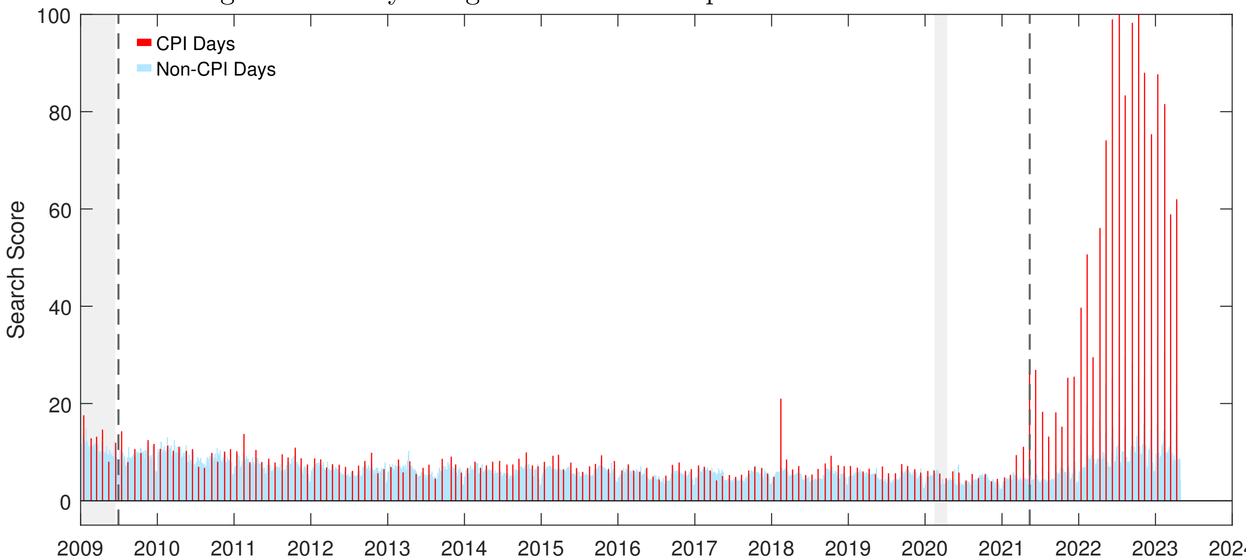
Based on the previous results, my primary focus is on the topic "Consumer Price Index". I want to measure to particular the specific release, I am not interested in searches for the word "inflation", as employed by Korenok, Munro, and Chen (2022), which cannot be directly linked to a release. For a given topic, I construct a daily search score series over the sample. While Google trends provides daily data per se, the construction involves various steps to create a internally consistent daily series over the entire sample period. Appendix B.3 provides the details of this construction. The resulting series for "Consumer Price Index" is shown in Figure 13.

As the figure shows, the searches on days with no CPI release (non-CPI days), the 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 are very similar across days, the search interest on release days is spiking up with the start of the high inflation period.

Similar to the analysis earlier, I also compare the patterns for topic "Consumer Price Index" with other topics which can be directly linked to a major macro release. In particular, I look at topics "Producer Price Index", "Nonfarm Payrolls", and "Gross Domestic Product". Figure 14 provides an overview of this. As the figure shows, topic "Producer Price Index" shows a similar pattern as the "Consumer Price Index". Note that the search scores are comparable across topics. That means that search magnitudes are smaller for the "Consumer Price Index" which is consistent the results in the previous sections. Looking at topics "Gross Domestic Product" and "Nonfarm Payrolls". Lastly, two points with validates that sanity of the data. First, in all cases the searches on data release dates are higher than on non-release

[15] https://gs.statcounter.com/search-engine-market-share/all/united-states-of-america/#monthly-200901-202305 (accessed on July 20, 2023).

Figure 13: Daily Google Searches for Topic “Consumer Price Index”



Notes: This figure 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. *Search Score* is normalized such that 100 corresponds to the largest observation over the sample period. See text for details on the construction. *CPI Days* refers to days with a CPI release, while *Non-CPI Days* to the rest.

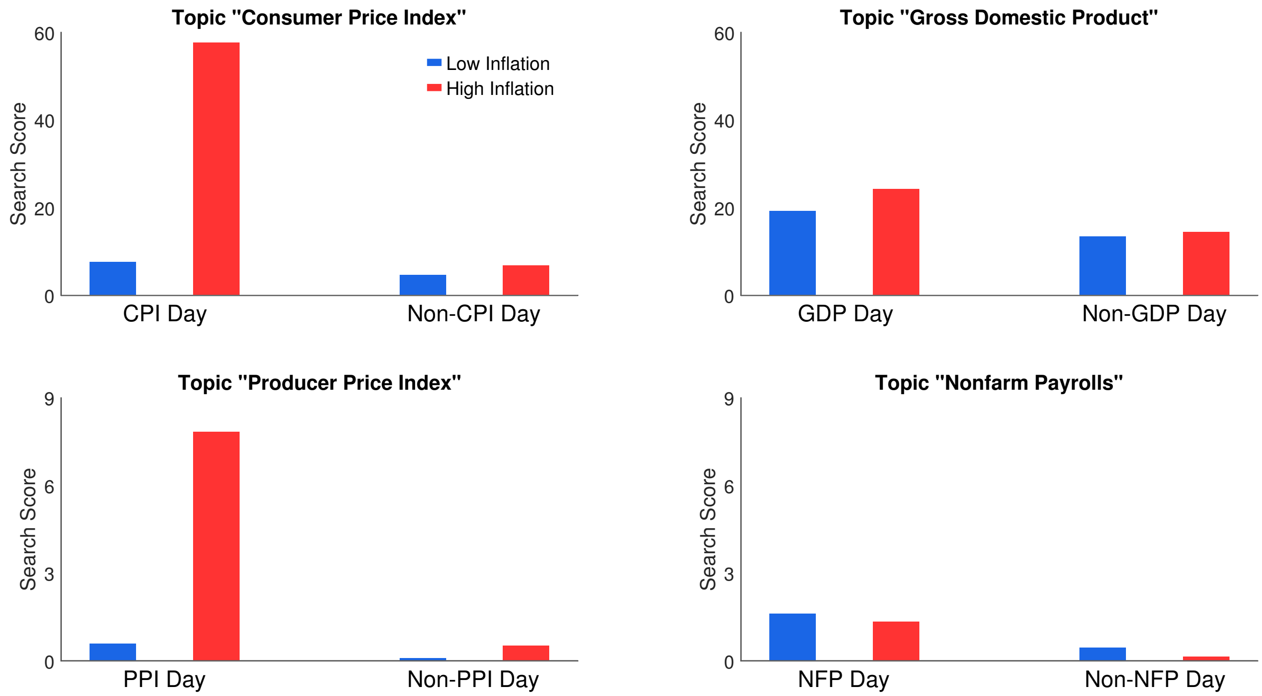
days. Second, the fact that “Gross Domestic Product” and “Consumer Price Index” have substantially larger search volumes on average seems also reasonable.

6 Discussion

Source of attention: inflation rate versus inflation uncertainty One point I have been agnostic about so far is why exactly people are paying more attention. As inflation is rising, it is not entirely clear if the inflation level is causally leading to the increased attention or if some other variable is behind it. From an econometric perspective, this is a difficult question to answer as the small sample of elevated inflation leads to a lack of statistical power to do a horse race across variables. That being said, the research design already ruled out many candidates as discussed throughout the draft.

One candidate which could also explain the findings, could be inflation uncertainty. Prior papers have shown that economic uncertainty can be directly linked to attention (Benamar, Foucault, and Vega, 2021; Andrei, Friedman, and Ozel, 2023). As inflation increased, inflation uncertainty likely increased as well. To investigate this, I plot the CPI inflation rate as well as three measures of inflation uncertainty in Figure 15. First, shown in the top-right

Figure 14: Average Google Searches for Different Macro Topics



Notes: This figure shows the average Google search scores for four different topics over the sample period. Each of the four panels corresponds to a specific topic and displays the average search scores on days on which the corresponding macroeconomic data series is released (left) and on other days (right). Blue bars display scores during the low-inflation period and red bars during the high-inflation period. *Search Score* is normalized such that 100 corresponds to the largest observation for the topic "Consumer Price Index" over the sample period.

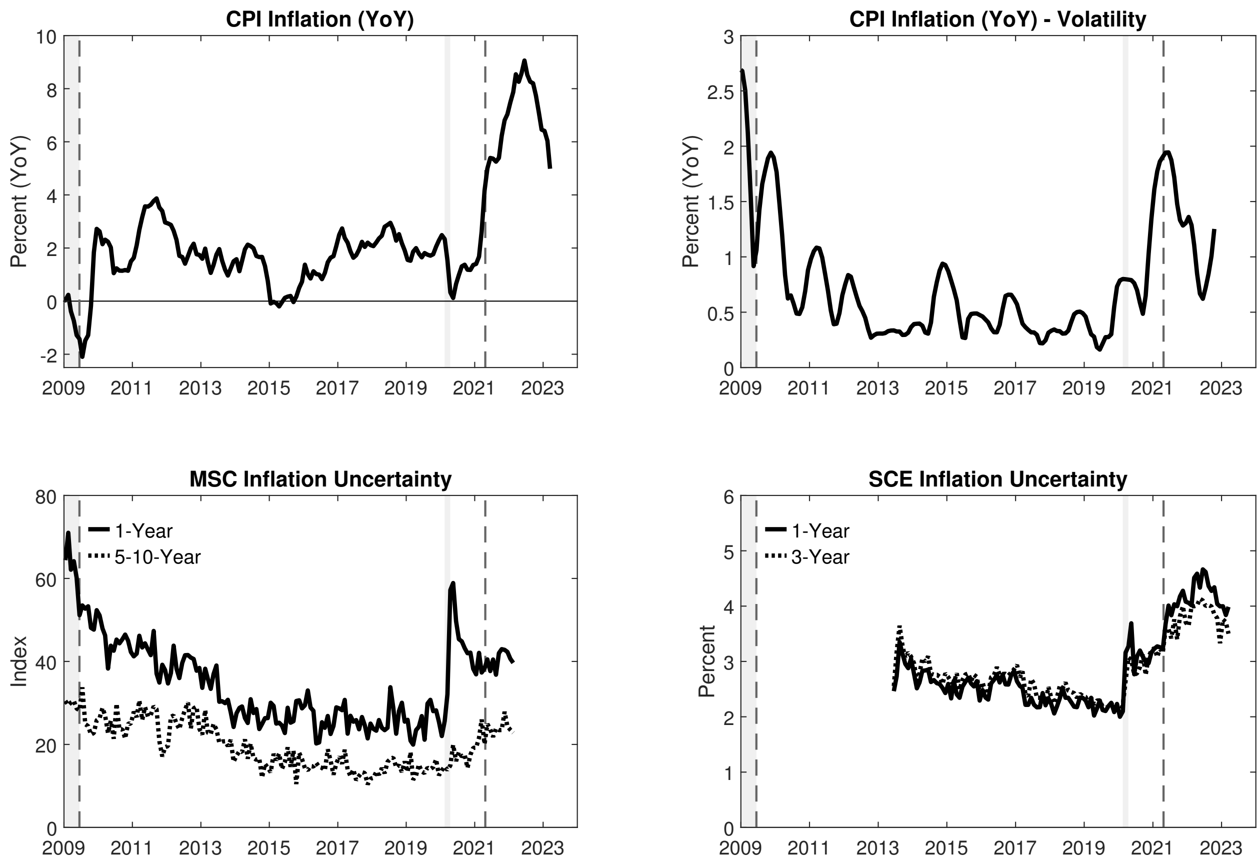
panel, I plot the 12-month realized volatility of CPI inflation. Second, I use the inflation uncertainty indexes by Binder (2017) shown in the bottom-left panel. Third, the bottom-right panel of 15 shows the inflation uncertainty measures from the Federal Reserve Bank of New York.

Looking at the realized volatility, one key difference to the inflation level is that it is as high coming out the Great Recession as it is during the 2021 inflation surge. However, looking at Figure 10, there is no increased sensitivity at the beginning of the sample. A similar picture emerges when looking at the inflation uncertainty indexes by Binder (2017). Binder (2017) uses the Michigan Survey of Consumers (MSC) to construct uncertainty measures exploiting the rounding of reported inflation expectations of survey participants. I refer the interested reader to Binder (2017) for details on the construction. Based on this measure, the 1-year uncertainty shows a somewhat similar pattern as the realized volatility.

The bottom-right panel of Figure 15 shows the inflation uncertainty measures from the

Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE). These are based on the interquartile range of the median density quartiles. See Armantier et al. (2017) for details on this. As the measures only start in 2013, I cannot look at the uncertainty around the Great Recession. Overall, the measure seems to be consistent with the empirical evidence so far. However, it should be noted that the size differences in uncertainty are relatively small between the low- and high-inflation sample. This is true for all uncertainty measures.

Figure 15: Inflation Rate and Inflation Uncertainty Measures



Notes: This figures plots CPI inflation (YoY), as well as measures of inflation uncertainty from January 2009 until March 2023 (or till available). The top-left panel displays the CPI inflation rate as shown as in Figure 2. The top-right panel plots the 12-month realized volatility of CPI inflation around a given point in the graph. The bottom-left panel shows the inflation uncertainty indexes by Binder (2017) based on the Michigan Survey of Consumers (MSC). The bottom-right panel plots the inflation uncertainty measures from the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE). The dotted, vertical lines illustrate the splits into the low- and high-inflation periods as defined in Section 3.1.

More recently, Londono and Samadi (2023) construct ex-ante uncertainty measures related to macro announcements based on daily S&P 500 index options. Their measure starts in 2017 and shows that uncertainty with respect to CPI release increasing during inflation surge. However, two patterns do not really match my findings. First, uncertainty for the CPI release increases during the COVID-19 pandemic. Second, uncertainty with respect to Nonfarm Payrolls shows a qualitatively similar pattern to the one for CPI releases.

In summary, while I cannot rule out that inflation uncertainty plays a role in the increased attention, certain patterns in the observable uncertainty measures do not fit in terms of timing as well as the actual level of inflation. Hence, the evidence seems to suggest that high levels of inflation are the actual driving forces of the findings presented in this paper.

7 Conclusion

In this paper, I provide novel evidence that the inflation environment is a key determinant of people's attention to inflation. I do so by studying the high-frequency effects of U.S. macroeconomic news releases on asset prices following the 2021 inflation surge. Consistent with increased attention to inflation, I find that price news releases, in particular the release of the CPI, have much larger effects on interest rates and on inflation expectations, measured by inflation swap rates, during the recent high-inflation period. This increase in sensitivity compared to the previous, low-inflation environment is economically and statistically significant. It is also present for a broader range of asset prices such as stocks, exchange rates, and foreign interest rates. Importantly, other, not price-related macro news releases, such as Nonfarm Payroll Employment, do not show any significant changes in effect sizes during the high-inflation period. Additional evidence from trading volumes and Google searches, two proxies of attention, further corroborates the interpretation that attention to CPI releases increased starkly with the increase in inflation.

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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. Plugging (A2) into (A1), 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

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

and

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

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 $\mathrm{E}_t^{\mu}[\cdot]$ be the expectation of attentive investors at date t, and let $\mathrm{E}_t^{1-\mu}[\cdot]$ be the expectation of inattentive investors at date t. Similarly, I define $\mathrm{Var}_t^{\mu}[\cdot]$ and $\mathrm{Var}_t^{1-\mu}[\cdot]$ 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

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

where ξ 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

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

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.,

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

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

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

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 λ_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 λ_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 λ_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 λ_2^i yields

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

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

$$\begin{aligned}
P_1 &= \mathrm{E}_1[V] \\
&= 1. \qquad \text{(A14)}
\end{aligned}$$

A.5.2 Price P_2

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

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

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

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

where I used

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

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

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

where the weighted average expectation is defined as $\mathrm{E}_t[\cdot] = b_t \mathrm{E}_t^{\mu}[\cdot] + (1-b_t)\mathrm{E}_t^{1-\mu}[\cdot]$, where the weight 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

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

and hence

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

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

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

Subsequently, expression b_2 can be written as

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

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

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

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^π

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

and inattentive investors still do not expect any changes

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

The average inflation expectation at date 2 is given by

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

which allows one to rewrite 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 β_μ^y and β_μ^π, as defined in (8) and (9), can be written as

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

and

$$\begin{aligned}
\beta_\mu^{\pi|\pi} &= \frac{\mu\xi}{1-\xi\,(1-\mu)} \\
&= b\xi.
\end{aligned}$$

As $0 \leq \xi, \mu \leq 1$, the partial derivative of b with respect to μ is

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

As ϕ, ξ, and τ are independent of μ, this implies that

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

B Data Appendix

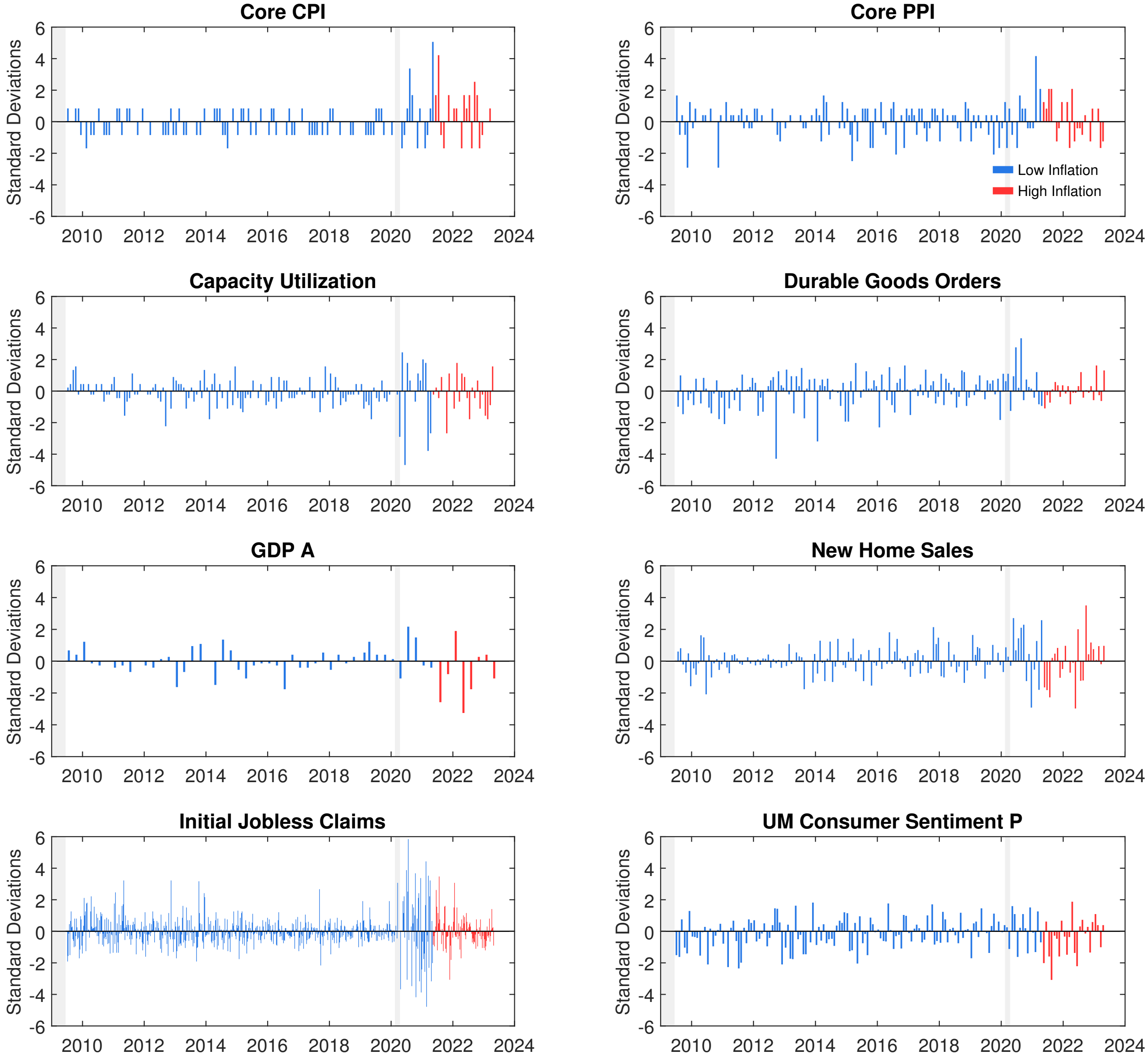
B.1 Macroeconomic News Releases

Table B1: Overview of Major US Macroeconomic News

Announcement	Release Time	Frequency	Category	Observations		
				Total	Low	High
Core CPI	8:30 am	Monthly	Price	164	141	23
Core PPI	8:30 am	Monthly	Price	166	142	24
CPI	8:30 am	Monthly	Price	164	141	23
PPI	8:30 am	Monthly	Price	166	142	24
Capacity Utilization	9:15 am	Monthly	Real Activity	165	142	23
CB Consumer Confidence	10:00 am	Monthly	Real Activity	166	142	24
Durable Goods Orders	8:30 am	Monthly	Real Activity	165	141	24
GDP A	8:30 am	Quarterly	Real Activity	56	48	8
Initial Jobless Claims	8:30 am	Weekly	Real Activity	707	604	103
ISM Mfg PMI	10:00 am	Monthly	Real Activity	166	143	23
New Home Sales	10:00 am	Monthly	Real Activity	165	141	24
Nonfarm Payrolls	8:30 am	Monthly	Real Activity	163	140	23
Retail Sales	8:30 am	Monthly	Real Activity	166	142	24
UM Consumer Sentiment P	10:00 am	Monthly	Real Activity	166	142	24

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 April 2023. *Frequency* refers to the frequency of the data releases and *Observations* to the number of observations (surprises) of a macroeconomic series in our sample. *Category* specifies if the news release is predominantly informative about real activity or prices. Abbreviations: A—advanced; P—preliminary; Mfg—Manufacturing; CB—Chicago Board; UM—University of Michigan; ISM—Institute for Supply Management; PMI—Purchasing Managers' Index.

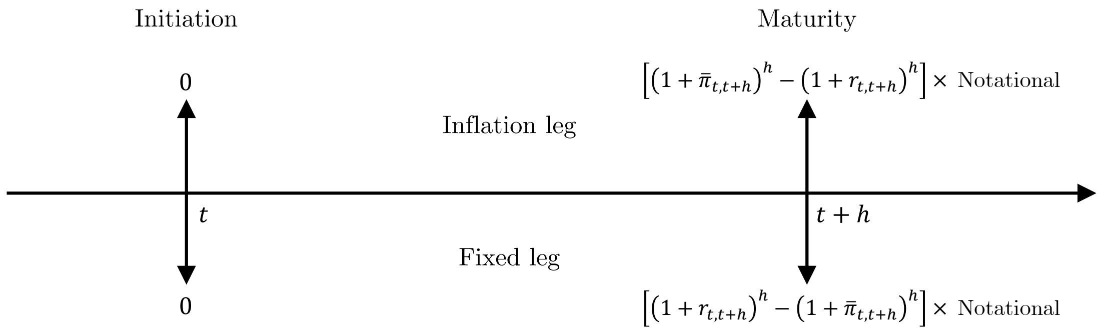
Figure B1: Low and High Inflation Sample based CPI Inflation



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

Figure B2: 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 h-year zero-coupon inflation swap in the U.S. See, e.g., Kerkhof (2005) for a more detailed discussion on inflation swaps.

B.3 Google Trends

This is mostly due the fact that a daily Google Trends request of maximum 90 days is allowed and a request is only a representative sample of the underlying data and search scores are relative to the requested.

The construction of the daily search score series is done in the following steps:

1. For given topic in Google Trends, 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 May 2023, I obtain 88 subsamples for a given topic.

2. I merge the 88 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 20 times. That is, for each topic I obtain 20 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 way Google Trends works 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

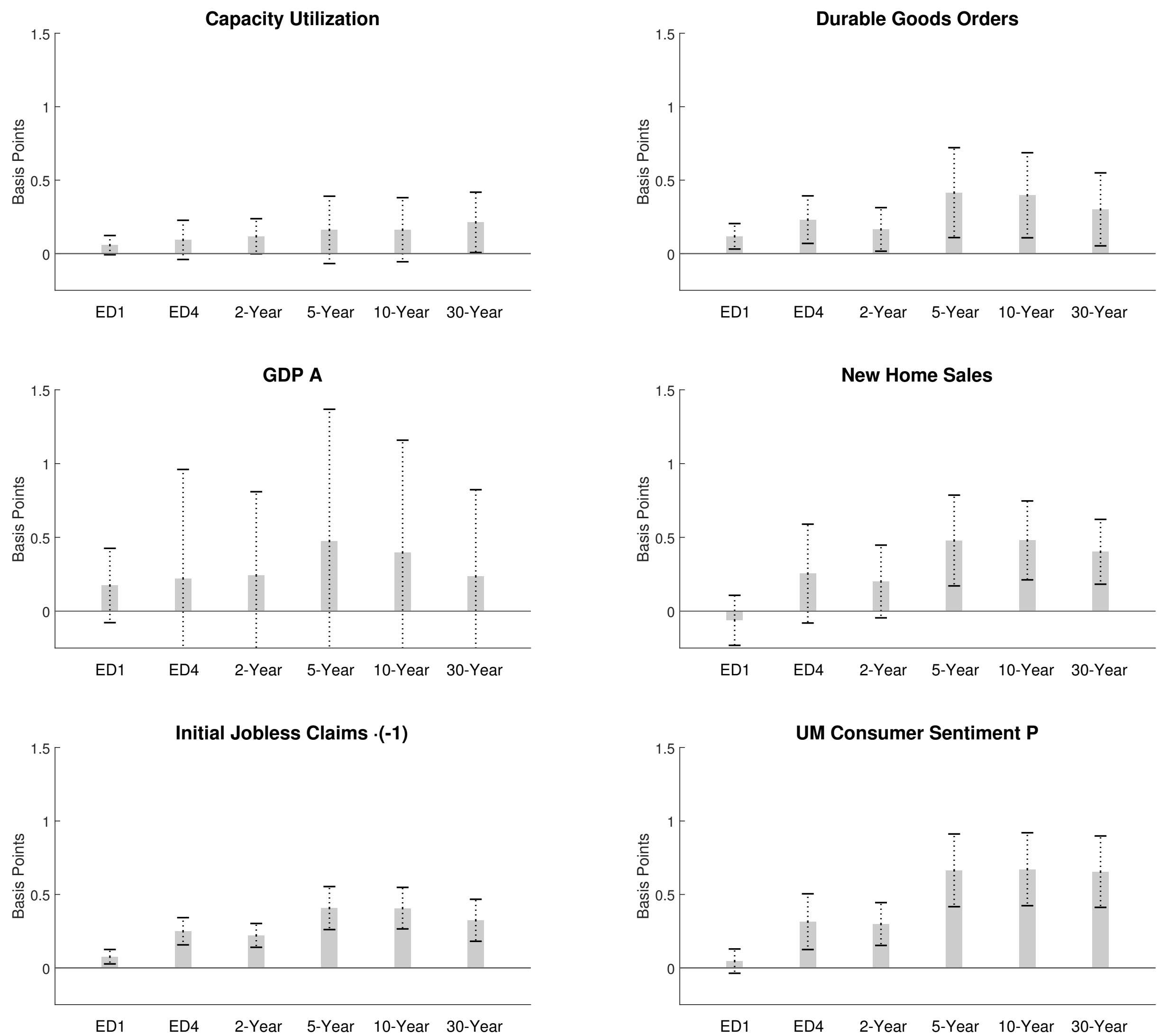
to the largest observation for topic “Consumer Price Inflation”. As before, I repeat the joint monthly download n times and use the median of that series for the rescaling.

C Additional Results

C.1 Additional Results for Section 4

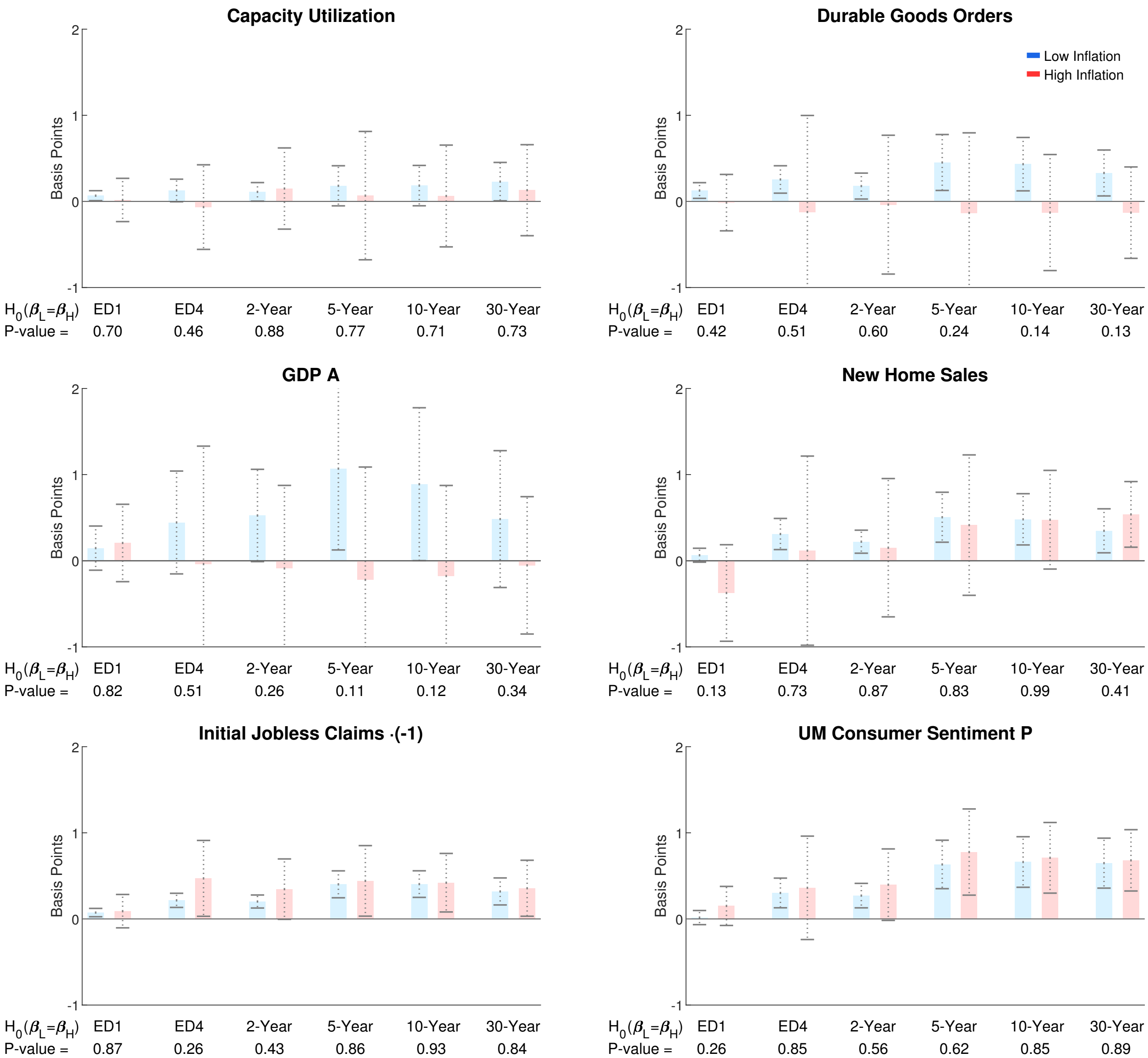
Interest Rates

Figure C1: Effects of Macro News on Interest Rates under Low and High Inflation



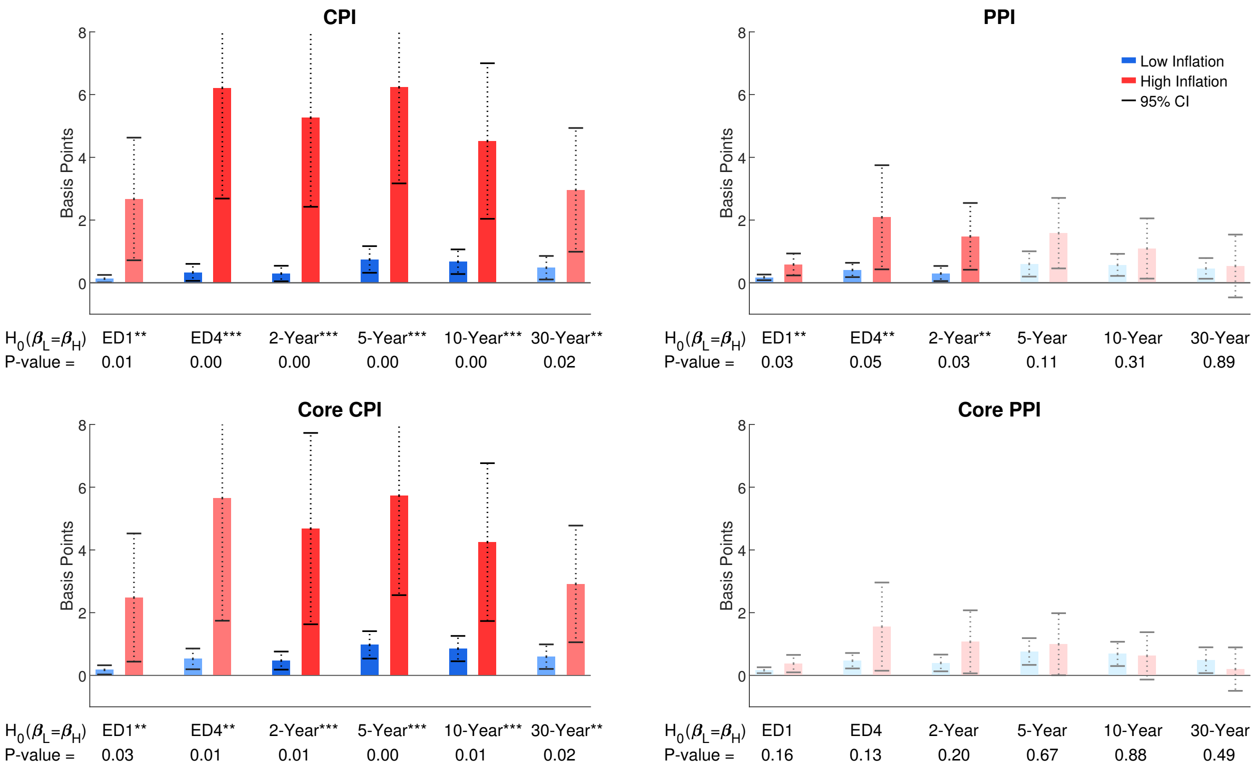
Notes: This figure shows the responses of the six interest rates for each of the six, additional macroeconomic announcements. Interest rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given interest rate, the grey bar shows the average effect, i.e., the estimate of coefficient $\beta^{y|k}$ of equation (12). 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 Interest Rates under Low and High Inflation



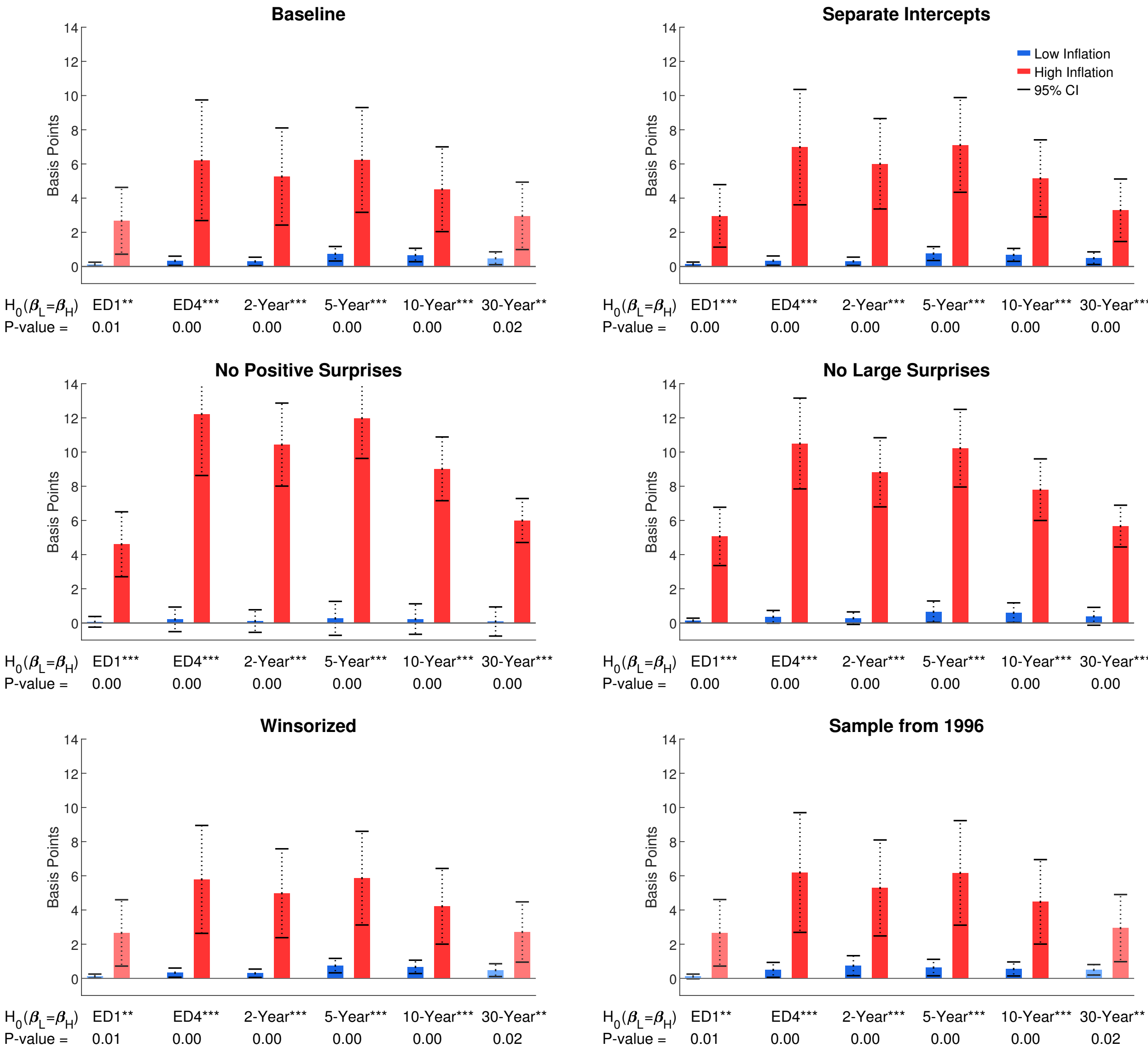
Notes: This figure shows the responses of the six interest rates under the low-inflation and high-inflation sample for each of the six, additional macroeconomic announcements. Interest rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given asset price, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{y|k}$ of equation (13), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{y|k}$ of equation (13). 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 C3: Effects on Interest Rates under Low and High Inflation—Headline vs. Core Price News



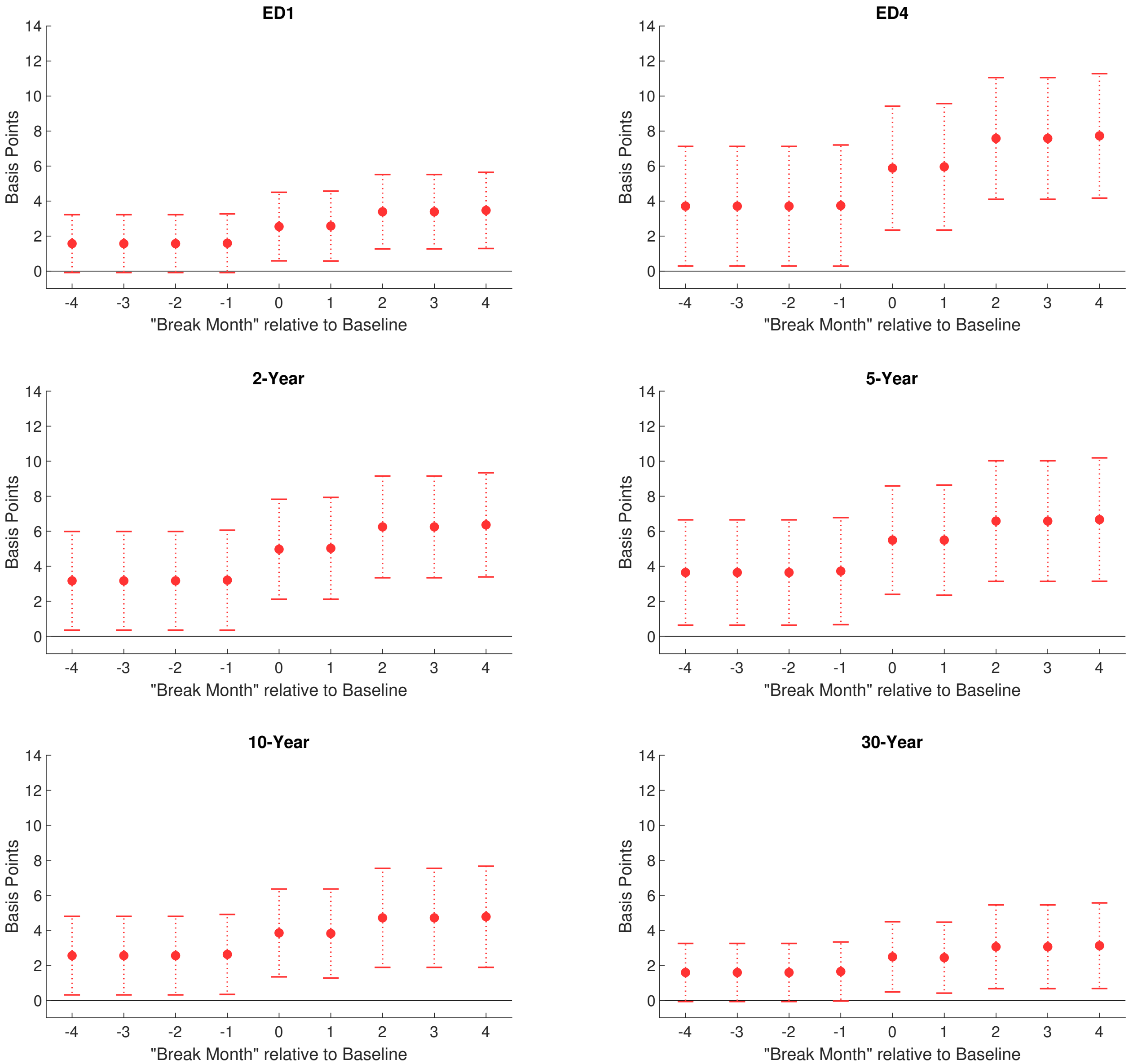
Notes: This figure shows the responses of the six interest rates under the low-inflation and high-inflation sample to the headline and the core surprises about the CPI and PPI. Interest rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given asset price, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{y|k}$ of equation (13), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{y|k}$ of equation (13). 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 CPI News on Interest Rates under Low and High Inflation—Robustness



Notes: This figure shows the responses of the six interest rates under the low-inflation and high-inflation sample to CPI news under different specifications. Details on the specifications are discussed in the robustness paragraph in Section 4.1. 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 (13), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{y|k}$ of equation (13). 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.

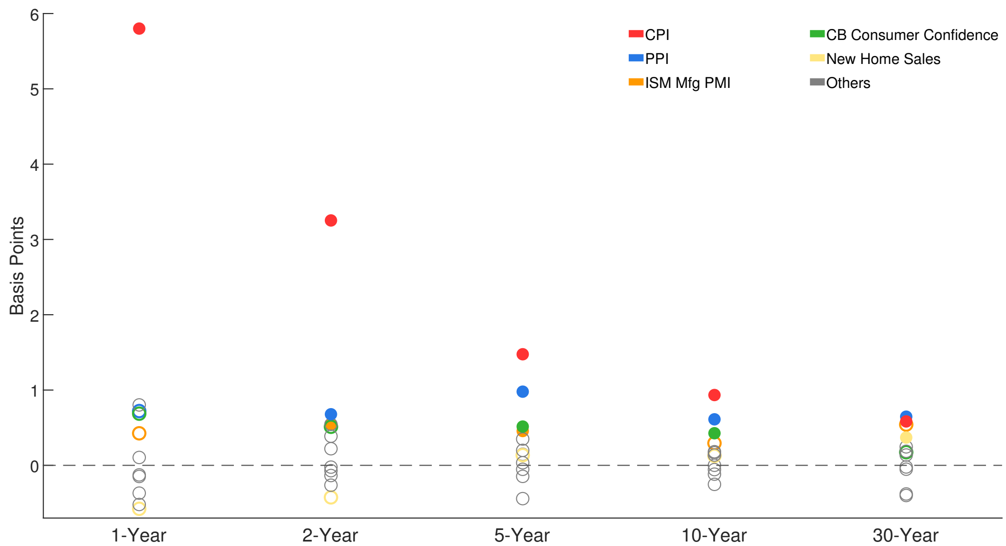
Figure C5: Increased Sensitivity for CPI releases—Robustness



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 (14), 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.

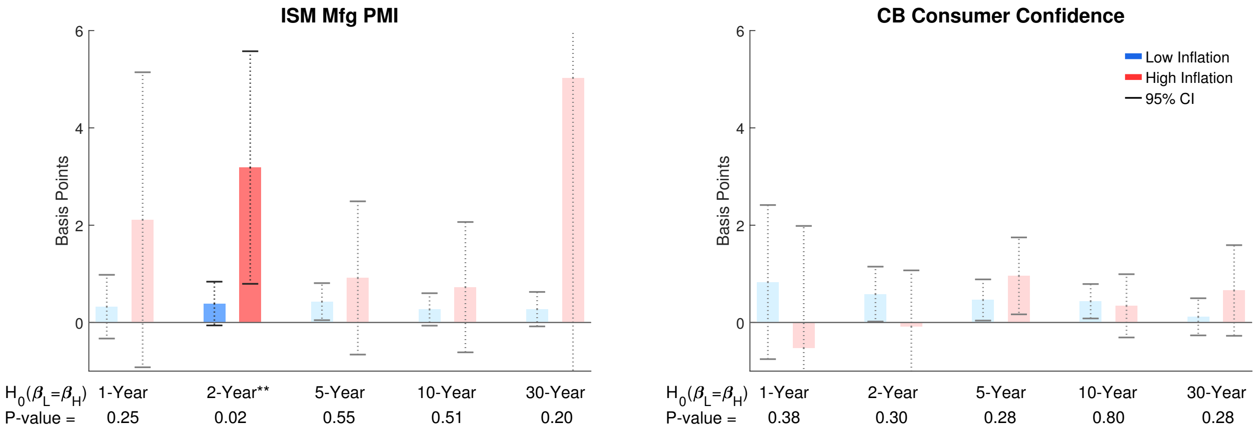
Inflation Swap Rates

Figure C6: Effects of Macro News on Inflation Swap Rates



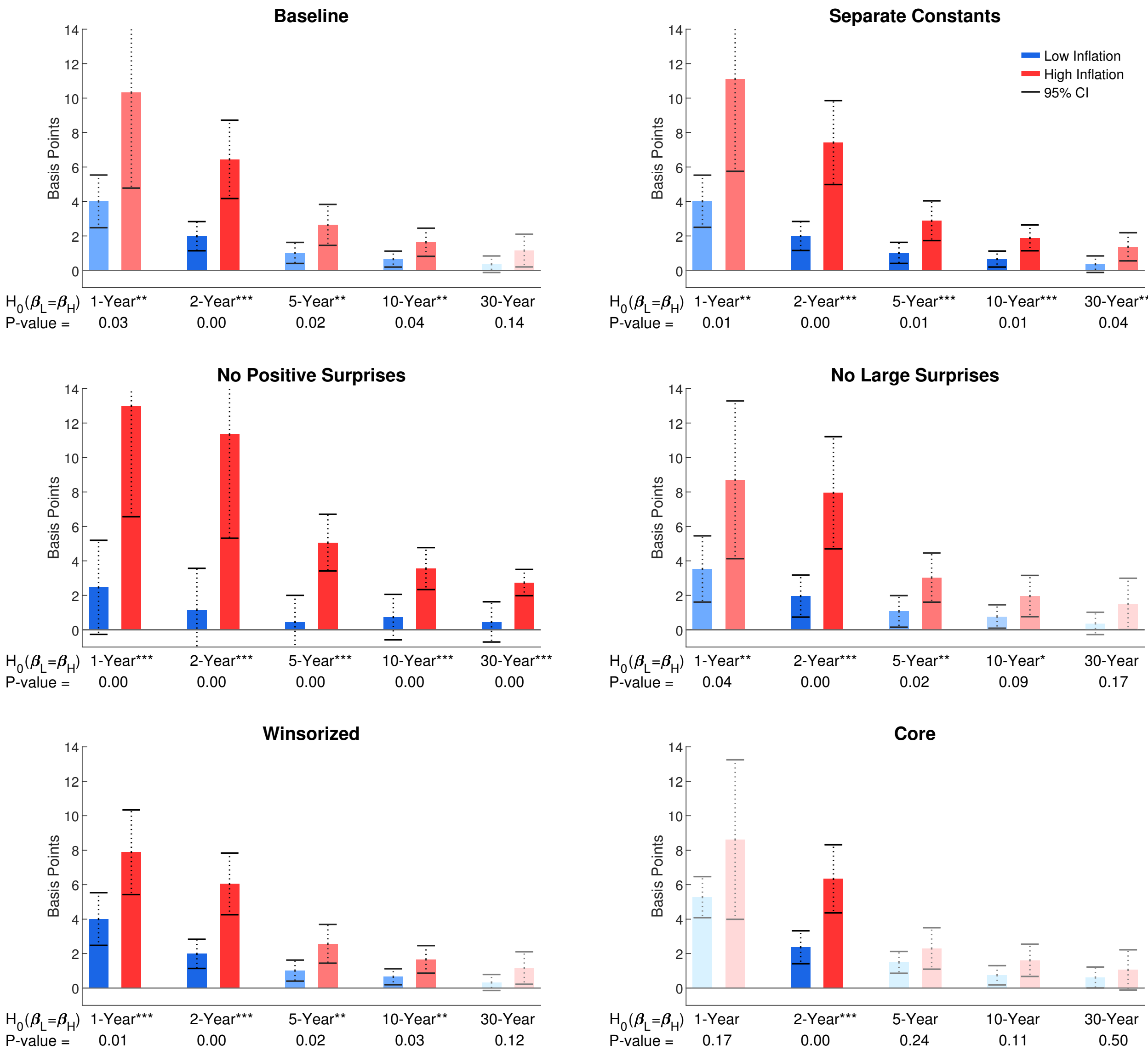
Notes: The figure displays responses of the five inflation swap rates to macro news releases. For a inflation swap rate, a circle indicates the estimate of coefficient $\beta_H^{\pi|k}$ of equation (7). Filled circles indicate significance at the 5 percent level while an empty circle indicates an insignificant effect. Heteroskedasticity-robust standard errors are employed. Results for the following releases are shown: CPI, PPI, Capacity Utilization, CB Consumer Confidence, Durable Goods Orders, GDP A, Initial Jobless Claims, ISM Mfg PMI, New Home Sales, Nonfarm Payrolls, Retail Sales UM Consumer Sentiment P. See Appendix Table B1 for details on the releases.

Figure C7: Effects of Real Activity News on Inflation Swap Rates under Low and High Inflation



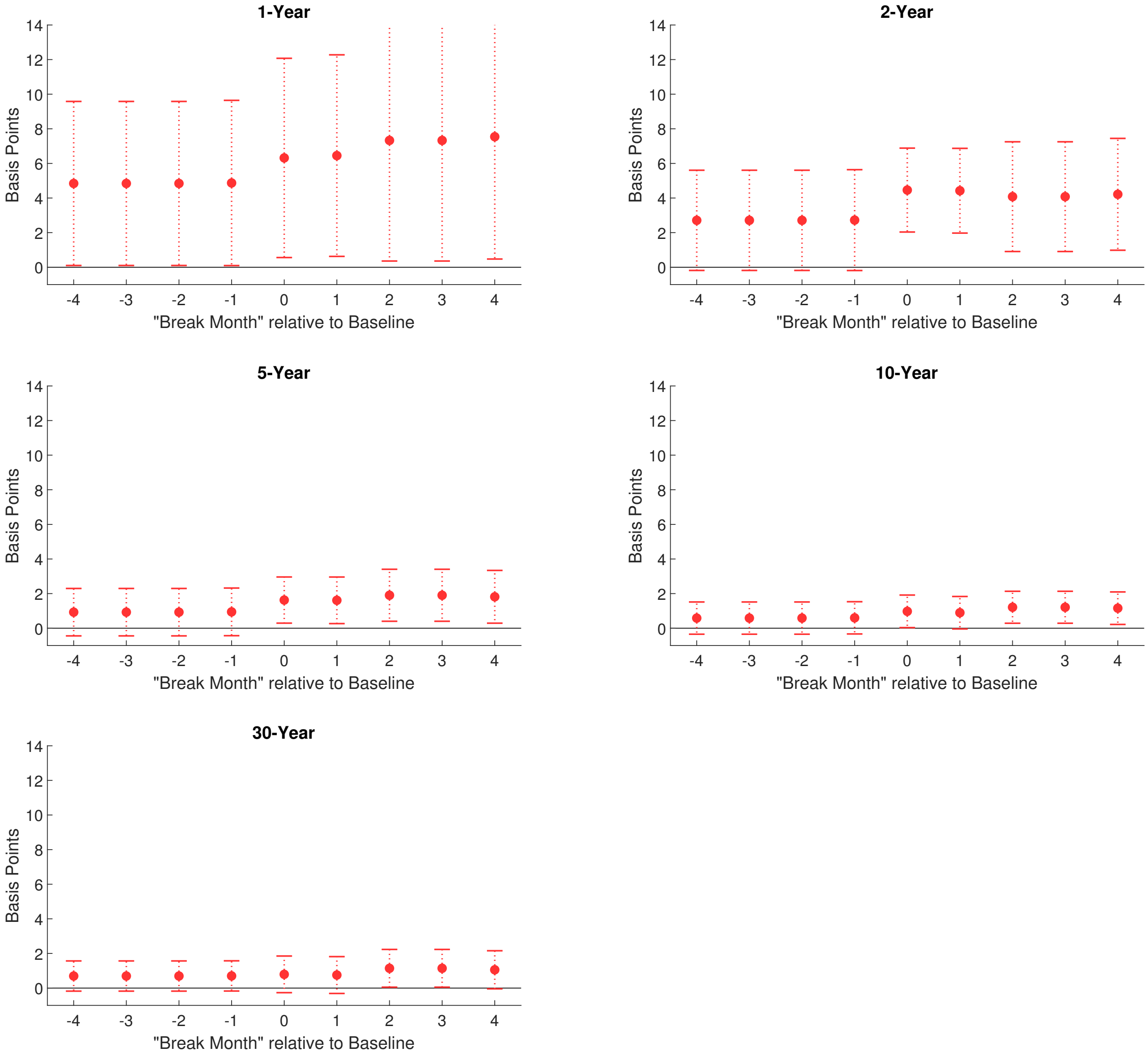
Notes: This figure shows the responses of the five inflation swap rates under the low-inflation and high-inflation sample for the real activity announcements. Inflation swap rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given inflation swap rate, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{\pi|k}$ of equation (16), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{\pi|k}$ of equation (16). 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 interest rate. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests.

Figure C8: Effects of CPI News on Inflation Swap Rates under Low and High Inflation—Robustness



Notes: This figure shows the responses of the 5 inflation swap rates under the low-inflation and high-inflation sample to CPI news under different specifications. Details on the specifications are discussed in the robustness paragraph in Section 4.1. Inflation swap rate changes 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 $\beta_L^{\pi|k}$ of equation (13), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{\pi|k}$ of equation (13). 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 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 C9: 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 (14), 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.