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

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Abstract

I present new evidence on the importance of investor attention for the link between the macroeconomy and financial markets. Using intraday data, I show that the Consumer Price Index (CPI) emerges as the most impactful data release during the 2021–2023 inflation surge. Bond yields and market-implied inflation expectations, as well as stocks and foreign asset prices respond significantly stronger on impact to a surprise about CPI inflation, compared to the prior low-inflation period. This increase in market sensitivity is unique among macro releases. The joint response of asset prices to CPI releases points to a faster incorporation of inflation news into inflation expectations, consistent with investors paying more attention to the releases. I corroborate this interpretation with a range of evidence, from documenting stark increases in trading volumes around CPI releases to showing that news providers for professional investors intensified their coverage of CPI releases during the inflation surge.

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

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1 Introduction

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

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

In this paper, I show that the inflation environment affects investors' attention to inflation and thereby changes how financial markets incorporate inflation news. I do this by studying the high-frequency effects of U.S. macroeconomic news announcements on asset prices during the 2021-2023 inflation surge. Consistent with a rise in investor attention to inflation, I find that surprises about the CPI have much larger effects on interest rates and on inflation expectations—as measured by inflation swap rates—in comparison to the prior low-inflation period. This increase in market sensitivity to CPI news can also be documented for a broad range of other asset prices. However, it is unique among macro releases. Overall, the evidence points towards a faster incorporation of inflation news into investors' inflation expectations due to increased attention. I support this interpretation by documenting that direct measures of investor attention, such as trading volumes or the news coverage from the Dow Jones Newswires and the Bloomberg Terminal, increased exceptionally around CPI

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

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

releases. I also show the results are not driven by changes in risk premia and that overall public attention to CPI releases also surged.

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

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

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

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

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

In the remainder of the paper, I provide additional evidence to support the attention-based interpretation of the main findings. To closer link the increase in CPI's market impact to investor attention, I look at two types of investor attention: trading volumes (e.g., Barber and Odean, 2008) and financial news coverage targeted at professional investors (e.g., Ben-Rephael, Da, and Israelsen, 2017). Specifically, I show that trading volumes of interest rate futures show an exceptional increase around CPI releases during the high-inflation period, both compared to average trading volumes and to other macro releases. Hence, the evidence suggests that more investors are trading around CPI releases, consistent with more of them paying attention to it. To confirm this, I also look at two prominent news sources for institutional investors—the Dow Jones Newswires and the Bloomberg Terminal. There, I find a stark increase in the news coverage of the CPI release during the inflation surge. Importantly, the number of CPI-related articles strongly rose not only at the time or after the release, but already the day and the morning before it. I also show that the attention to the CPI release by the broader public surged during the high-inflation period. Here, I study the CPI-related articles by popular news providers, such as New York Times, Wall Street Journal, or Fox News, as well as the CPI-related Google searches. Lastly, I employ the decompositions by Adrian, Crump, and Moench (2013), Kim and Wright (2005), and d'Amico, Kim, and Wei (2018)—each available at the daily frequency—to provide further evidence that the increased market sensitivity to CPI news is primarily driven by expected inflation and interest rates rather than risk premia.

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

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

Lastly, my paper relates to recent work in macroeconomics which provides support of "rational inattention" models (Sims, 2003) by documenting the relationship between the inflation environment and individuals' attention to inflation.[4] Bracha and Tang (2019) and Pfäuti (2021) show that key properties of survey data in the U.S. and Euro Area are consistent with higher inattention during low-inflation periods. Korenok, Munro, and Chen (2023) show for various countries that there is a positive relationship between country's inflation rate and inflation-related Google searches. Pfäuti (2023) directly estimates attention levels for the low- and high-inflation period from U.S. survey data which he then maps into a macroeconomic model to study the implications. Cavallo, Cruces, and Perez-Truglia (2017) conduct two randomized controlled trials, one in a low-inflation environment (U.S.), and one in a high-inflation environment (Argentina).[5] Providing information treatments about inflation, they show that households in Argentina change their inflation belief less, consistent with the idea that they were more informed prior to the treatment. Weber et al. (2023) confirm the findings by Cavallo, Cruces, and Perez-Truglia (2017) in a broader setting for both households and firms. Employing a set of randomized control trials across countries and over time, including the 2021-2023 inflation surge, the authors are also able to more directly link the difference in treatment responses to the inflation environment. My findings complement these papers by showing that the inflation environment also affects investors' attention to inflation and that this changes how fast new information gets incorporated into financial markets under high inflation.

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

2 Research Design

I am interested in assessing if people are more attentive to inflation news when inflation is high. To do so, I study the effects of surprises about U.S. macroeconomic data releases. In this section, I first introduce a simple framework to provide intuition on which factors the

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

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

market reaction to macro news likely depends on. In particular, it allows me to analyze how the market reaction changes under different scenarios, such as rational inattention. Guided by this analysis, I then move on to discuss the empirical strategy in the latter part of the section.

2.1 Illustrative Model

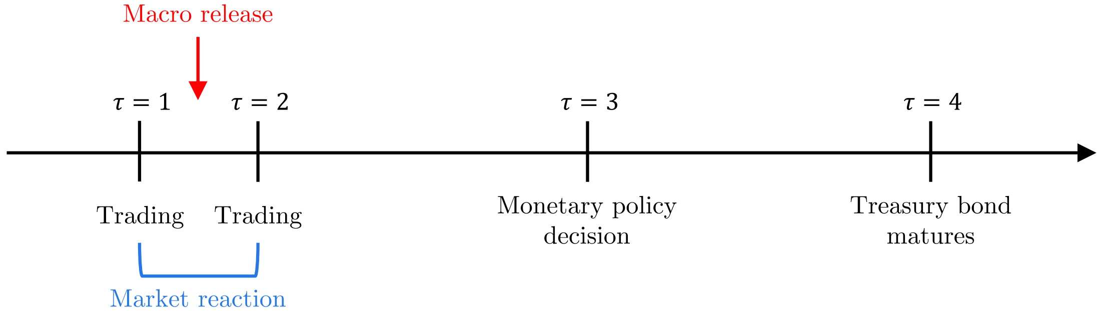
The framework is in the tradition of portfolio choice models under noisy information. Classic references are Grossman and Stiglitz (1980), Verrecchia (1982), Kim and Verrecchia (1991), Kandel and Pearson (1995), and Veronesi (2000). The news from a macroeconomic announcement is modeled as a public noisy signal and the attention to the announcement as the share of investors incorporating the signal into their decisions (DellaVigna and Pollet, 2009). In the following, I lay out the model setup and solution, and discuss how the market reaction changes under different scenarios. All technical details are relegated to Online Appendix A.

Setup The model has *four dates*, i.e., $\tau = \{1, 2, 3, 4\}$, and consequently three periods. Figure 1 outlines the timeline of the model. Dates 1 and 2 are depicting the trading dates around the macroeconomic release. As the period from date 1 to 2 corresponds to the intraday window defined below in the empirical analysis, 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

Figure 1: Model Timeline



Notes: This figure illustrates the four dates in the model including a summary headline for each date. Date 1 and 2 correspond to the trading periods around a given macro release, whereas date 3 and 4 show the events the investor problem focused on. Details are provided in the text.

that period. As the level of the risk-free rate is not important for the model mechanism, I will also assume that the risk-free rate is zero, $R_f = 0$, when I solve the model. This makes the model very tractable.

Monetary policy is set according to a Taylor rule which is given by $\Delta R = \phi^{\pi}\Delta\bar{\pi} + \phi^{z}\Delta\bar{z}$, where $\Delta\bar{\pi}$ and $\Delta\bar{z}$ are the change in inflation and output from date 2 to 3, respectively, i.e., $\bar{\pi}_3 = \Delta\bar{\pi} + \bar{\pi}_2$ and $\bar{z}_3 = \Delta\bar{z} + \bar{z}_2$. Further, $\Delta\bar{\pi}$ is assumed to be normally distributed with mean zero, $\Delta\bar{\pi} \sim N(0, \sigma_{\pi}^2)$, and output is related to inflation by $\Delta\bar{z} = \varrho\Delta\bar{\pi}$. Similar to the risk-free rate, I assume $\bar{\pi}_2 = 0$ and $\bar{z}_2 = 0$ for tractability. I also impose the following standard restrictions on the policy rule coefficients: $\phi^{\pi} > 0$, $\phi^{z} > 0$, and $\phi^{\pi} > -\varrho\phi^{z}$, where the last condition ensures that the policy rate always increases if inflation increases.

Investors cannot observe $\Delta\tilde{\pi}$ and $\Delta\bar{z}$ prior to the monetary policy decision at date 3. However, before date 2, investors receive a public noisy signal either about $\Delta\bar{\pi}$ by observing the CPI release or about $\Delta\bar{z}$ by observing the Nonfarm Payrolls (NFP) release. The signals are given by $s^{\text{CPI}} = \Delta\bar{\pi} + \eta$, with $\eta \sim N\big(0, \sigma_{\eta}^2\big)$, and $s^{\text{NFP}} = \Delta\bar{z} + \nu$, with $\nu \sim N\big(0, \varrho^2\sigma_{\eta}^2\big)$. Following DellaVigna and Pollet (2009), I assume that for each signal s^k, $k \in \{\text{CPI}, \text{NFP}\}$, only μ^k investors (attentive investors) incorporate it into their expectations, while $1 - \mu^k$ inattentive investors ignore it.[6]

At date 2, each agent i faces 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^k investors make this decision based on signal s^k which they incorporate using the signal-to-noise ratio as they face a standard signal extraction problem. Both date 3 and 4 do not

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

involve any portfolio optimization as the investors' wealth is assumed to be held in the risk-free asset.

Solution The model solution is derived by solving each investor's portfolio choice problem and then using market clearing conditions to obtain the equilibrium prices for date 1 and 2. Each investor is assumed to have a quadratic utility function with risk aversion parameter γ. Further, let $\mathrm{E}_\tau^i[\cdot]$ and $\mathrm{Var}_\tau^i[\cdot]$ denote investor i's expectation and variance conditional on date τ information, respectively. At date 1, investor i solves

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

where W_τ^i is i's wealth at date τ, and P_τ is the price of the Treasury security at date τ. 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

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

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

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

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

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

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

$$P_1 = \mathrm{E}_1[V] = 1 \quad \text{and} \quad P_2 = \mathrm{E}_2[V] = \begin{cases} 1-\phi\,\Theta(\mu^{\mathrm{CPI}})\,s^{\mathrm{CPI}} \\ 1-\frac{\phi}{\varrho}\,\Theta(\mu^{\mathrm{NFP}})\,s^{\mathrm{NFP}} \end{cases}, \tag{5}$$

where $\mathrm{E}_\tau[\cdot]$ denotes the average expectation across investors, ϕ is the overall policy response to inflation, $\phi = (\phi^\pi + \phi^z\varrho)$, $\Theta(\mu^k)$ is the average updating of signal k's underlying fundamental, $\Theta(\mu^k) = \frac{\mu^k \xi}{1-\xi\left(1-\mu^k\right)}$, and ξ is the signal-to-noise ratio, $\xi = \frac{\sigma_\pi^2}{\sigma_\pi^2+\sigma_\eta^2}$.[7] Similarly, the inflation expectations in the model are given by

$$\mathrm{E}_1[\bar{\pi}_3] = \mathrm{E}_1[\Delta\bar{\pi}] = 0 \quad \text{and} \quad \mathrm{E}_2[\bar{\pi}_3] = \mathrm{E}_2[\Delta\bar{\pi}] = \begin{cases} \Theta(\mu^{\mathrm{CPI}})\, s^{\mathrm{CPI}} \\ \frac{1}{\varrho}\,\Theta(\mu^{\mathrm{NFP}})\, s^{\mathrm{NFP}} \end{cases}. \tag{6}$$

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

$$P_\tau = 1 - \phi \mathrm{E}_\tau[\Delta\bar{\pi}]\,, \tag{7}$$

where $\phi > 0$ holds due to the parameter restrictions defined above.

Market reaction to macro news With the model solution at hand, I can now characterize the market reaction to macro news in the model. As mentioned above, I focus on the effect on interest rates and inflation expectations—measured by bond yields and inflation swap rates, respectively. I use bond yields rather than bond prices, as yields are more commonly referenced. Let ω be the period from date 1/2 to date 4, denoted in years. Consequently, ω is also the maturity of the bond and the inflation swap. Following Gürkaynak, Kısacıkoğlu, and Wright (2020) and others,[8] the change between date 1 and 2 of *bond yield* y_τ is given by

$$y = y_2 - y_1 = -\frac{P_2 - P_1}{\omega}. \tag{8}$$

The corresponding change of *inflation swap rate* π_τ is

$$\pi = \pi_2 - \pi_1 = \frac{\mathrm{E}_2[\bar{\pi}_3] - \mathrm{E}_1[\bar{\pi}_3]}{\omega}. \tag{9}$$

As the period from date 2 to 4 can be thought of a flexible time span, equations (5) and (6) can refer to bond yields and inflation swap rates over different horizons. The derivations of equations (8) and (9) are shown in Appendix A.6.1.

Using equations (5) and (6), the *market reaction to CPI news* can be written as

$$y = \underbrace{\frac{\phi}{\omega}\Theta(\mu^{\mathrm{CPI}})}_{\beta^{y|\mathrm{CPI}}} s^{\mathrm{CPI}} \quad \text{and} \quad \pi = \underbrace{\frac{1}{\omega}\Theta(\mu^{\mathrm{CPI}})}_{\beta^{\pi|\mathrm{CPI}}} s^{\mathrm{CPI}}, \tag{10}$$

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

[8]In this simple framework, maturity, duration, and modified duration are essentially the same as shown in Appendix A.6.1. In Section 3, I discuss the empirical construction.

and the *market reaction to Nonfarm Payrolls news* as

$$y = \underbrace{\frac{\phi}{\omega\varrho}\Theta(\mu^{\mathrm{NFP}})}_{\beta^{y|\mathrm{NFP}}} s^{\mathrm{NFP}} \quad \text{and} \quad \pi = \underbrace{\frac{1}{\omega\varrho}\Theta(\mu^{\mathrm{NFP}})}_{\beta^{\pi|\mathrm{NFP}}} s^{\mathrm{NFP}}. \tag{11}$$

Since $\omega > 0$, $\phi > 0$, and $\Theta(\mu^k) > 0$ holds, the effects of CPI news are always larger than zero, whereas the effects of Nonfarm Payrolls news depend on the sign of ϱ,

$$\beta^{y|CPI}, \beta^{\pi|CPI} > 0 \quad \text{and} \quad \beta^{y|NFP}, \beta^{\pi|NFP} \begin{cases} > 0 \text{ if } \varrho > 0 \\ < 0 \text{ if } \varrho < 0 \end{cases}.$$

Identification strategy Based on the market reactions characterized by equations (10) and (11), I can now discuss how different scenarios would affect the market reactions. In particular, it allows me to illustrate the distinct moments of the rational inattention story under high inflation compared to other ex-ante likely narratives. Table 1 provides a summary of the analysis and Appendix A.6 provides the calculations underlying the discussion and results.

I start with the *rational inattention* scenario in which leads investors to pay more attention to the CPI release under high inflation. Note that both the CPI and the Nonfarm Payrolls release are equally informative about inflation in the model. In reality, all macro releases are to some degree informative about inflation. However, if information acquisition is costly, the release of the CPI is ex-ante the one for which investor attention is most likely to increase during high inflation. I will come back to this point below in the empirical implementation. Let μ_L^{CPI} and μ_H^{CPI} be the investor attention to CPI releases under low and high inflation, respectively. The rational inattention scenario implies that $\mu_L^{\mathrm{CPI}} < \mu_H^{\mathrm{CPI}}$, with all other parameters being unchanged across periods. Under this scenario, we have a stronger response to the CPI release for both interest rates and inflation swap rates, i.e., $\beta_H^{y|CPI} > \beta_L^{y|CPI}$ and $\beta_H^{\pi|CPI} > \beta_L^{\pi|CPI}$. However, responses to the Nonfarm payrolls release are unchanged. The first row in Table 1 summarizes the implications under the rational inattention scenario.

Another likely scenario is that the *monetary policy* rule is changing or investors perceive the rule to be changing under high inflation (Bauer, Pflueger, and Sunderam, 2022). This can happen either through an increase in the responsiveness to inflation ($\phi_L^{\pi} < \phi_H^{\pi}$) or output ($\phi_L^{x} < \phi_H^{x}$). The second and third row in Table 1 summarize changes in market reactions under each of these scenarios. There are two key differences to the rational inattention case.

Table 1: Market Reaction to Macro News under Different Model Scenarios

Scenarios	Interest Rates			Inflation Swap Rates		
	Low Inflation		High Inflation	Low Inflation		High Inflation
Rational Inattention $\mu_L^{CPI} < \mu_H^{CPI}$	$\beta_L^{y\|CPI}$	$<$	$\beta_H^{y\|CPI}$	$\beta_L^{\pi\|CPI}$	$<$	$\beta_H^{\pi\|CPI}$
	$\beta_L^{y\|NFP}$	$=$	$\beta_H^{y\|NFP}$	$\beta_L^{\pi\|NFP}$	$=$	$\beta_H^{\pi\|NFP}$
Monetary Policy $\phi_L^{\pi} < \phi_H^{\pi}$	$\beta_L^{y\|CPI}$	$<$	$\beta_H^{y\|CPI}$	$\beta_L^{\pi\|CPI}$	$=$	$\beta_H^{\pi\|CPI}$
	$\beta_L^{y\|NFP}$	$\underset{(\varrho>0)}{<} / \underset{(\varrho<0)}{>}$	$\beta_H^{y\|NFP}$	$\beta_L^{\pi\|NFP}$	$\underset{(\varrho>0)}{<} / \underset{(\varrho<0)}{>}$	$\beta_H^{\pi\|NFP}$
Monetary Policy $\phi_L^{z} < \phi_H^{z}$	$\beta_L^{y\|CPI}$	$\underset{(\varrho>0)}{<} / \underset{(\varrho<0)}{>}$	$\beta_H^{y\|CPI}$	$\beta_L^{\pi\|CPI}$	$=$	$\beta_H^{\pi\|CPI}$
	$\beta_L^{y\|NFP}$	$>$	$\beta_H^{y\|NFP}$	$\beta_L^{\pi\|NFP}$	$=$	$\beta_H^{\pi\|NFP}$
Demand- to Supply-Shocks $\varrho_L^{z} > 0 > \varrho_H^{z}$	$\beta_L^{y\|CPI}$	$>$	$\beta_H^{y\|CPI}$	$\beta_L^{\pi\|CPI}$	$=$	$\beta_H^{\pi\|CPI}$
	$\beta_L^{y\|NFP}$	$>$	$\beta_H^{y\|NFP}$	$\beta_L^{\pi\|NFP}$	$>$	$\beta_H^{\pi\|NFP}$

Notes: This table summarizes how the market reactions change between the low- and high-inflation period under different scenarios. The first column provides the name of the scenario as well as the parameter change across periods. The second and third column displays the effects of CPI and Nonfarm Payrolls (NFP) news on interest rates and inflation swap rates, respectively. Here, $\beta_p^{x|k}$ denotes the reaction of asset price x to release k during inflation period p. The specific scenarios are discussed in the text and the calculations underlying the results are shown in Appendix A.6.

First, the effects of CPI news on inflation swap rates is unaffected. Second, the effects of Nonfarm Payrolls are actually affected. In particular, they are amplified, that is, the changes in the market reactions are positive (negative) if ϱ is positive (negative).

In the last scenario I consider, the inflation surge is associated with a structural shift in the economy from *demand- to supply-driven*. In the framework, this can be modeled by flipping the relationship between inflation and output from positive to negative ($\varrho_L^z > 0 > \phi_H^z$). Under this scenario, yields are less sensitive to CPI news and inflation swap rates are unaffected by it. Further, the market reactions to Nonfarm Payrolls flip from positive to negative.

Overall, the theoretical framework illustrates how the market reactions to macro news can be useful to identify the rational inattention mechanism in the data. It is very likely that the data presents a mixture of the scenarios presented here. Hence, most of the subsequent empirical analysis can be understood as finding evidence for the rational inattention channel rather than ruling out the presence of any other channels which might affect changes in the market reactions during the high inflation period.

2.2 Empirical Implementation

To take the theoretical setting to the data, I first need to construct a news measure for each macro release. Consider the release of macroeconomic variable k at time t. I construct the surprise (news) by subtracting from the macro series k its forecast, that is,

$$s_t^k = \frac{k_t - \mathrm{E}[k_t|\mathcal{I}_{t-\Delta^-}]}{\hat{\sigma}^k}, \tag{12}$$

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

With the macro surprises at hand, I can turn to the main specification which I use to test the theoretical predictions outlined above. In particular, I estimate the following equation for each announcement series k:

$$x_t = \beta_L^{x|k} s_t^k \mathbb{1}_{t\in L} + \beta_H^{x|k} s_t^k \mathbb{1}_{t\in H} + \varepsilon_t^k, \tag{13}$$

where x_t denotes the change in an interest or inflation swap rate, i.e., $x \in y, \pi$, in a narrow window around the announcement time t. Further, s_t^k is news about macro series k, $\mathbb{1}_{t\in L}$ and $\mathbb{1}_{t\in H}$ are indicator functions denoting if the announcement t is during high or low inflation, and 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.

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. As I will show below for the CPI, a one standard deviation surprise maps to a 0.11 percent forecast error in the month-over-month (MoM) CPI inflation across both inflation periods. Further, 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 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. However, differences across $\beta_L^{x|k}$ and $\beta_H^{x|k}$ cannot be easily interpreted without providing more structure as done in this section.

Besides CPI and Nonfarm Payrolls releases, I also consider other major macroeconomic releases in the empirical analysis. While this allows me to more cleanly identify systematic patterns across both inflation periods, it also introduces some potential complications by including releases, such as the Producer Price Index, which might also experience increased attention. As indicated above, the *headline CPI* number is the natural pick to study. It is not only the most cited inflation measure by the press (e.g., Bullard, 2022), but also of unique importance for investors as it is used to index both inflation swaps as well as Treasury inflation-protected securities (TIPS). Further, the CPI release is relatively timely compared to other common inflation measures. For example, the PCE price index, the Federal Reserve's preferred measure of inflation, comes usually out two weeks after the CPI.[9] Ultimately, while other releases might also experience increased investor attention during high inflation, the CPI release should be a priori the release for which this effect is by far the strongest. With this in mind, the main hypothesis I test in the empirical analysis can be summarized as follows:

Hypothesis 1: *If investors pay more attention to inflation news under high-inflation, one should observe stronger market reactions of interest rates and inflation swap rates to CPI news. In comparison, the market reactions to other macro releases should be less affected by an inflation-induced attention. Estimating equation (13) for different macro releases, this yields the following predictions:*

$$\beta_H^{x|CPI} > \beta_L^{x|CPI} \quad \text{and} \quad \beta_H^{x|\neg CPI} \approx \beta_L^{x|\neg CPI} \qquad \text{for } x \in \{y, \pi\},$$

where $\neg CPI$ describes the set of non-CPI releases, i.e., $\neg CPI = \{k \mid k \neq CPI\}$.

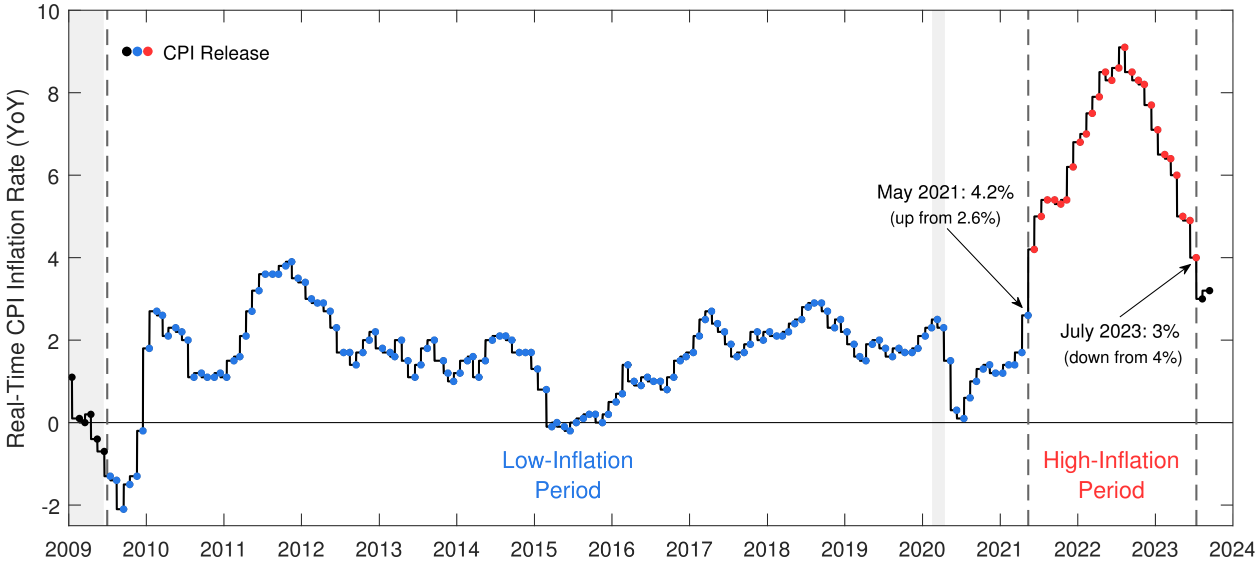
The rest of the paper is structured around Hypothesis 1. In the next section, I discuss the data I use to estimate equation (13), before I provide the main results of the analysis in Section 4. There, I document strong evidence in support of Hypothesis 1. Lastly, I go beyond equation (13) and provide additional evidence in support of increased investor attention to CPI releases, i.e., $\mu_H^{CPI} > \mu_L^{CPI}$.

3 Data

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

[9] The PCE release is usually found to not lead to strong financial market reactions. I will confirm this in my analysis below.

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



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

3.1 Low- and High-Inflation Period

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

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

3.2 Macroeconomic News

I use Bloomberg's U.S. Economic Calendar to obtain the data on the macroeconomic news releases. Bloomberg provides all required information for my analysis such as release date and time, released value, and the market expectations prior to the release. I consider 16 major macro releases throughout my analysis which are mostly chosen based on their importance documented in prior papers (e.g., Rigobon and Sack, 2008; Gürkaynak, Kısacıkoğlu, and Wright, 2020; Boehm and Kroner, 2023). For a succinct exposition, I often show results for only 8 of the 16 releases in the main text. Table 2 provides the summary statistics of these 8 releases and Appendix B1 shows the entire set of releases.

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

For as each release, I construct surprises based on equation (12). In particular, I use the average market expectation of the release as the measure of $\mathrm{E}\left[k_t|\mathcal{I}_{t-\Delta^-}\right]$. Bloomberg 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

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

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

Table 2: Overview of Macroeconomic News Announcements

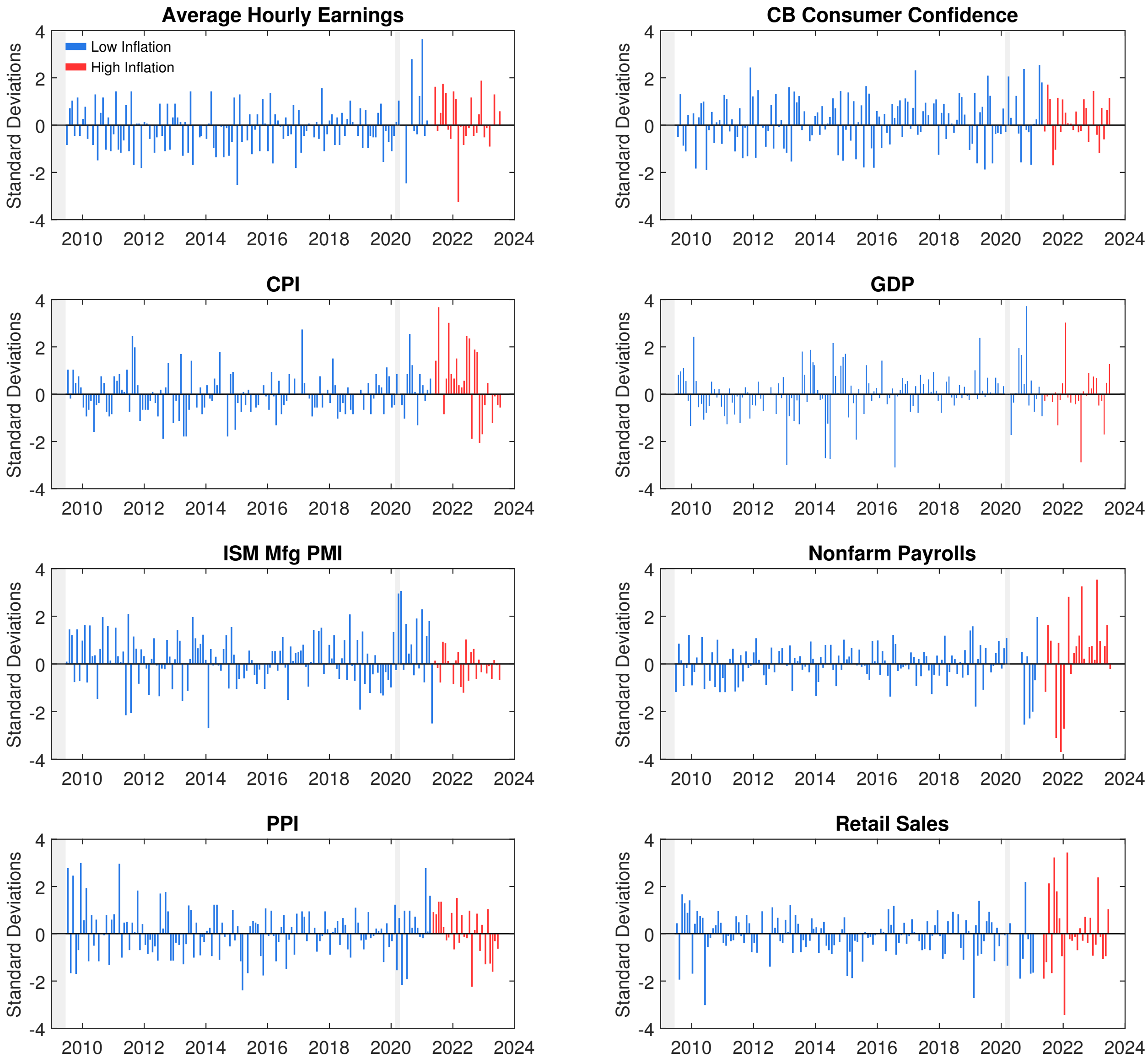
Announcement	Release Time	Frequency	Observations Total	Observations Low	Observations High	Unit	Surprise (+1 SD)
Average Hourly Earnings	8:30	Monthly	160	135	25	% MoM	0.15
CB Consumer Confidence	10:00	Monthly	168	142	26	Index	4.99
CPI	8:30	Monthly	166	140	26	% MoM	0.11
GDP	8:30	Monthly	164	140	24	% QoQ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

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

deviation surprise for the entire sample. Notice that I use average rather median forecast to construct. While both are highly correlated (correlation between for the 16), the surprise based on average leads to more small surprises which allow me to have sufficient power when excluding larger surprises in robustness exercises. I compare both series for CPI in Appendix Figure B1 and also show that the main findings are robust to using both surprise series later in my analysis.

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

Figure 3: Time Series of Standardized Surprises



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

3.3 Financial Data

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

Table 3: Intraday Financial Data

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

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

mitigating noise in outcome variable. This allows me to investigate systematic differences in the financial markets responses, even in a small sample (in my case, the high-inflation sample with less 30 observations). Table 3 provides an overview of the employed asset prices which I go through in the following.

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

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

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

Inflation Expectations To measure inflation expectations, I employ (zero-coupon) inflation swaps. These are based on the CPI. Broadly speaking, two counterparties agree at given point in time to exchange a fixed rate, the swap rate, in exchange for a floating payment based on the realized CPI over the maturity of the swap.[13] Appendix Figure B3 illustrates the timing of the payoffs. Hence, the h-year inflation swap rate measures the risk-neutral expectation of the annual CPI inflation over next h-years. Inflation swap rates are preferred to break-even rates from inflation-indexed Treasury bonds (TIPS) as they are less prone to liquidity issues (Fleckenstein, Longstaff, and Lustig, 2014; Cieslak and Pflueger, 2023). Table 3 provides on overview of the employed swap rates covering maturities from 1 to 30 years. For a given swap, the rate is constructed as the midpoint of the bid and ask prices. As the inflation swap measures the risk-neutral expectation, it captures the expected inflation rate adjusted for an inflation risk premium. In the subsequent analysis, I assume that inflation risk premia are not the dominant component driving changes in a narrow window around announcements. While non-innocuous, one would need a model to clean the rates from the premia, which does not come without its own problems.

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

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

4 The Effects of Macro News under Low and High Inflation

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

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

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

4.1 Interest Rates

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

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

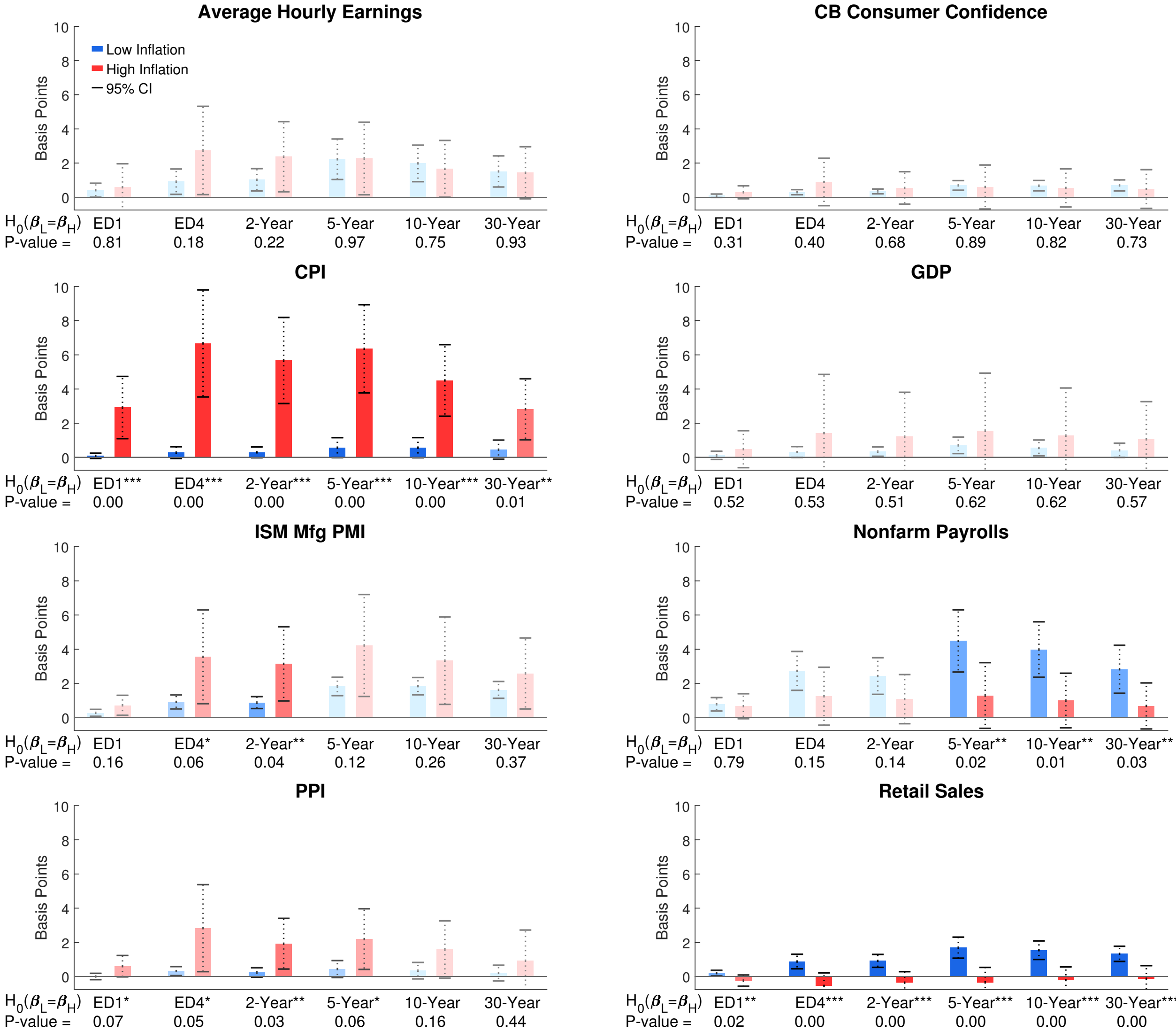
$$y_t = \alpha_L^k + \alpha_H^k + \beta_L^{y|k} s_t^k \mathbb{1}_{t \in L} + \beta_H^{y|k} s_t^k \mathbb{1}_{t \in H} + \varepsilon_t^k, \tag{14}$$

where s_t^k is the announcement surprise of interest and y_t is the 60-minute change in one of the 6 interest rates described in Table 3. $\mathbb{1}_{t \in L}$ is an indicator function, which equals one if the announcement t is in during the low-inflation period and zero otherwise. $\mathbb{1}_{t \in H}$ is defined accordingly. Note that $\mathbb{1}_{t \in L} = 1 - \mathbb{1}_{t \in H}$. Further, I allow each period to have a separate intercept, α_L^k and α_H^k.

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

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

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



Notes: This figure shows the responses of interest rates under the low-inflation and the high-inflation period for each of the 8 main macro announcements. Interest rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given interest rate, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{y|k}$ of equation (14), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{y|k}$ of equation (14). The black error bands depict 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level of rejecting the null hypothesis that $\beta_L^{y|k}$ 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 3. Appendix Figure C3 shows the results for the other 8 macro announcements.

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

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

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

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

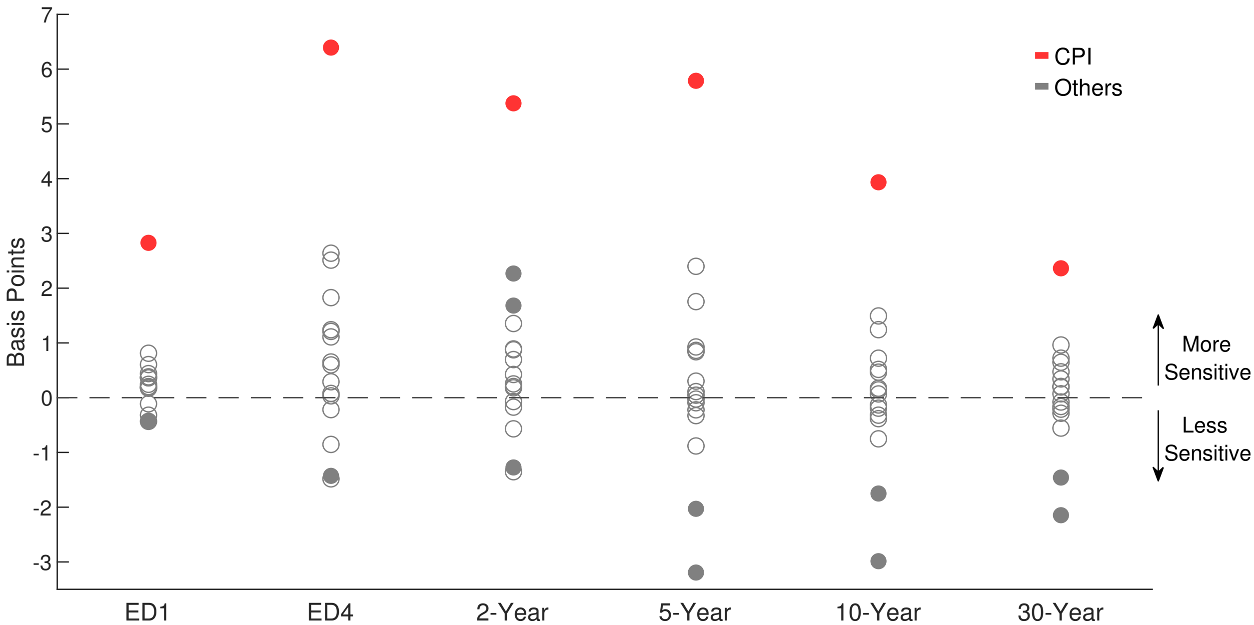
$$y_t = \alpha_L^k + \alpha_H^k + \beta_L^{y|k} s_t^k + \delta_H^{y|k} s_t^k \mathbb{1}_{t\in H} + \varepsilon_t^k, \tag{15}$$

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 (14). As Figure 5 illustrates, the CPI release is unique in how its impact on interest rates rose during the recent inflation surge. None of the other 15 macro releases experiences a comparable statistically and economically significant in effect size.

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

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

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



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

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

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

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

4.2 Inflation Expectations

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

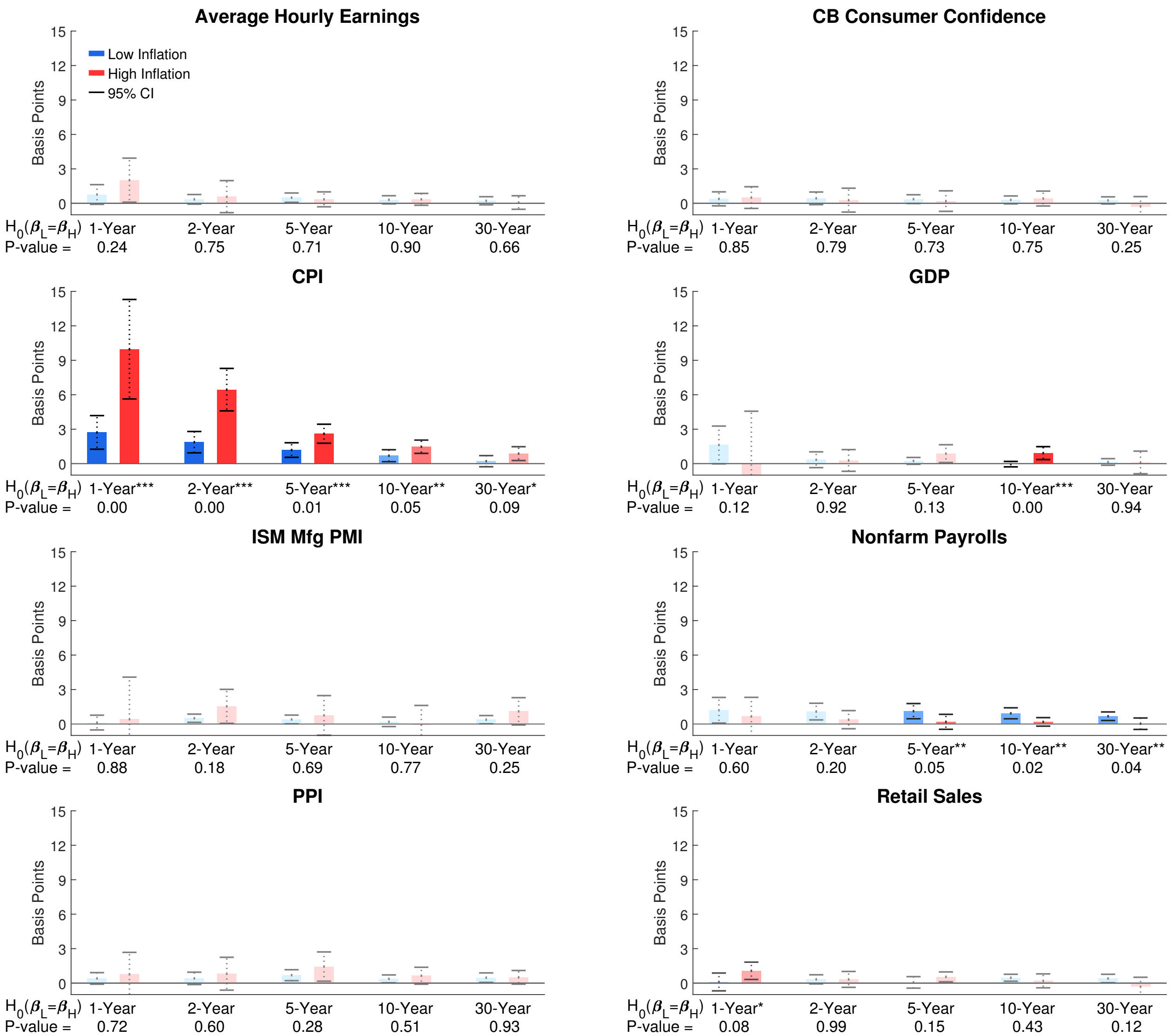
As with the interest rates, I begin by studying in Appendix C.1 the average of the macro news on inflation expectations over my sample releases. Consistent with the argument laid out in Section 2, a higher-than-expected CPI release leads by far to the largest increases in inflation expectations. That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

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

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

where s_t^k is the announcement surprise of interest, and π_t is the 60-minute change in one of the five inflation swap rates described in Table 3. $\mathbb{1}_{t\in L}$ is an indicator function, which equals one if the announcement t is during the low-inflation period and zero otherwise. $\mathbb{1}_{t\in H}$ is defined accordingly. Note that $\mathbb{1}_{t\in L} = 1 - \mathbb{1}_{t\in H}$. Further, I allow each period to have a separate intercept, α_L^k and α_H^k.

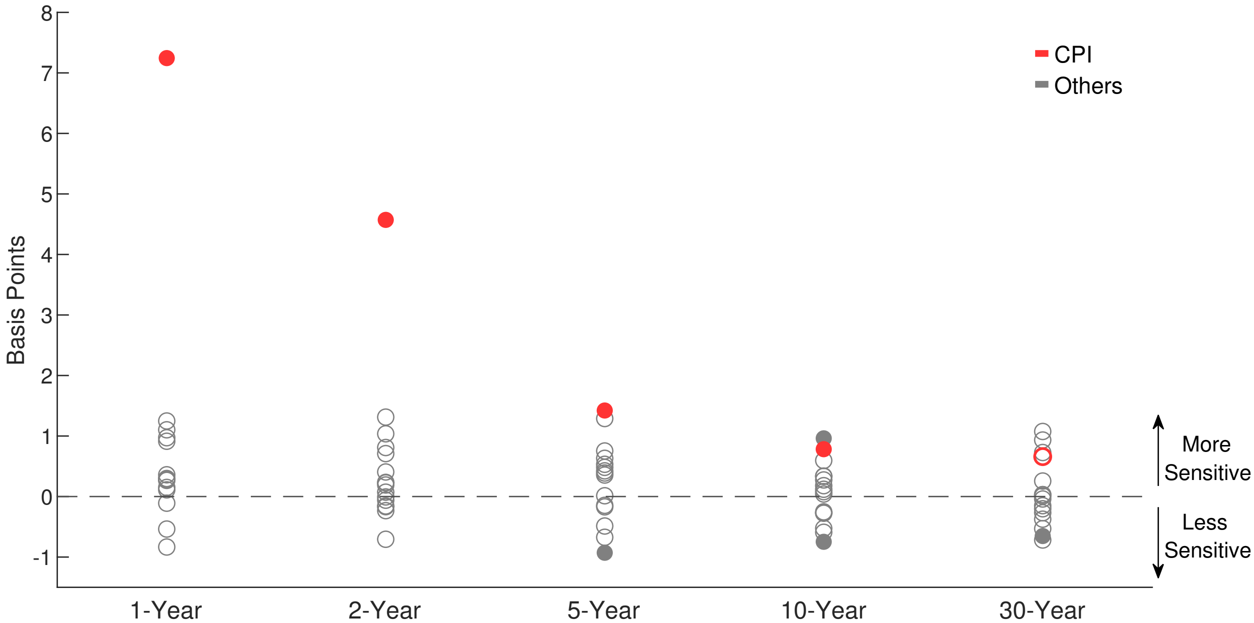
Figure 6: Effects of Macro News on Inflation Expectations under Low and High Inflation



Notes: This figure shows the responses of inflation swap rates under the low-inflation and the high-inflation period for each of the 8 main macro announcements. Inflation swap rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given inflation swap rate, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{\pi|k}$ of equation (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 inflation swap rate. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests. Appendix Figure C4 shows the results for the other 8 macro announcements.

Figure 6 displays the results for equation (16). A couple of things stand out: First and foremost, CPI news has substantially stronger effects on inflation swap rates during the high

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



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

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

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

$$\pi_t = \alpha_L^k + \alpha_H^k + \beta_L^{\pi|k} s_t^k + \delta_H^{\pi|k} s_t^k \mathbb{1}_{t \in H} + \varepsilon_t^k, \tag{17}$$

where $\delta_H^{\pi|k} = \beta_H^{\pi|k} - \beta_L^{\pi|k}$. Note that testing the null $\delta^{\pi|k} = 0$ is equivalent to testing $\beta_L^{\pi|k} = \beta_H^{\pi|k}$ for equation (16). As Figure 7 illustrates, the CPI release is unique in how its impact on interest rates rose during the recent inflation surge. None of the other 15 macro releases experiences a comparable statistically and economically significant in effect size.

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

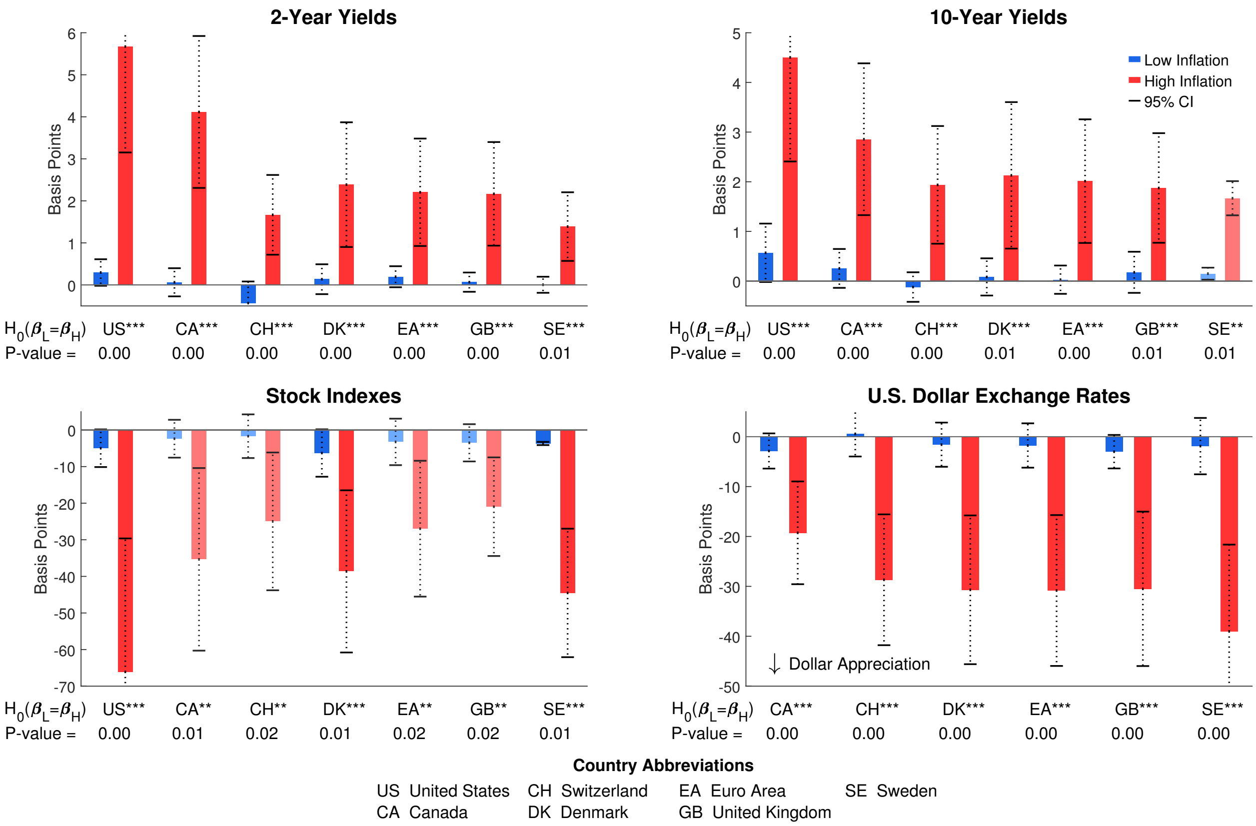
Lastly, in Appendix Figure C8, I investigate the robustness of my analysis with respect to the break date between low- and high-inflation period. As the figure shows, the main findings are robust to choosing different break months around the baseline one. To sum up, the key finding of the increased impact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

4.3 Stocks, Exchange Rates and International Spillovers

After documenting the results for interest rates and inflation swap rates, I now turn to other asset prices; in particular, stock prices, exchange rates, and foreign interest rates. For a clearer presentation, I now exclusively focus on CPI news. The goal of this section is to show that the stronger effects of CPI releases are a broad phenomenon across asset classes. To do so, I rerun equation (14) with a variety of different asset prices on the left-hand side. Figure 8 illustrates the results of this analysis.

The top-left and top-right panel of Figure 8 displays estimates of equation (14) for various countries' 2-year and 10-year government yields, respectively. For comparison, I also plot the earlier results for the U.S. Across countries, we see an increase in yield sensitivity to CPI news, which is both economically and statistically significant. Compared to the U.S., the effect sizes are smaller and similar across countries except for Canadian yields, which display a somewhat stronger response. The findings are consistent with market participants believing that U.S. inflation spills over to other countries leading the central banks to increase their policy rates in the near- and medium-term future.

Figure 8: Effects of CPI News on International Asset Prices



Notes: This figure shows the effects of CPI news on a variety of asset prices under the low-inflation and the high-inflation period. The top-left and top-right panels display the results for countries' 2-year and 10-year yields, while the bottom-left and bottom-right panels show the estimates for stock returns and U.S. dollar exchange rates. Each panel shows the results of estimating $\beta_L^{x|k}$ and $\beta_H^{x|k}$ of equation (13) after replacing the left-hand side with the 60-minute change or (log-change) of the corresponding asset prices. For a given asset, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{x|k}$, while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{x|k}$. The black error bands depict 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level of rejecting the null hypothesis that $\beta_L^{x|k}$ and $\beta_H^{x|k}$ are equal. The p-value of this hypothesis test is reported below each announcement. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used for all hypothesis tests. Appendix Table B2 provides an overview of the employed asset prices.

Moving on to stocks, the bottom-left panel of Figure 8 displays estimates of equation (14) for various countries' major stock indexes.[17] Consistent with a dominant interest rate

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

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

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

4.4 Time-Varying Coefficient Approach

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

$$x_t = \alpha^k + \beta_t^{x|k} s_t^k + \varepsilon_t^k, \tag{18}$$

for $k \in$ CPI, and x_t is the 60-minute change in the asset price of interest. 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 simple words, the estimation does a series of weighted least squares regressions around each point $\frac{t}{T}$, where points further away are less weighted based on the Gaussian density function with a standard deviation of 12 months (12 observations), determined by the chosen bandwidth. Confidence intervals are constructed following the

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

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

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

Notes: This figure shows the time-varying high-frequency effects of CPI news on asset prices over the sample period. Each panel displays the estimates of $\beta_t^{x|k}$ of equation (18) for three different left-hand side variables: the 2-year interest rate, 2-year inflation swap rate, and the S&P 500. The blue and red color indicate if estimates are during the low- or high-inflation period, respectively. Shaded areas show 95 percent bootstrap confidence intervals. See text for details on the estimation.

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

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

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

5 An Attention-Based Explanation

5.1 Trading Volume

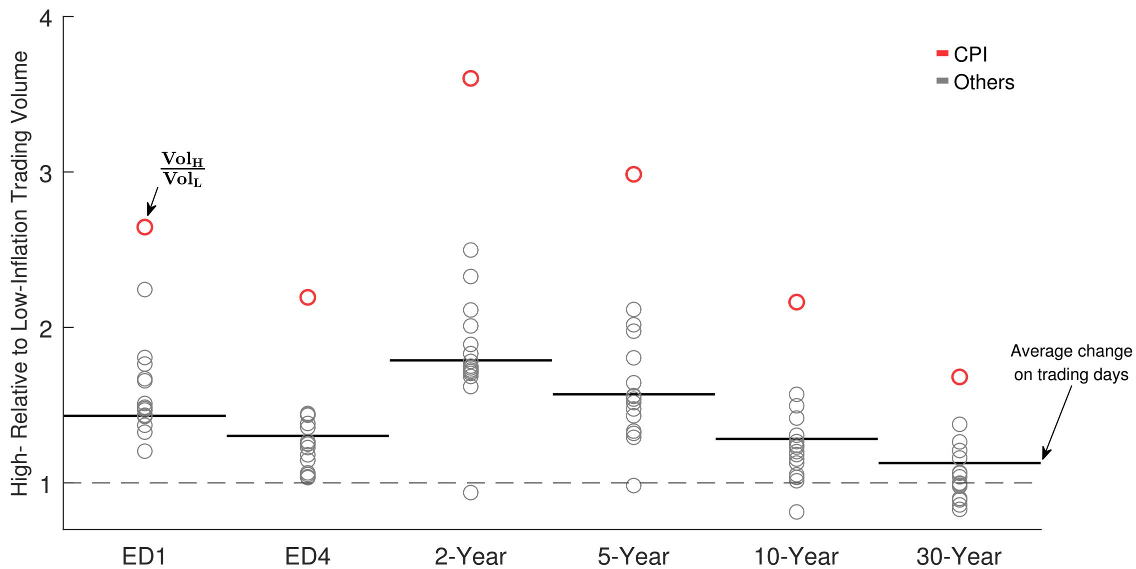
Based on the findings in the previous section, I now seek to provide direct evidence that the increased sensitivity to CPI releases is driven by investors attention. While attention is generally difficult to measure, I begin by studying the trading volume around macro releases in this subsection. Trading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

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

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

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

Figure 10: Change in Trading Volume around Macro News



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

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

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

5.2 Investor Attention based on Financial News Services

After focusing on trading volume, I now turn to other measures of investors' attention. Since the markets on interest rates futures and inflation swaps are dominated by institutional investors, the market reactions in Section 4 are almost surely driven by them.[21] As

[21] In Appendix B.2.3, I provide more discussion on the prevalence of institutional investors in these markets.

a consequence, I now focus on directly measuring *institutional investor attention* around macro releases. To do so, I follow the previous literature and construct measures which are based on news providers for professional investors (e.g., Ben-Rephael, Da, and Israelsen, 2017; Boguth, Grégoire, and Martineau, 2019).

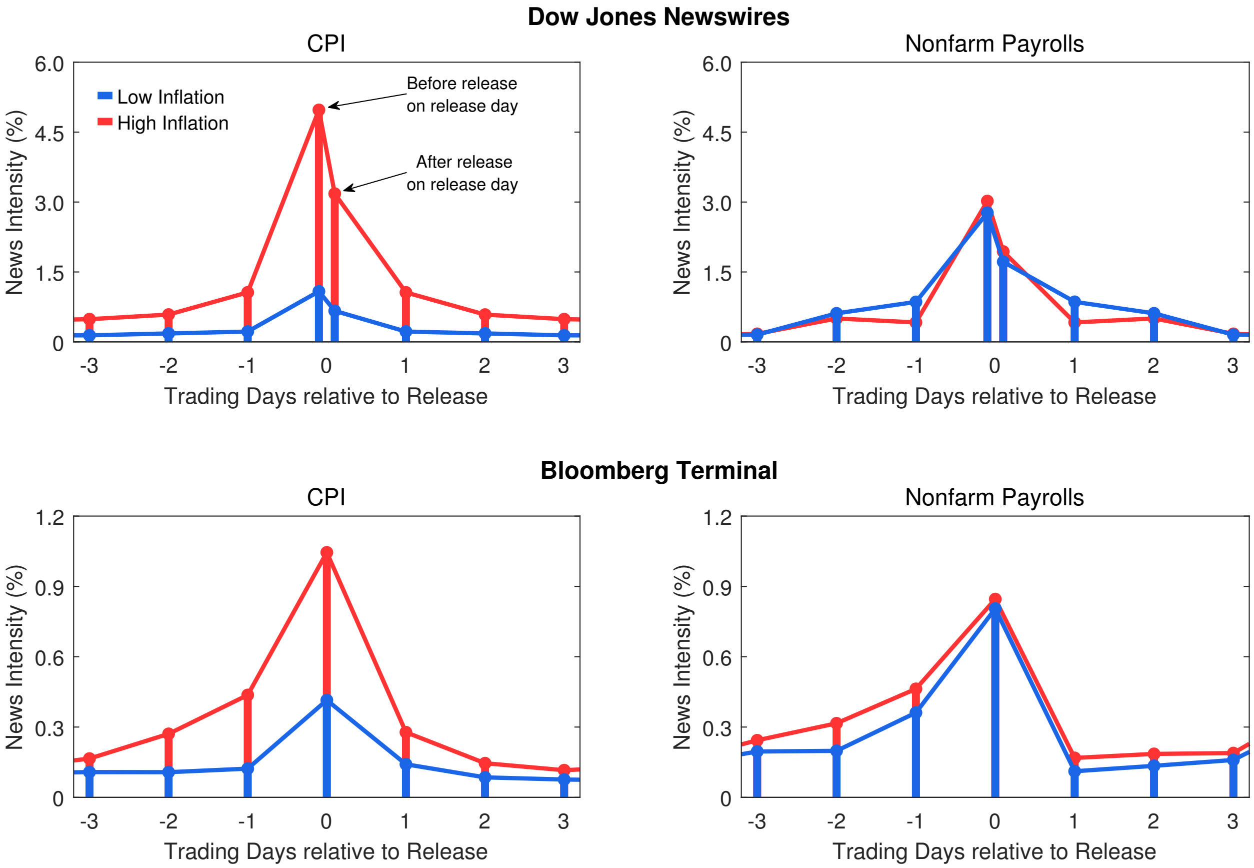
The first set of attention measures is based on news articles from the *Dow Jones Newswires* which provides real-time news for financial professionals.[22] I obtain the data from RavenPack Analytics which manages a dataset of economic- and business-related news articles (including timestamps) from a wide range of news sources. The second set is based on news articles from the *Bloomberg Terminal*. As shown by Ben-Rephael, Da, and Israelsen (2017), the large majority of Bloomberg terminal users are institutional investors.

For both news sources, I construct CPI-related attention based on the following steps. First, I find the number of articles covering the CPI release over a given time interval, e.g., a day. Second, I divide this number by the average number of articles over the same time interval, where the average is taken over the last 12 months. This step ensures that the measure is comparable across time periods. It also means that it reflects news intensity, i.e., the percentage of all news articles from the Dow Jones Newswires or Bloomberg Terminal related to the CPI. For comparison, I create for both sources in a similar manner a measure of Nonfarm-Payrolls-related attention. All details on the construction are relegated to Appendix B.3.

Figure 11 plots the average path of the CPI- and Nonfarm-Payrolls-related attention around the respective news releases, both during the low- and high-inflation period. The figure shows for both news sources a large increase in investor attention to CPI releases during the inflation surge. In contrast, institutional investors' attention to releases of Nonfarm Payroll numbers is essentially unchanged. The results are consistent with an increase in market sensitivity due to increased investor attention. Lastly, note that investor attention always increases around the release days across both inflation periods, and that the paths converge when moving away from release days. Both patterns validate the construction of the attention measures.

[22] https://www.sec.gov/Archives/edgar/data/1308161/000119312511221637/d10k.htm (accessed March 4, 2024).

Figure 11: Institutional Investor Attention around Macro Releases



Notes: The figure plots the attention by institutional investors to the CPI and Nonfarm Payrolls around the respective releases. The measures are based on news articles from the Dow Jones Newswires (top row) and Bloomberg Terminal (bottom row). For each news source, the left panel shows the average CPI-related attention around CPI releases during the low-inflation and the high-inflation period, while the right panel depicts the same applied to Nonfarm Payrolls. For a given source, each measure is constructed as the number of relevant articles on that day divided by the average daily number of articles over the last 12 months. See text for details on the construction.

5.3 Attention by Broader Public

While I documented the increased attention by investors to CPI releases, I now turn to the attention by the broader public. Despite not being crucial for the market reaction, studying the broader public's attention to CPI releases is still a worthwhile exercise for at least two reasons: First, from a macroeconomic perspective, the expectation formation of the general population is what is of interest in many instances. Second, from a financial perspective, more attentive retail investors might affect markets in which they are more prominent, e.g., cryptocurrency ones.

In order to analyze public attention around macro releases, I employ two types of attention measures. The first one is based on *News Coverage* and is constructed from news articles from 9 major news sources in the US: CNN, Fox News, Los Angeles Times, MSN, New York Post, New York Times, Wall Street Journal, Washington Post, and USA Today. The data comes from RavenPack Analytics. I construct CPI-related attention as before in Section 5.2. First, I find the number of CPI-related articles over a given time interval, e.g., a day. Second, I divide this number by the average number of articles over the same time interval, where the average is taken over the last 12 months. This step ensures that the measure is comparable across time periods. For comparison, I create an attention measure for Nonfarm Payrolls in the same manner. As RavenPack Analytics only provides economic- and business-related news, the units should be interpreted as shares of the overall number of economic and business articles from the sources. More details on the construction are provided in Appendix B.3.

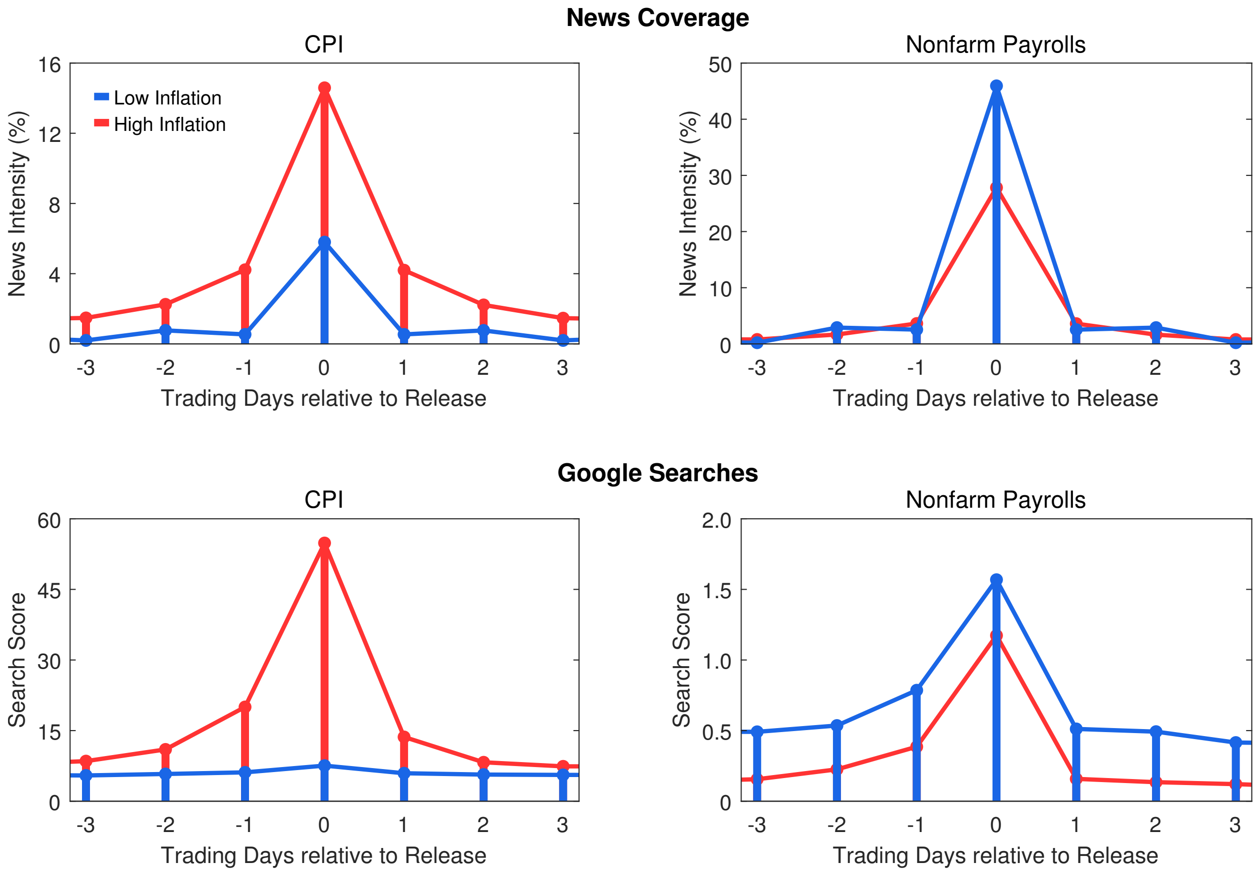
The top row of Figure 12 shows the results for the news-based measures. First and foremost, we see a large increase in attention to the CPI releases during the high-inflation period. In contrast, coverage of Nonfarm Payrolls releases declined compared to the low-inflation period. Note that the levels for CPI- and Nonfarm-Payrolls-related attention are significantly different. This is due to the fact that RavenPack Analytics does only cover articles related to the economy and businesses and that I include the term "employment" in the search for relevant articles. Hence, the attention measure quantifies the importance of the whole employment report among economic and business articles on the release days. As the construction is consistent throughout the sample, these should not affect the differences across inflation periods which is the main interest of the analysis. Overall, the results based on the news coverage are well in line with the other evidence so far.

As the second type of attention measure, I employ *Google searches* which has been used to proxy for retail investor attention (e.g., Da, Engelberg, and Gao, 2011; Ben-Rephael, Da, and Israelsen, 2017), as well as public attention (e.g., Korenok, Munro, and Chen, 2023). Google provides data on search interest over time via its platform *Google Trends*.[23] For my analysis, I focus on searches within the US for release-specific topics. A "topic" is defined by Google and summarizes a group of search terms that share the same concept in any language (Google, 2023). In contrast to prior research, I construct a daily search score series for a given topic. As Google trends provides historical daily data only for short time intervals,

[23] Over the employed sample period, from January 2009 until July 2023, 84 percent of all search queries in the United States have been performed through Google. Source: `https://gs.statcounter.com/search-engine-market-share/all/united-states-of-america/#monthly-200901-202307` (accessed on January 20, 2024).

various steps are needed to construct an internally consistent daily series over the entire sample period. Appendix B.4 provides the details of this construction. For the analysis here, I focus on the topics "Consumer Price Index" and "Nonfarm Payrolls".

Figure 12: Public Attention around Macro Releases



Notes: This figure plots the measures of public attention to the CPI and Nonfarm Payrolls around the respective releases. The top row shows measures based on news articles from a broad range of popular news sources, whereas the bottom shows proxies based on Google Searches. For each row, the left panel shows the average CPI-related attention around CPI releases during the low- and high-inflation period, while the right panel depicts the same applied to Nonfarm Payrolls. Attention measures in the top row are constructed as number of relevant articles on that day divided by the average daily number of articles over the last 12 months. Measures in the bottom row are constructed as the number of Google searches normalized such that 100 corresponds to the largest observation for the topic "Consumer Price Index" over the sample period. See text for more details on the construction.

The bottom row of Figure 12 plots the average path of the CPI- and Nonfarm-Payrolls-specific Google searches around the respective releases, both during the low-inflation period (blue) and the high-inflation period (red). Consistent with the evidence so far, the figure shows a large upward spike on the day of the CPI release. It also highlights that the searches are very similar once moving away from the releases. In comparison, for Nonfarm Payrolls searches seem to be lower during the high-inflation period. However, note that the search scores are generally very much smaller in comparison to the CPI. This makes it hard to associate the differences across periods to attention rather than noise. Overall, it is safe to say that there is no substantial increase in attention to Nonfarm Payrolls releases. In Appendix D.2, I provide more results. There, I show that the Google searches for the CPI are also exceptional in comparison with other macro releases.

5.4 Expectations versus Risk Premia

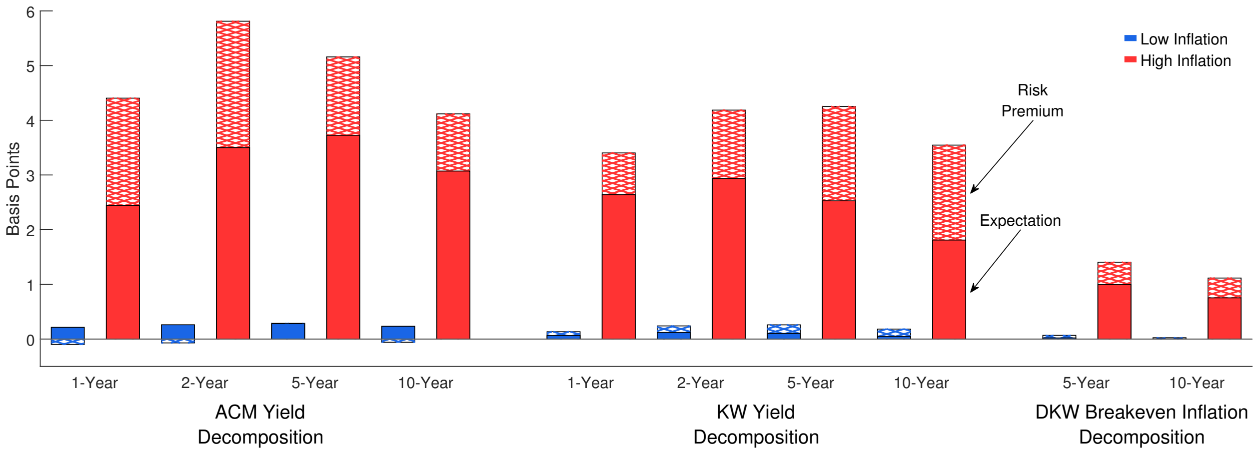
One aspect I mostly ignored so far in my analysis is that asset prices contain generally a risk premium, i.e., a compensation investors demand for the uncertainty of the asset's payoff. With respect to my analysis, the concern is that the increased sensitivity to CPI news is actually not driven by policy rate and inflation expectations but rather by the premia components of the asset prices. To mitigate this concern, I employ in this section three popular decompositions of yields and inflation compensation into expectations and risk premia and study the effects of CPI news on them. Before I go into the details, it is important to note that risk premia are generally very hard to measure and that the following analysis will be based on daily changes due to the availability of the decompositions.

I start by looking at yield curve decompositions into expected short rates and term premia. To do so, I use the estimates by Adrian, Crump, and Moench (2013) (ACM) and Kim and Wright (2005) (KW), which are the two most widely used and readily available off-the-shelf. For a given maturity, I regress the daily changes in the expected short rates and risk premium on the CPI surprises. Figure 13 displays the estimates. The blue and red filled bars show the effects on expected short rates under low and high inflation, respectively. The hatched bars display the effects on risk premia.

As Figure 13 displays, the largest portion of the increase in sensitivity is driven by expectations. In fact, while both decompositions lead to slightly different estimates, the average relative importance of short rate expectations across maturities is almost identical, 66 percent under the ACM decomposition and 65 percent under the KW decomposition. In sum, while the sensitivity of risk premia also increases, it is not the dominant force.

Moving on to inflation compensation, I employ the decomposition by d'Amico, Kim, and Wei (2018) (DKW) which decomposes TIPS breakeven inflation for given maturity into the average expected inflation and the inflation risk premium. Unfortunately, to the best of knowledge, an off-the-shelf decomposition for inflation swap rates does not exist. Hence, I

Figure 13: Daily Effects of CPI news on Expectations and Risk Premia



Notes: This figure shows the daily effects of CPI news on expectations and risk premia of yields and breakeven inflation rates under the low-inflation and the high-inflation period. The figure shows estimates for three decompositions: the yield decompositions by Adrian, Crump, and Moench (2013) (ACM) and Kim and Wright (2005) (KW), as well as the decomposition of breakeven inflation rates by d'Amico, Kim, and Wei (2018) (DKW). For a given maturity, the red filled and red hatched bars depict the effects on expectation and risk premium under high inflation, respectively, i.e., estimates of coefficient $\beta_H^{y|k}$ of equation (14), where the left-hand side is now either the change in the expectation or risk premium of the corresponding decomposition. Similarly, the blue bars depict the effects under low inflation, i.e., estimates of coefficient $\beta_L^{y|k}$ of equation (14).

can only look at maturities of 5- and 10-years. As discussed in Section 4.2, the results for inflation swap rates and breakeven inflation are very similar for these maturities.

Figure 13 displays the estimate for the DKW decomposition. Consistent with the results on yields, the large increase in inflation compensation is also driven by inflation expectations. Across both maturities, 69 percent of the sensitivity under high inflation comes from inflation expectations. The fact that importance of expectations are similar across all three decompositions also indicates potentially a common mechanism consistent with the suggested in this paper. Lastly, while I do not have direct evidence on shorter maturities, evidence from other papers, as discussed Diercks et al. (2023), suggests that inflation risk premia are less crucial for short horizons.

5.5 Additional Analyses

FOMC announcements Besides inflation news, monetary models of "rational inattention" would also predict that attention to monetary policy increases during high-inflation periods. Employing Google searches for the topic "Federal Open Market Committee", I show in Appendix Figure D3 that attention to FOMC announcements increased similar to CPI releases.

Lower Frequency Effects In Appendix Figure D4, I show the effects of CPI news over the next trading days following the release. There a couple of things to note. Generally, the lack of statistical power, which is due to the surprises being small and the short high-inflation period, makes it difficult to draw many conclusion at lower frequencies. That being said, there are couple of things I want to emphasize: First, the effect over the first five trading days is qualitatively consistent with the intraday results. Second, in all cases, one cannot reject that the responses are different after 15 days. In other words, the effect differences do seem to fade. Unfortunately, it is hard to draw much conclusions with respect to delayed reactions. The arguably cleanest evidence is one the initial underreactions of the 1- and 2-year yield during the low-inflation period which is consistent with the model channel.

6 Conclusion

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

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Online Appendix

for

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

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Federal Reserve Board

Table of Contents

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

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A Model Appendix

A.1 Intertemporal Budget Constraint

The budget constraints at the four dates are given by

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

where $\tilde{W}_\tau^i$ depicts investor i's wealth from date τ's perspective. Hence, the intertemporal budget constraint is given by

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

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

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

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

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

where we define $V = \frac{1}{\left(1+R_f\right)\left(1+R_f+\Delta R\right)}$ 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

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

and

$$\begin{aligned}
\mathrm{E}_2^i\big[W_4^i\big] &= \mathrm{E}_2^i\Big[\tilde{\lambda}_2^i\,(V-P_2)+\lambda_1^i\,(P_2-P_1)+W_0^i\Big] \\
&= \tilde{\lambda}_2^i\,\big(\mathrm{E}_2^i[V]-P_2\big)+\lambda_1^i\,(P_2-P_1)+W_0^i. \qquad \text{(A5)}
\end{aligned}$$

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

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

and

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

A.3 Treasury Bond Value V and Its Conditional Moments

The Treasury bond value V can be simplified as follows:

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

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 $\Delta R=\phi^\pi\Delta\bar{\pi}+\phi^z\Delta\bar{z}$ in the last step. For brevity, I define $\phi=(\phi^\pi+\phi^z\varrho)$ for the rest of this section, which allows me to write

$$\begin{aligned}
V &= 1-\phi^\pi\Delta\bar{\pi}-\phi^z\Delta\bar{z} \\
&= 1-(\phi^\pi+\phi^z\varrho)\Delta\bar{\pi} \\
&= 1-\phi\Delta\bar{\pi}.
\end{aligned}$$

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

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

The conditional variance of V at date 1 is given by

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

At date 2, inattentive investors, $i \in (1 - \mu^k, 1]$, have still the same expectation and conditional variance as at date 1, i.e.,

$$\mathrm{E}_2^i[V] = \mathrm{E}_2^{1-\mu^k}[V] = 1, \tag{A8}$$

and

$$\mathrm{Var}_2^i[V] = \mathrm{Var}_2^{1-\mu^k}[V] \quad = \quad \phi^2\sigma_\pi^2. \tag{A9}$$

Upon observing macro release k, attentive investors, $i \in [0, \mu^k]$, update their expectation to

$$\mathrm{E}_2^i[V] = \mathrm{E}_2^{\mu^k}[V] = \begin{cases} 1 - \phi\xi s^k & \text{if } k = \text{CPI} \\ 1 - \frac{\phi}{\varrho}\xi s^k & \text{if } k = \text{NFP} \end{cases}, \tag{A10}$$

where ξ is the signal-to-noise ratio. Note the noise variances are defined such that both signal are scaled versions of each other, $s^{\text{NFP}} = \varrho s^{\text{CPI}}$. As a consequence, the signal-to-noise ratio is the same across both releases

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

and the conditional variance as well

$$\begin{aligned}\mathrm{Var}_2^{\mu^{\text{CPI}}}[V] &= \mathrm{E}_2^i\Big[V - \mathrm{E}_2^{\mu^{\text{CPI}}}[V]\Big] \\ &= \mathrm{E}_2^i\Big[\big((1 - \phi\Delta\bar{\pi}) - \big(1 - \phi\xi s^{\text{CPI}}\big)\big)^2\Big] \\ &= \mathrm{E}_2^i\left[\left((1 - \phi\Delta\bar{\pi}) - \left(1 - \frac{\phi}{\varrho}\xi s^{\text{NFP}}\right)\right)^2\right] \\ &= \mathrm{E}_2^i\Big[V - \mathrm{E}_2^{\mu^{\text{NFP}}}[V]\Big] \\ &= \mathrm{Var}_2^{\mu^{\text{NFP}}}[V]\,.\end{aligned}$$

The conditional variance for attentive investors, $i \in [0, \mu^k]$, is given by

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

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

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

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, $\mathrm{E}_\tau[\cdot]$ denotes the weighted average expectation across investors at date τ and is defined formally below.

Similarly, the market clearing for λ_2^i yields

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

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

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

A.5.2 Price P_2

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

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

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

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

where I used

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

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

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

where the weighted average expectation is defined as $\mathrm{E}_\tau[\cdot] = b_\tau \mathrm{E}_\tau^{\mu^k}[\cdot] + (1-b_\tau) \mathrm{E}_\tau^{1-\mu^k}[\cdot]$. The weight b_τ 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

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

and hence

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

Plugging expressions (A11) and (A9) (for $\mathrm{Var}_2^{\mu^k}[V]$ and $\mathrm{Var}_2^{1-\mu^k}[V]$, respectively) into the expression for a_2 yields

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

Subsequently, expression b_2 can be written as

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

Plugging expressions (A17), (A10) and (A8) (for b_2, $\mathrm{E}_2^{\mu^k}[V]$, and $\mathrm{E}_2^{1-\mu^k}[V]$, respectively) into (A16) yields for the CPI release

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

Hence, the solution for the equilibrium price at date 2 is given by

$$P_2 = \left\{ \begin{array}{l} 1 - \phi\,\Theta(\mu^{\mathrm{CPI}})\,s^{\mathrm{CPI}} \\ 1 - \frac{\phi}{\varrho}\,\Theta(\mu^{\mathrm{NFP}})\,s^{\mathrm{NFP}} \end{array} \right., \tag{A18}$$

where

$$\Theta(\mu^k) = \frac{\mu^k\xi}{1-\xi(1-\mu^k)}.$$

A.5.3 Inflation Expectations

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

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

while at date 2, attentive investors expect changes based on signal s^k

$$\mathrm{E}_2^{\mu^k}[\Delta\bar{\pi}] = \begin{cases} \xi s^k & \text{if } k = \text{CPI} \\ \frac{1}{\varrho}\xi s^k & \text{if } k = \text{NFP} \end{cases},$$

and inattentive investors still do not expect any changes

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

The average inflation expectation at date 2 is given by

$$\begin{aligned} \mathrm{E}_2[\Delta\bar{\pi}] &= b_2\mathrm{E}_2^{\mu^k}[\Delta\bar{\pi}] + (1-b_2)\,\mathrm{E}_2^{\mu^k}[\Delta\bar{\pi}] \\ &= \begin{cases} \Theta(\mu^{\text{CPI}})\, s^{\text{CPI}} \\ \frac{1}{\varrho}\,\Theta(\mu^{\text{NFP}})\, s^{\text{NFP}} \end{cases}, \end{aligned}$$

which allows one to rewrite the equilibrium price as

$$P_\tau = 1 - \phi\mathrm{E}_\tau[\Delta\bar{\pi}]\,.$$

A.6 Market Reaction to Macro News

A.6.1 Bond yields and inflation swap rates

The price of a zero-coupon bond at date 1 or 2 is given by

$$\begin{aligned} P_\tau &= \frac{1}{(1+y_\tau)^\omega} \\ 1 + P_\tau &\approx 1 - \omega y_\tau \\ y_1 &\approx -\frac{P_1}{\omega}, \end{aligned}$$

where I use a first order approximation around $y_\tau = 0$ in the first step. Hence, the change in the bond yield is

$$y = y_2 - y_1 = -\frac{P_2 - P_1}{\omega}.$$

Note that for the zero-coupon bond, the maturity is equal to the duration

$$\begin{aligned} D &= -\frac{\partial \log\left(P_\tau\right)}{\partial y_\tau}\left(1+y_\tau\right) = -\frac{\partial \log\left(\frac{1}{(1+y_\tau)^\omega}\right)}{\partial y_\tau}\left(1+y_\tau\right) \\ &= \omega \frac{1}{1+y_\tau}\left(1+y_\tau\right) = \omega, \end{aligned}$$

and approximately equal to the modified duration

$$D_{mod,\tau} = -\frac{\partial \log\left(P_\tau\right)}{\partial y_\tau} = \frac{D}{1+y_\tau} \approx D = \omega.$$

The inflation swap rate π_τ of maturity ω is given by

$$\begin{aligned} \left(1+\pi_\tau\right)^\omega &= \mathrm{E}_\tau[\left(1+\bar{\pi}_2\right)\left(1+\bar{\pi}_3\right)] \\ \left(1+\pi_\tau\right)^\omega &= \mathrm{E}_\tau[1+\bar{\pi}_3] \\ 1+\omega\pi_\tau &\approx \mathrm{E}_\tau[\left(1+\bar{\pi}_3\right)] \\ \pi_\tau &\approx \frac{\mathrm{E}_\tau[\bar{\pi}_3]}{\omega}, \end{aligned}$$

where I use $\bar{\pi}_2 = 0$ in the first step and a first order approximation around $\pi_\tau = 0$ in the second step. The change in the inflation swap rate is then

$$\pi = \pi_2 - \pi_1 = \frac{\mathrm{E}_2[\bar{\pi}_3] - \mathrm{E}_1[\bar{\pi}_3]}{\omega}.$$

A.6.2 Marginal effect of μ^k

Note that the partial derivative of $\Theta(\mu^k)$ with respect to μ^k is given by

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

where the last inequality comes the fact that $0 < \xi < 1$ and $0 < \mu^k < 1$. Since

As ϕ and ω are great and independent of μ^k, this implies that the effects of CPI news vary with μ^k as follows

$$\frac{\partial\beta^{y|\mathrm{CPI}}}{\partial\mu^{\mathrm{CPI}}} = \frac{\partial\left(\frac{\phi}{\omega}\Theta(\mu^{\mathrm{CPI}})\right)}{\partial\mu^{\mathrm{CPI}}} > 0,$$

and

$$\frac{\partial \beta^{\pi|\text{CPI}}}{\partial \mu^{CPI}} = \frac{\partial \left(\frac{1}{\omega}\Theta(\mu^{\text{CPI}})\right)}{\partial \mu^{k}} > 0.$$

Further, the effects of Nonfarm Payrolls news vary with μ^k as follows

$$\frac{\partial \beta^{y|\text{NFP}}}{\partial \mu^{\text{NFP}}} = \frac{\partial \left(\frac{\phi}{\omega\varrho}\Theta(\mu^{\text{NFP}})\right)}{\partial \mu^{\text{NFP}}} \begin{cases} > 0 \text{ if } \varrho > 0 \\ < 0 \text{ if } \varrho < 0 \end{cases},$$

and

$$\frac{\partial \beta^{\pi|\text{NFP}}}{\partial \mu^{\text{NFP}}} = \frac{\partial \left(\frac{1}{\omega\varrho}\Theta(\mu^{\text{NFP}})\right)}{\partial \mu^{\text{NFP}}} \begin{cases} > 0 \text{ if } \varrho > 0 \\ < 0 \text{ if } \varrho < 0 \end{cases}.$$

A.6.3 Marginal effect of ϕ^π

Since

$$\frac{\partial \phi}{\partial \phi^{\pi}} = \frac{\partial \left(\phi^{\pi} + \phi^{z}\varrho\right)}{\partial \phi^{\pi}} = 1 > 0,$$

the effects of CPI and Nonfarm Payrolls news vary with ϕ^z as follows

$$\frac{\partial \beta^{y|\text{CPI}}}{\partial \phi^{\pi}} = \frac{\partial \left(\frac{\phi}{\omega}\Theta(\mu^{\text{CPI}})\right)}{\partial \phi^{\pi}} = \frac{1}{\omega}\Theta(\mu^{\text{CPI}}) > 0,$$

$$\frac{\partial \beta^{\pi|\text{CPI}}}{\partial \phi^{\pi}} = \frac{\partial \left(\frac{1}{\omega}\Theta(\mu^{\text{CPI}})\right)}{\partial \phi^{\pi}} = 0,$$

$$\frac{\partial \beta^{y|\text{NFP}}}{\partial \phi^{\pi}} = \frac{\partial \left(\frac{\phi}{\omega\varrho}\Theta(\mu^{\text{NFP}})\right)}{\partial \phi^{\pi}} \begin{cases} > 0 \text{ if } \varrho > 0 \\ < 0 \text{ if } \varrho < 0 \end{cases},$$

and

$$\frac{\partial \beta^{\pi|\text{NFP}}}{\partial \phi^{\pi}} = \frac{\partial \left(\frac{1}{\omega\varrho}\Theta(\mu^{\text{NFP}})\right)}{\partial \phi^{\pi}} = 0.$$

A.6.4 Marginal effect of ϕ^z

Since

$$\frac{\partial \phi}{\partial \phi^{z}} = \frac{\partial \left(\phi^{\pi} + \phi^{z}\varrho\right)}{\partial \phi^{z}} = \varrho,$$

the effects of CPI and Nonfarm Payrolls news vary with ϕ^z as follows

$$\frac{\partial \beta^{y|\text{CPI}}}{\partial \phi^{z}} = \frac{\partial \left(\frac{\phi}{\omega}\Theta(\mu^{\text{CPI}})\right)}{\partial \phi^{z}} = \frac{\varrho}{\omega}\Theta(\mu^{\text{CPI}}) \begin{cases} > 0 \text{ if } \varrho > 0 \\ < 0 \text{ if } \varrho < 0 \end{cases},$$

$$\frac{\partial \beta^{\pi|\text{CPI}}}{\partial \phi^{\pi}} = \frac{\partial \left(\frac{1}{\omega}\Theta(\mu^{\text{CPI}})\right)}{\partial \phi^{\pi}} = 0,$$

$$\frac{\partial \beta^{y|\mathrm{NFP}}}{\partial \phi^z} = \frac{\partial \left(\frac{\phi}{\omega\varrho}\Theta(\mu^{\mathrm{NFP}})\right)}{\partial \phi^z} = \frac{1}{\omega}\Theta(\mu^{\mathrm{CPI}}) > 0,$$

and

$$\frac{\partial \beta^{\pi|\mathrm{NFP}}}{\partial \phi^z} = \frac{\partial \left(\frac{1}{\omega\varrho}\Theta(\mu^{\mathrm{NFP}})\right)}{\partial \phi^z} = 0.$$

A.6.5 Marginal effect of ϱ

Since

$$\frac{\partial \phi}{\partial \varrho} = \frac{\partial \left(\phi^\pi + \phi^z \varrho\right)}{\partial \varrho} = \phi^z,$$

the effects of CPI and Nonfarm Payrolls news vary with ϱ as follows

$$\frac{\partial \beta^{y|\mathrm{CPI}}}{\partial \varrho} = \frac{\partial \left(\frac{\phi}{\omega}\Theta(\mu^{\mathrm{CPI}})\right)}{\partial \varrho} = \frac{\phi^z}{\omega}\Theta(\mu^{\mathrm{CPI}}) > 0,$$

$$\frac{\partial \beta^{\pi|\mathrm{CPI}}}{\partial \varrho} = \frac{\partial \left(\frac{1}{\omega}\Theta(\mu^{\mathrm{CPI}})\right)}{\partial \varrho} = 0,$$

$$\frac{\partial \beta^{y|\mathrm{NFP}}}{\partial \varrho} = \frac{\partial \left(\frac{\phi}{\omega\varrho}\Theta(\mu^{\mathrm{NFP}})\right)}{\partial \varrho} = \frac{1}{\omega}\Theta(\mu^{\mathrm{NFP}})\frac{(\phi^z \varrho - \phi)}{\varrho^2} = -\frac{1}{\omega}\Theta(\mu^{\mathrm{NFP}})\frac{\phi^\pi}{\varrho^2} < 0,$$

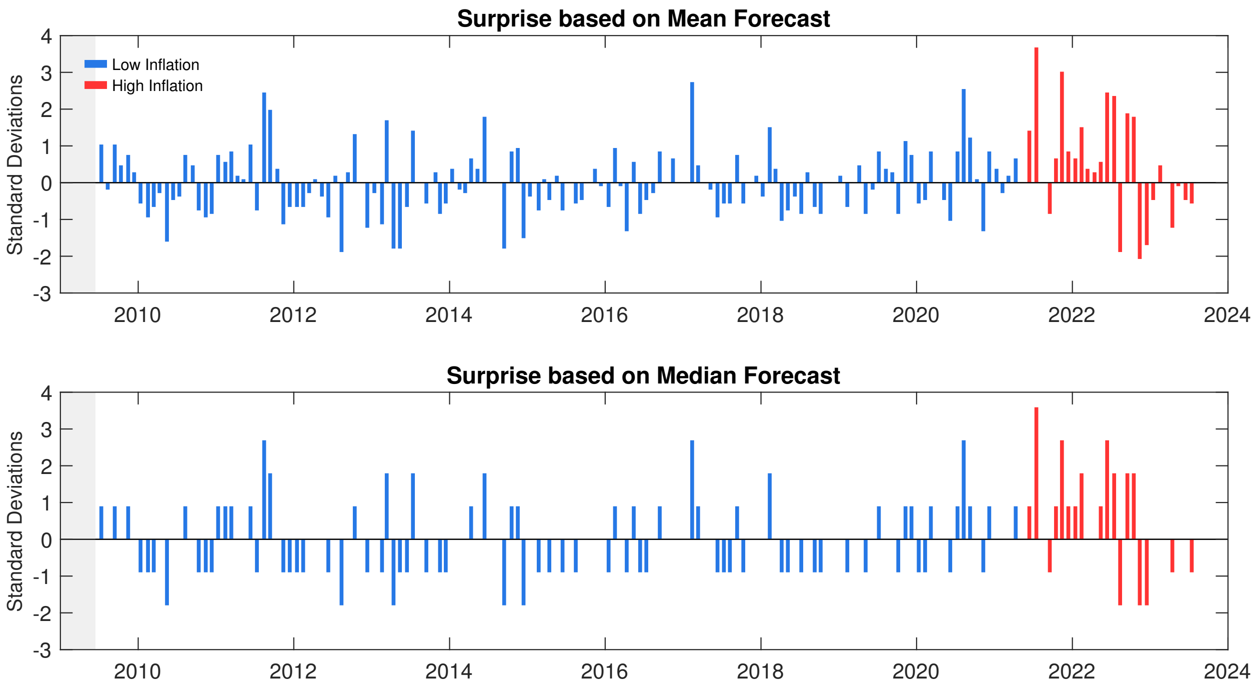
and

$$\frac{\partial \beta^{\pi|\mathrm{NFP}}}{\partial \varrho} = \frac{\partial \left(\frac{1}{\omega\varrho}\Theta(\mu^{\mathrm{NFP}})\right)}{\partial \varrho} = -\frac{1}{\varrho^2}\Theta(\mu^{\mathrm{NFP}}) < 0.$$

B Data Appendix

B.1 Macroeconomic News Releases

Figure B1: Time Series of CPI Surprises



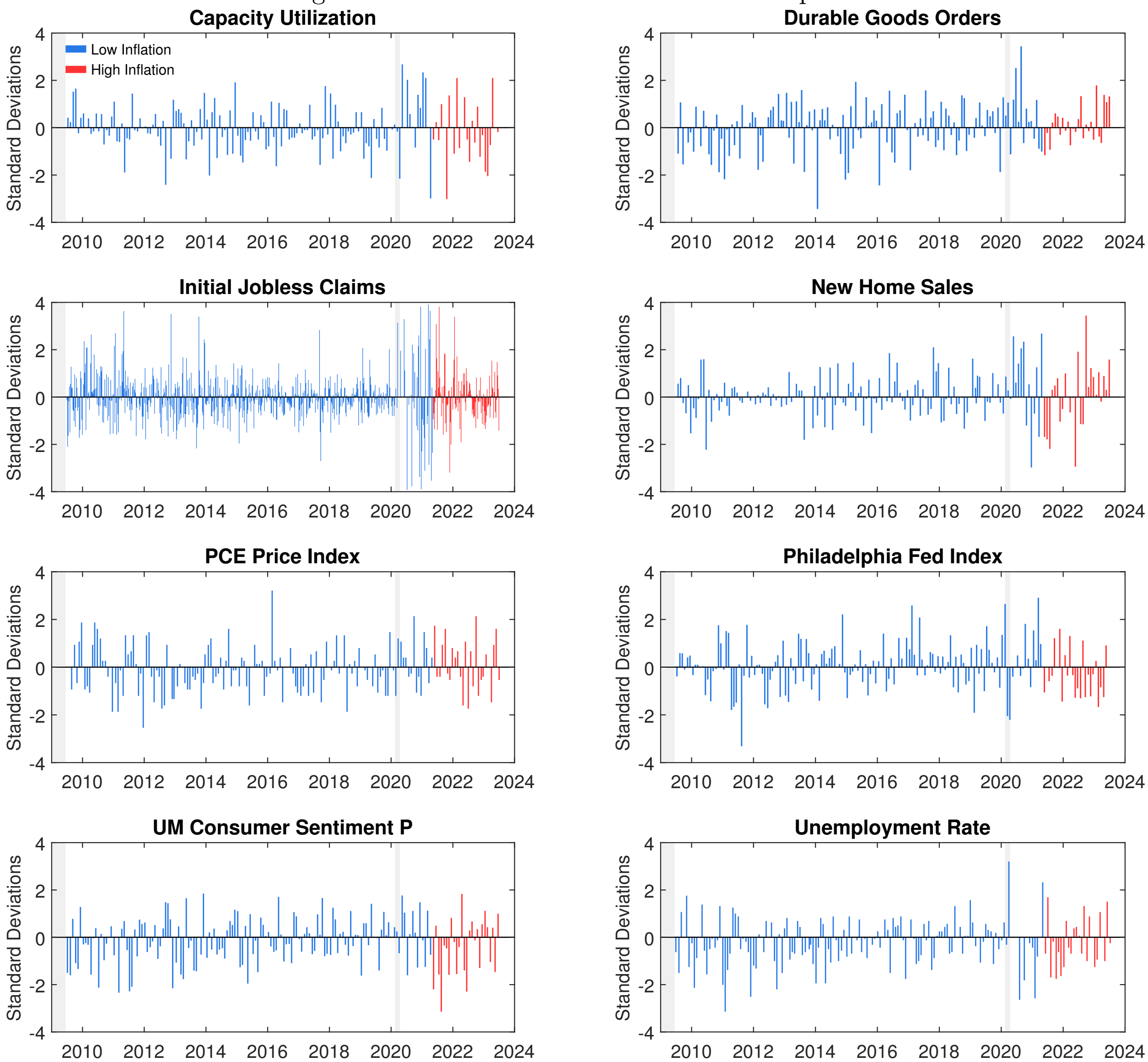
Notes: This figure shows in the top panel the baseline CPI surprises constructed from Bloomberg's mean forecast, and the CPI surprises constructed from Bloomberg's median forecast in the bottom panel.

Table B1: Overview of All Macroeconomic News Announcements

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

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

Figure B2: Time Series of Standardized Surprises



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

B.2 Financial Data

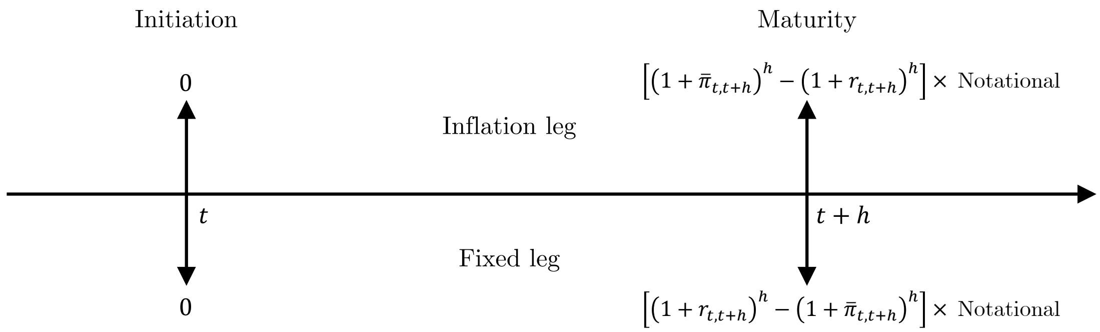
Table B2: Intraday Financial Data on International Markets

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

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

B.2.1 Inflation Swaps

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



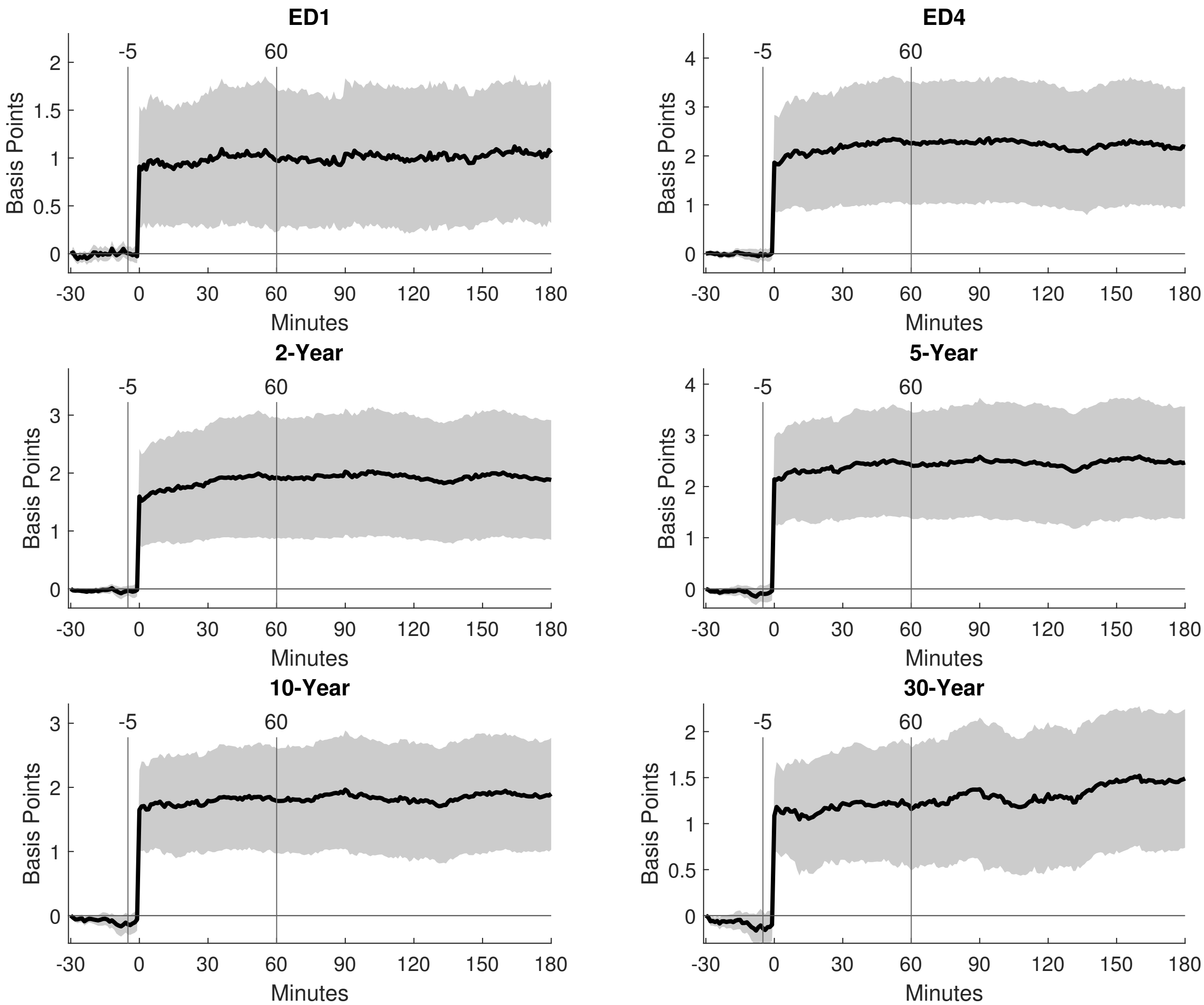
$r_{t,t+h}$: h-year inflation swap rate at t

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

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

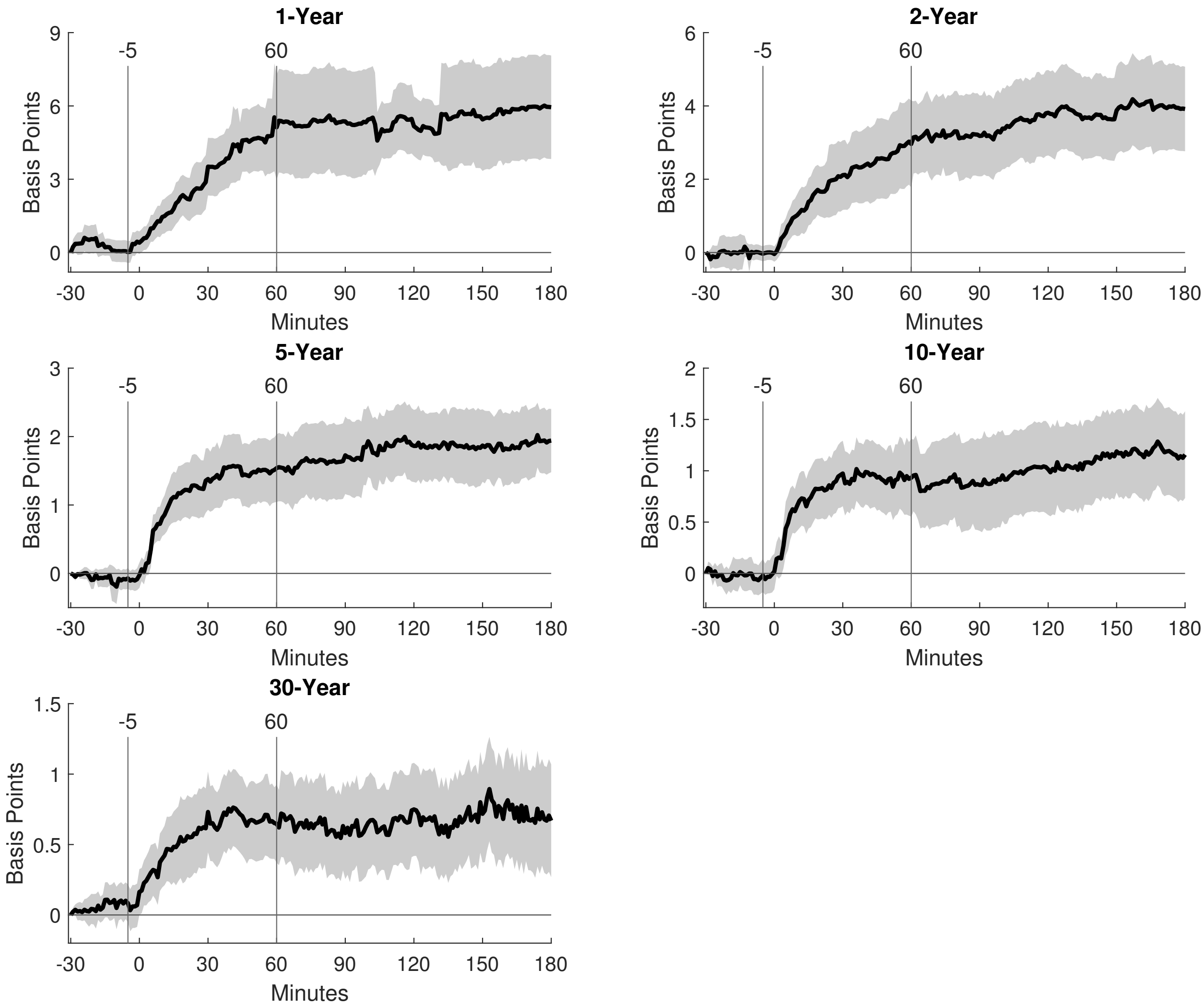
B.2.2 Event Window

Figure B4: Impulse Responses of Interest Rates to CPI News



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

Figure B5: Impulse Responses of Inflation Expectations to CPI News



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

B.2.3 Role of Institutional Investors

The Commodity Futures Trading Commission (CFTC) provides numbers on open interest for futures markets in the U.S. In particular, specific institutional investors are required to report their positions to the CFTC. As a consequence, for futures contracts with relatively large contract sizes, as the ones employed in this paper, the share of non-reportable open interest can be seen as an upper bound for the share of retails investors in the market. In 2023, the shares were between 13 percent for 30-year bond futures to less than 1 percent for SOFR futures. As shown by Ferko, Mixon, and Onur (2024) in the case of E-mini S&P 500 futures, the share of retail traders can be potentially only a tiny fraction of the overall non-reportable share. While similar numbers do not exist for inflation swaps markets in the US, retail investors should be almost non-existent, as inflation swaps trade exclusively in over-the-counter (OTC) markets which are not easily accessible to retail investors (Fleming and Sporn, 2013).

B.3 News-based Attention Measures

Dow Jones News Wires I obtain the data on the Dow Jones News Wires articles from *RavenPack Analytics*. To construct the CPI-attention measure, I consider articles with the following keywords in their headline: "consumer price index", "CPI", "inflation report", or "inflation". For the Nonfarm-Payrolls-attention measure, I consider articles with the following keywords in their headline: "nonfarm", "payroll", "non-farm", "employment", or "jobs".

Bloomberg Terminal I obtain the data on relevant articles directly from the *Bloomberg Terminal*. In particular, I retrieve the story count for the term "Consumer Price Index" and the count for the term "Nonfarm Payrolls" to construct my two attention measures.

News Coverage I obtain the data to construct my attention measure on broader news coverage from *RavenPack Analytics*. The articles are selected based on the same keywords in the headline as above. However, the considered news sources are different and much broader. In particular, I include the following newspapers based on their circulation at the beginning of my sample and at the end of my sample: Wall Street Journal, New York Times, New York Post, Washington Post, USA Today, and "Los Angeles Times.[1] I also use include articles by CNN, Fox News, MSN based being beside New York Times the most visited news websites in the US as of July 2023.[2]

B.4 Google Trends

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

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

2. I merge the 91 subsamples into a continuous series by minimizing the Euclidean distance between the overlapping period of two consecutive subsamples.

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

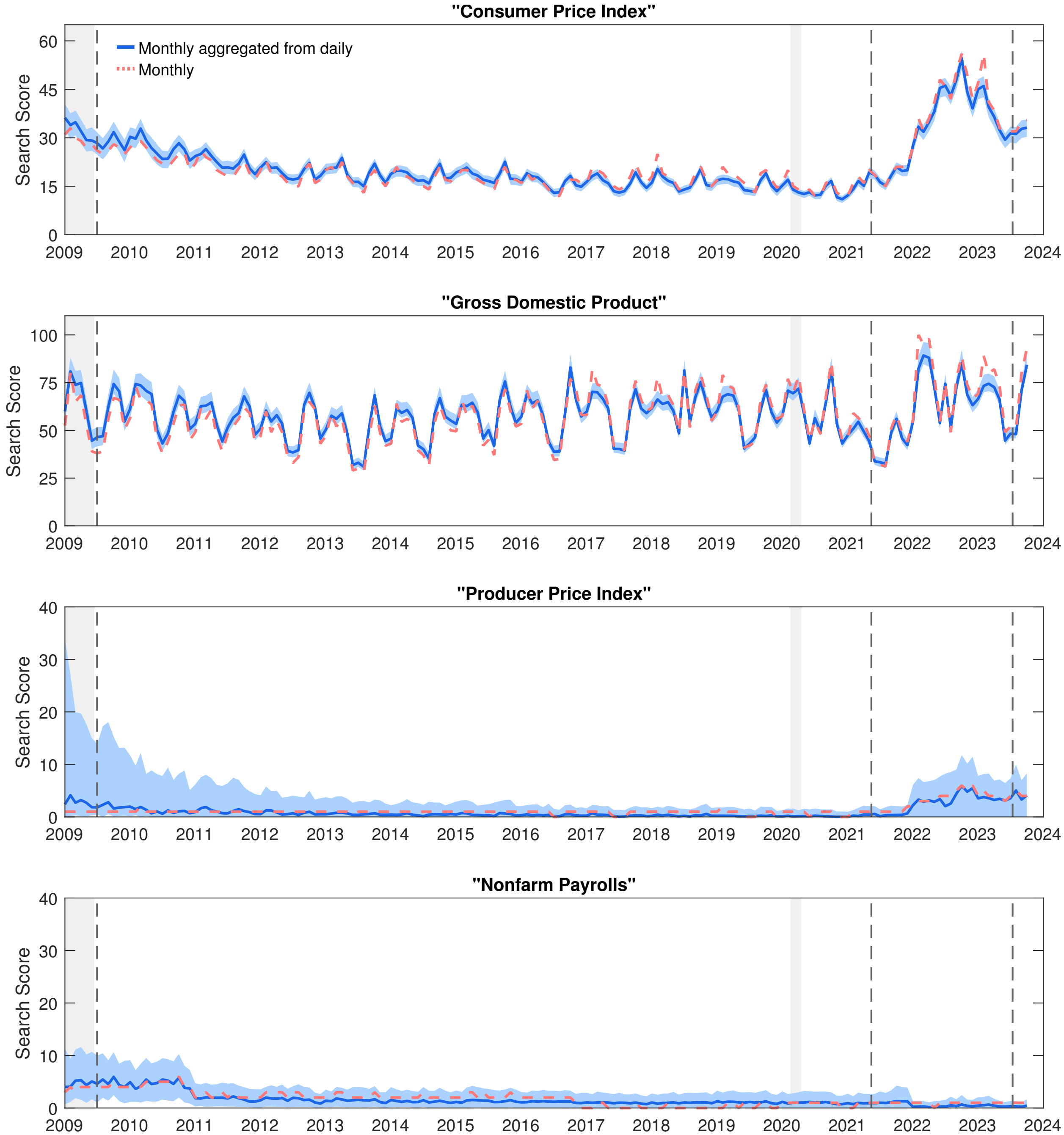
[1] https://www.businessinsider.com/23-of-top-25-newspapers-post-circulation-declines-2009-4 and https://pressgazette.co.uk/media-audience-and-business-data/media_metrics/us-newspaper-circulation-2023/ (accessed on February 28, 2024).

[2] https://pressgazette.co.uk/media-audience-and-business-data/media_metrics/most-popular-websites-news-us-monthly-3/ (accessed on February 28, 2024).

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

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

Figure B6: Time Series of Google Search Scores



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

C Additional Results for Section 4

C.1 Average Effects

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

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

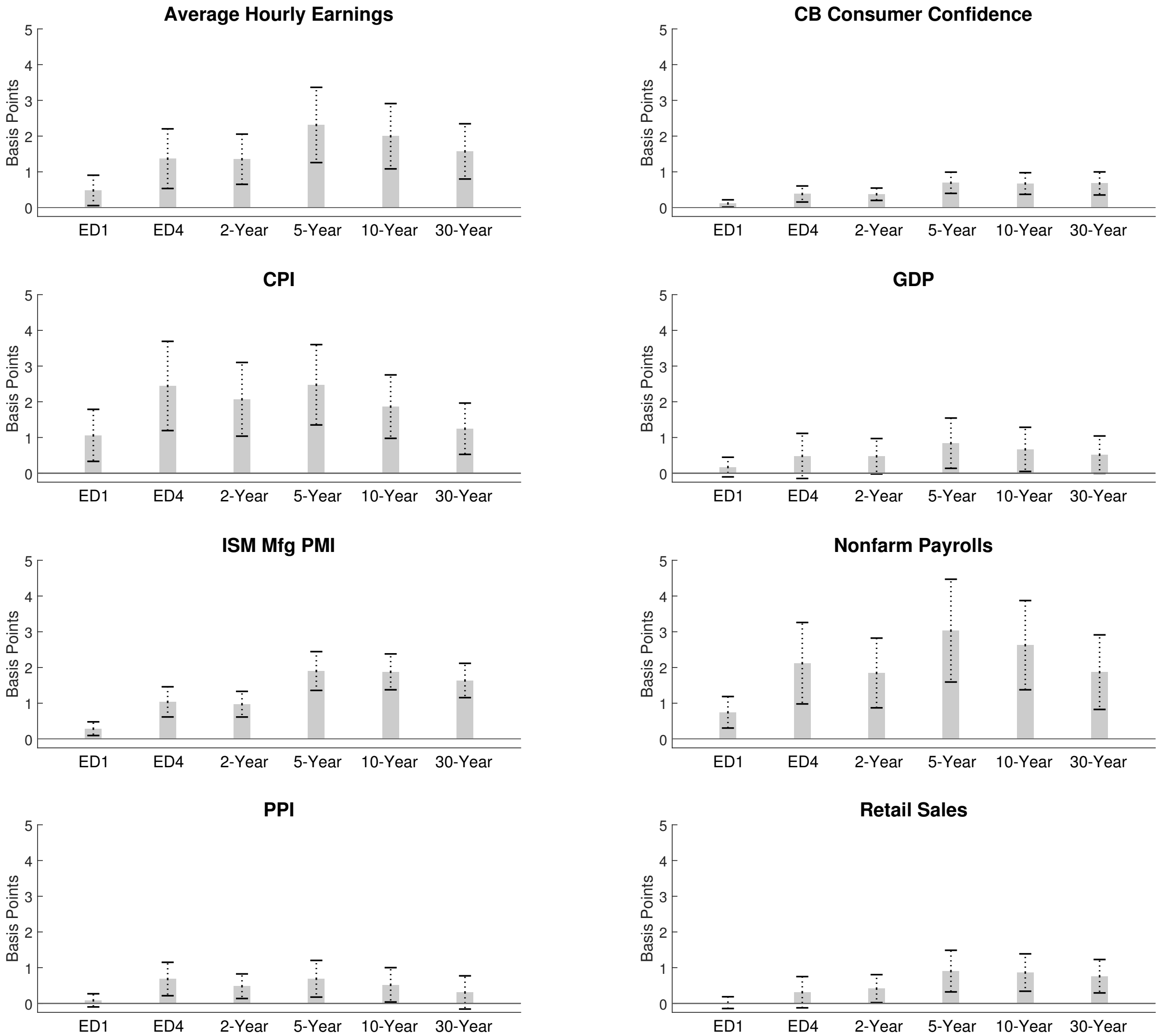
where s_t^k is the announcement surprise of interest, and y_t is the 60-minute change in one of the 6 interest rates described in Table 3.

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

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

where s_t^k is the announcement surprise of interest, and π_t is the 60-minute change in one of the 5 inflation swap rates described in Table 3.

Figure C1: Effects of Macro News on Interest Rates



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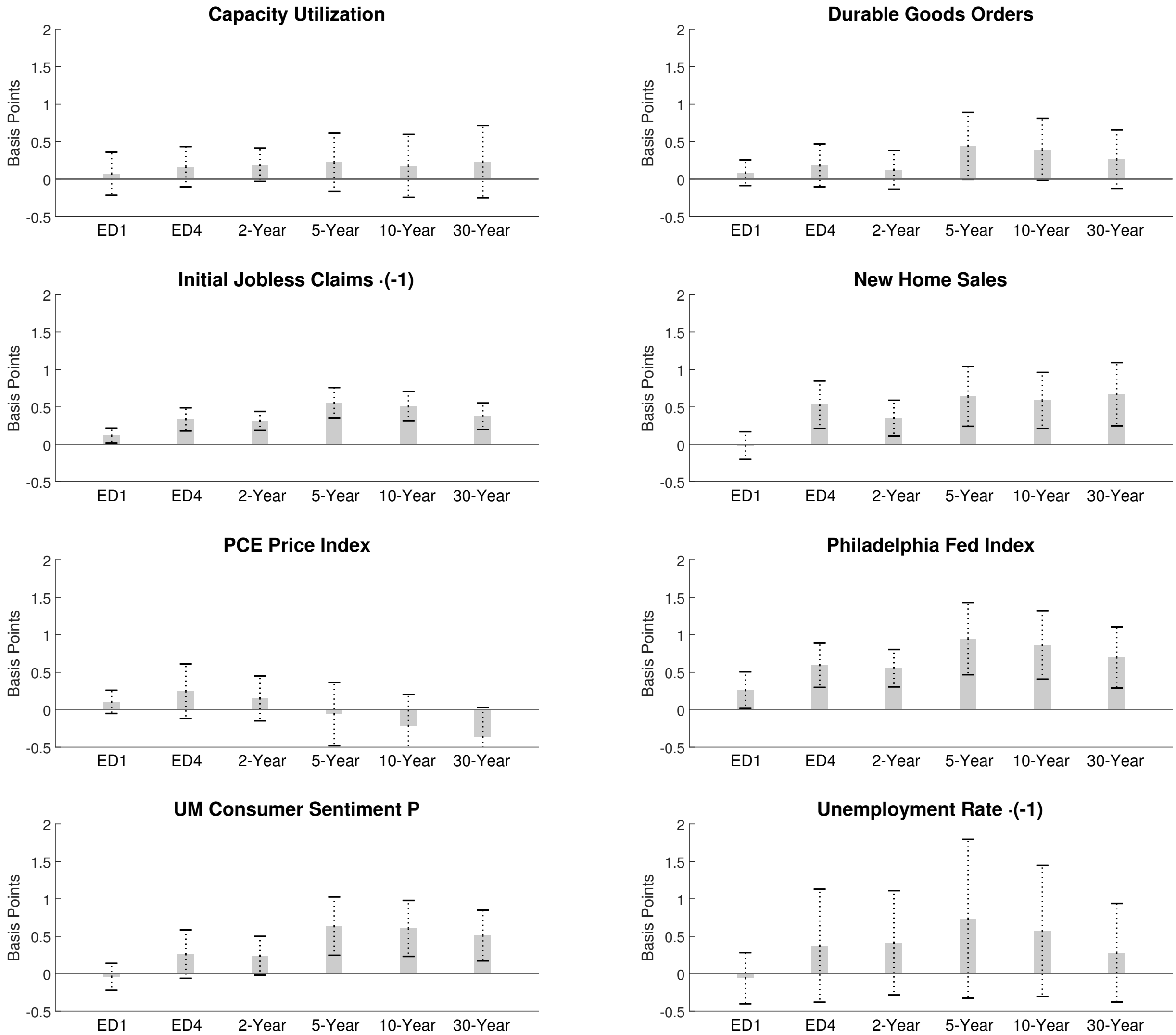
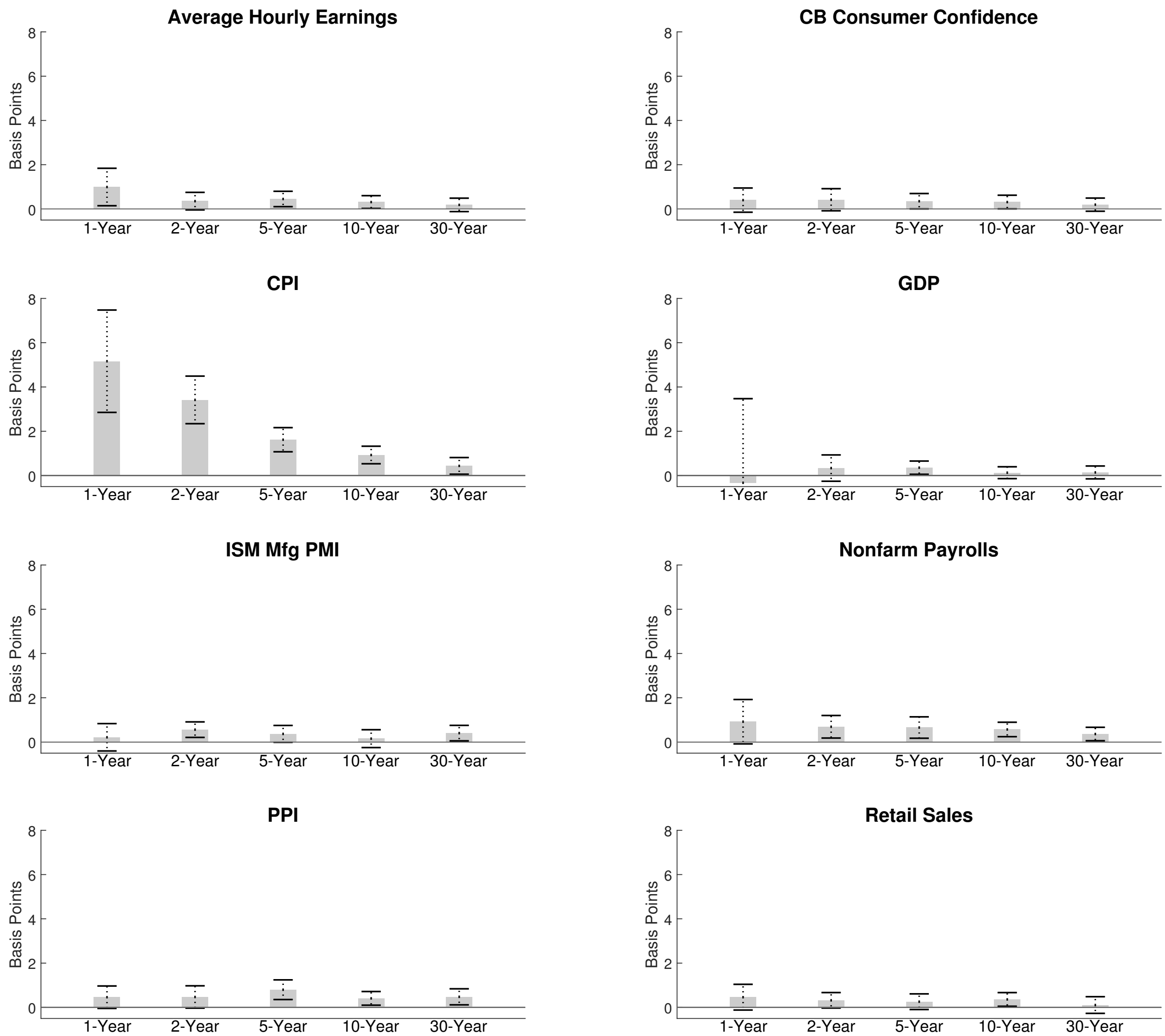


Notes: This figure shows the responses of interest rates for each of the 16 major macro announcements. Interest rate changes are expressed in basis points and announcement surprises are normalized to standard deviations. For a given interest rate, the grey bar shows the average effect, i.e., the estimate of coefficient $\beta^{y|k}$ of equation (C1). The black error bands depict 95 percent confidence intervals, where standard errors are heteroskedasticity-robust. The interest rate abbreviations are explained in Table 3.

Figure C2: Effects of Macro News on Inflation Expectations



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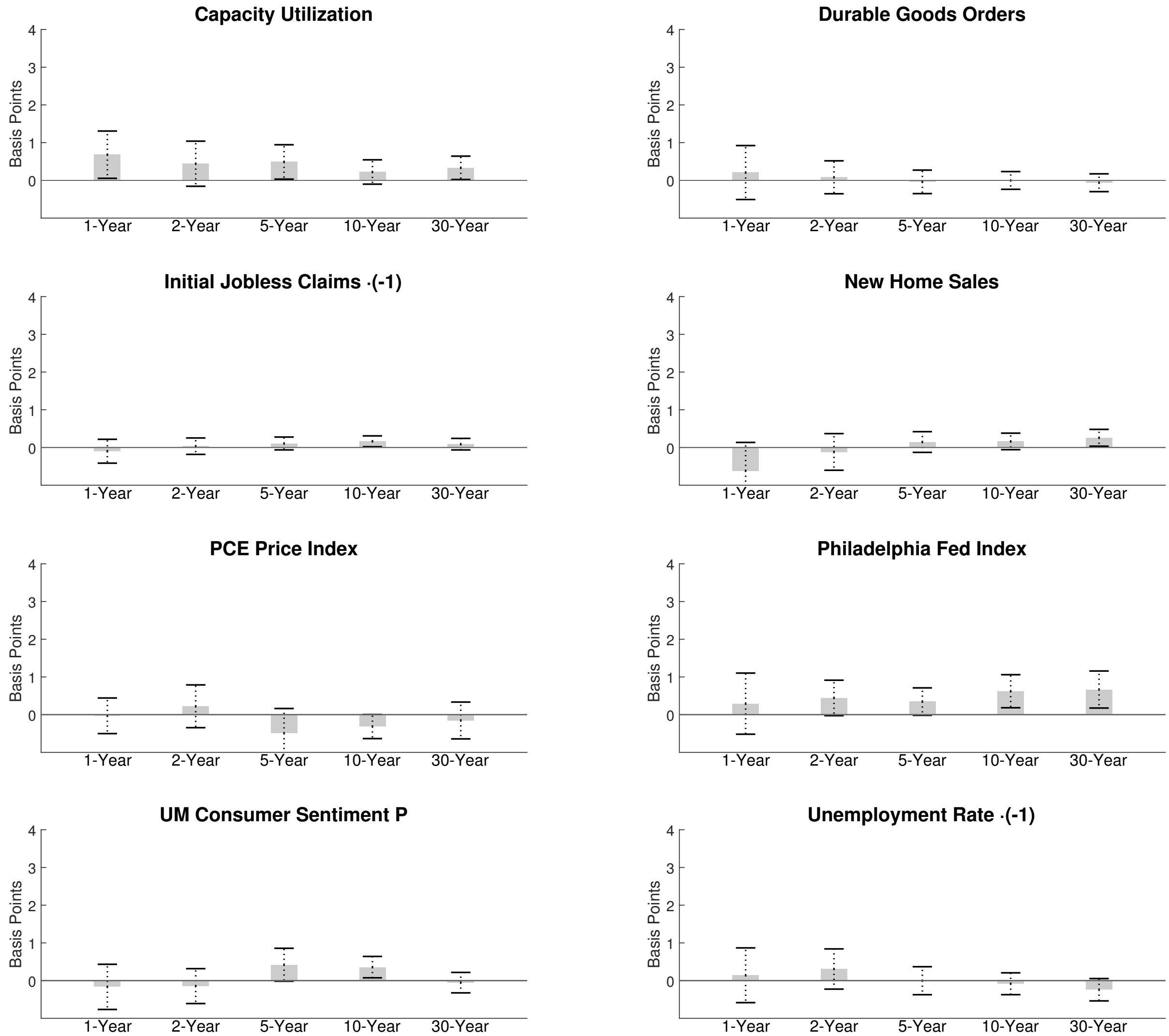
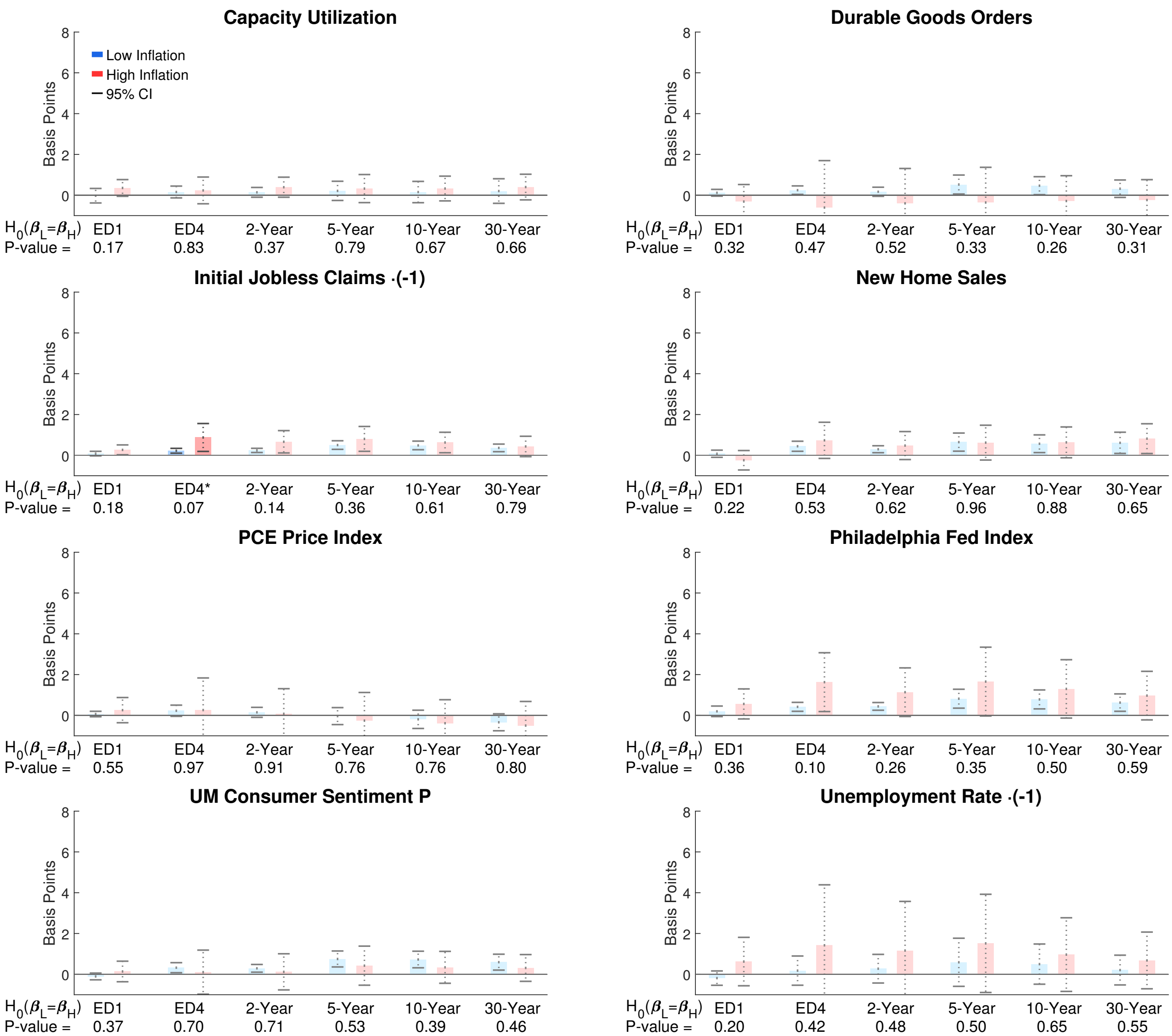


Notes: This figure shows the responses of inflation swap rates for each of the 16 macro announcements. Inflation swap rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given inflation swap rate, the grey bar shows the average effect, i.e.,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

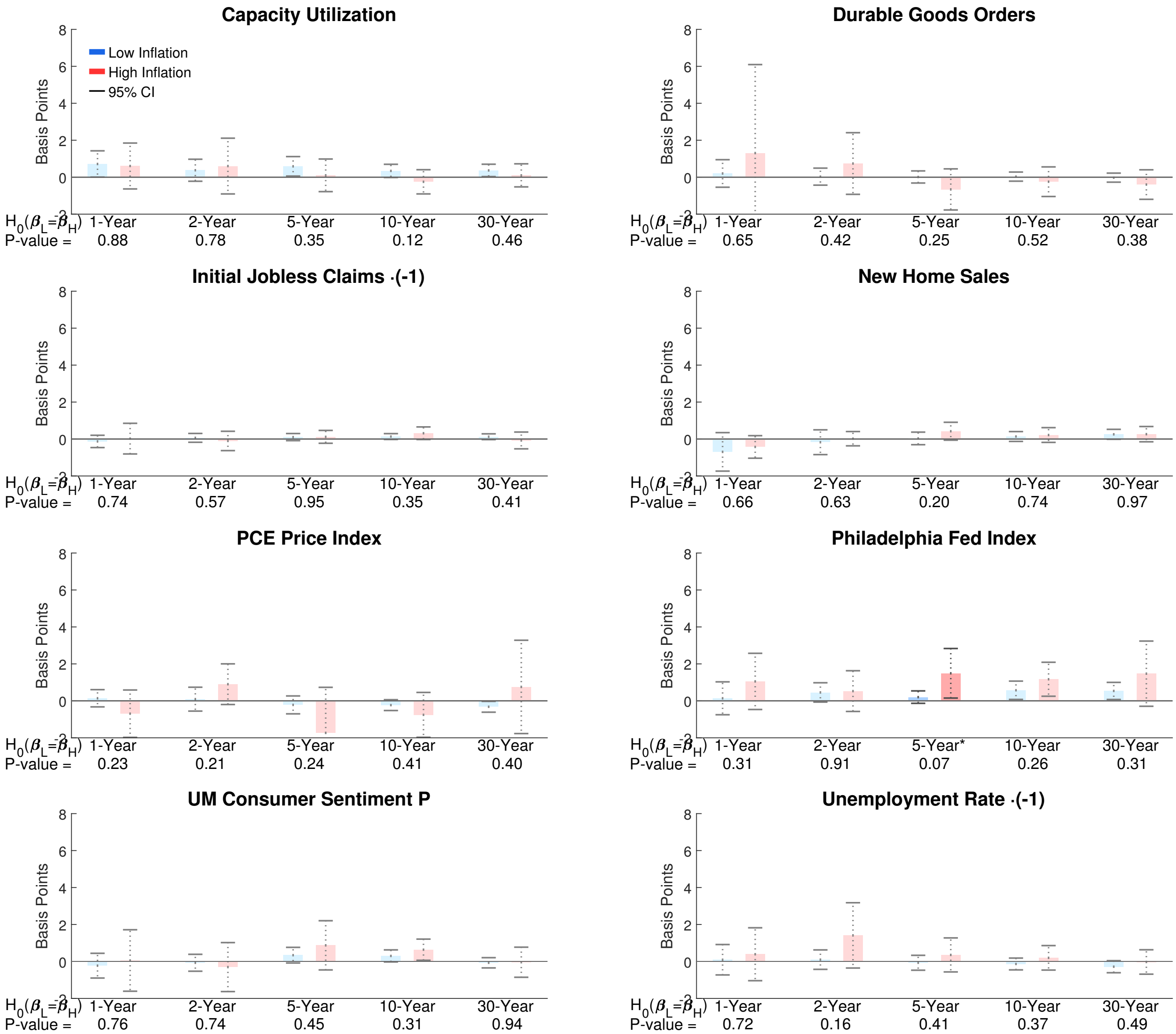
C.2 Additional Macroeconomic Releases

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



Notes: This figure shows the responses of interest rates under the low-inflation and high-inflation sample for each of the 8 other macroeconomic announcements. Interest rate changes are expressed in basis points and announcements surprises are normalized to standard deviations. For a given asset price, the blue bar depicts the effect under low inflation, i.e., the estimate of coefficient $\beta_L^{y|k}$ of equation (14), while the red bar depicts the effect under high inflation, i.e., the estimate of coefficient $\beta_H^{y|k}$ of equation (14). The black error bands depict 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level of rejecting the null hypothesis that $\beta_L^{y|k}$ 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 3.

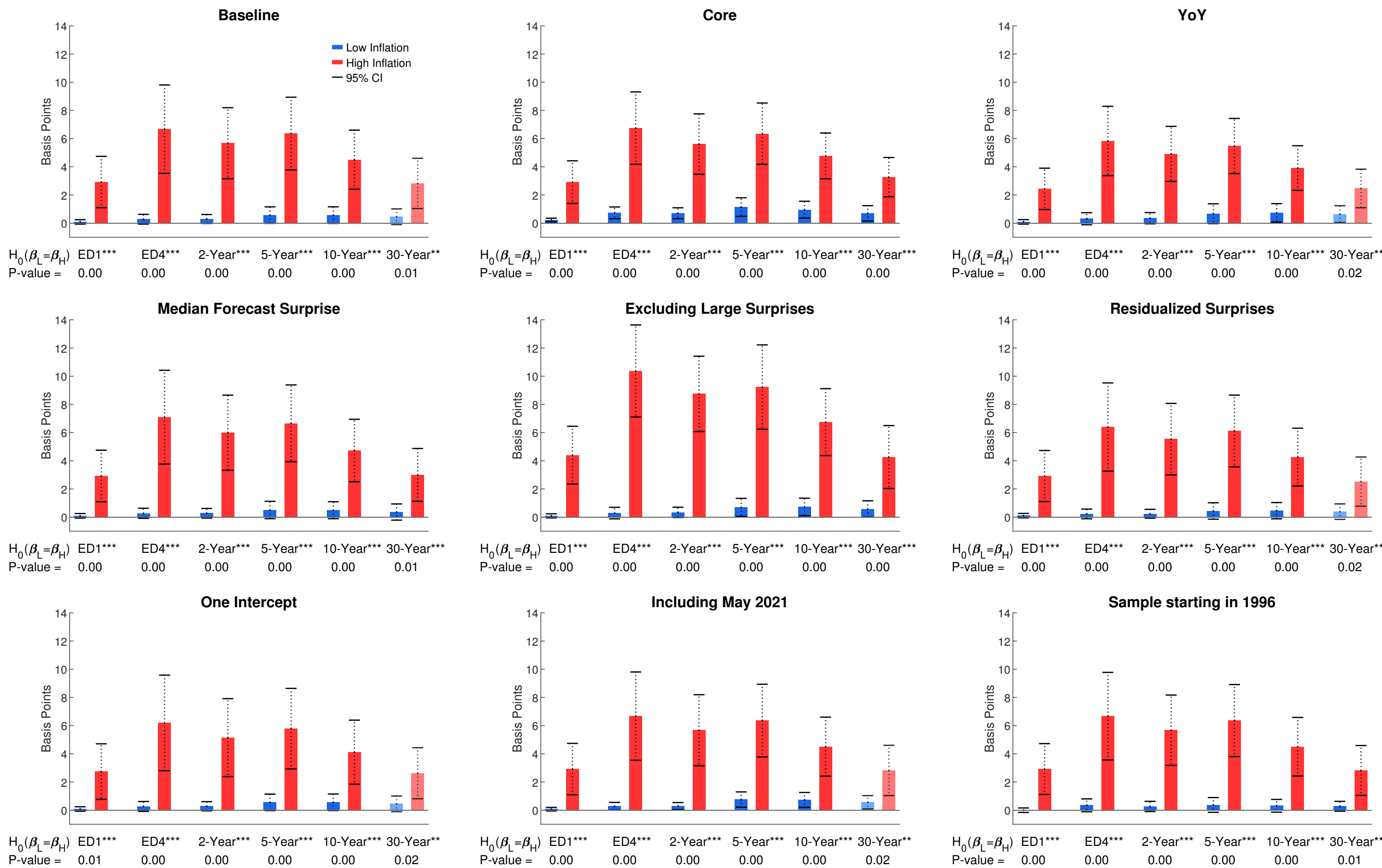
Figure C4: Effects of Macro News on Inflation Expectations under Low and High Inflation



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

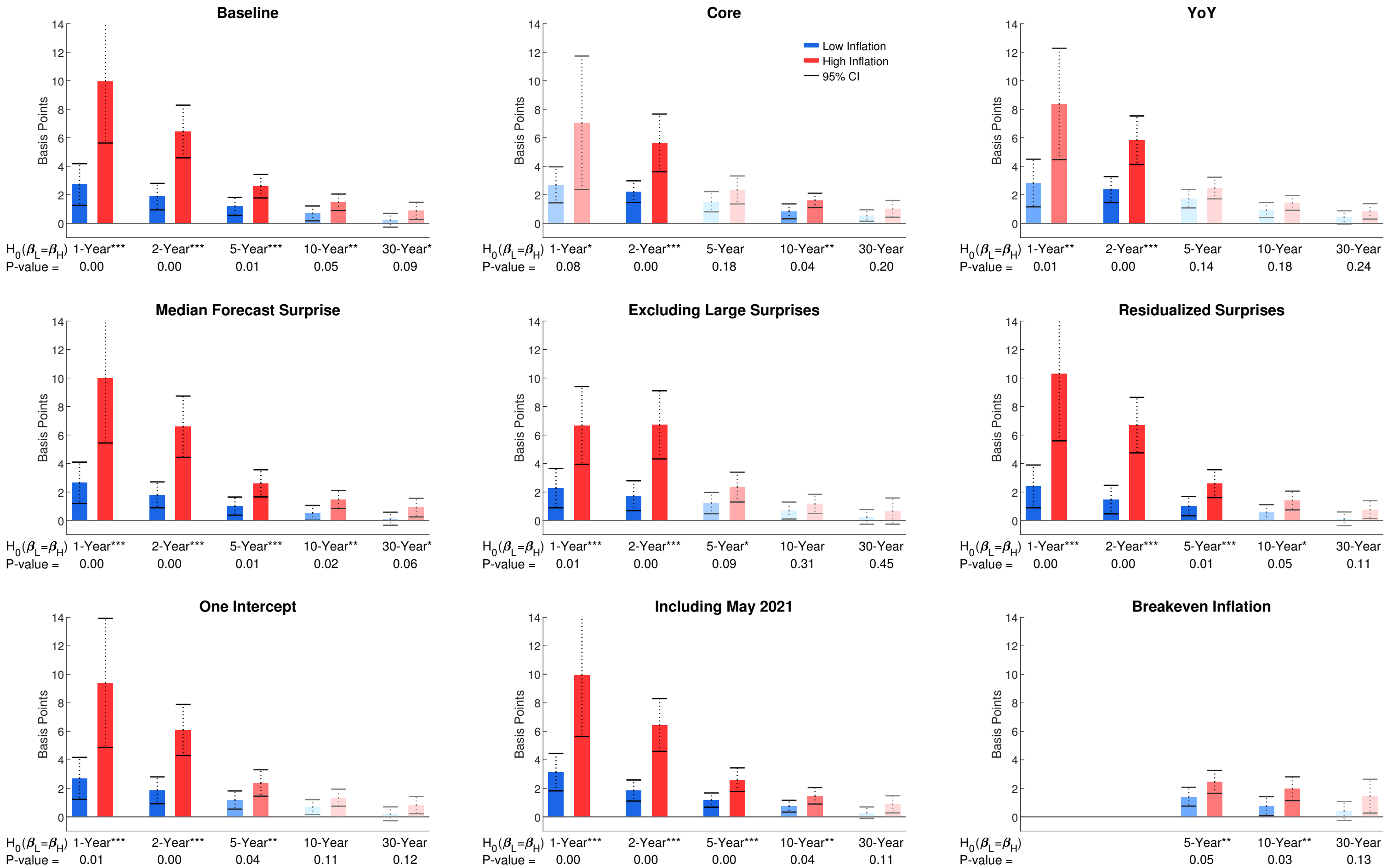
C.3 Sensitivity Analysis

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



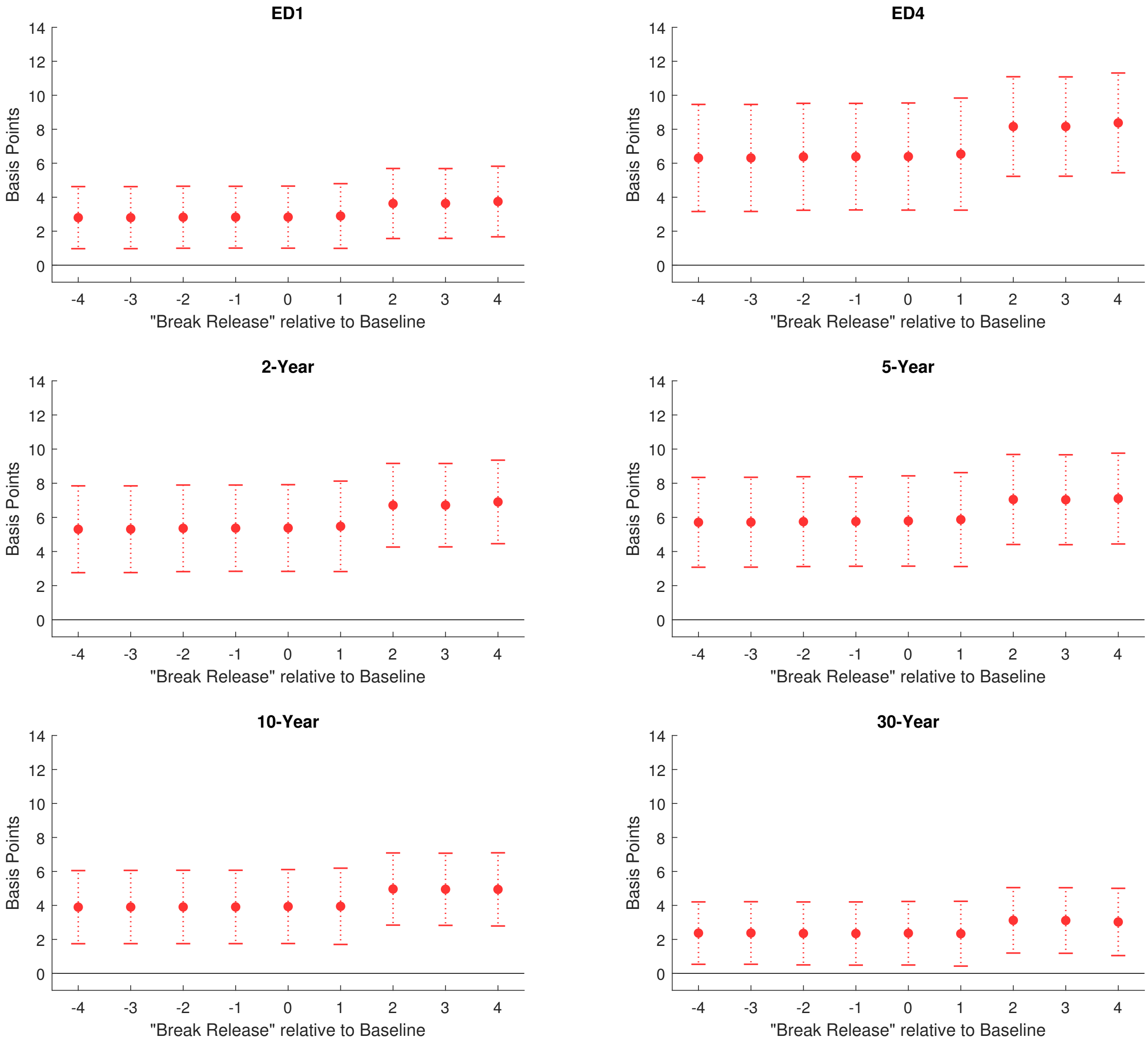
Notes: This figure shows the responses of interest rates to CPI news for different specifications. Each panel displays the results for a given specification and Appendix C.3 provides the details on each. Interest rate changes are expressed in basis points and announcements surprises are normalized to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

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



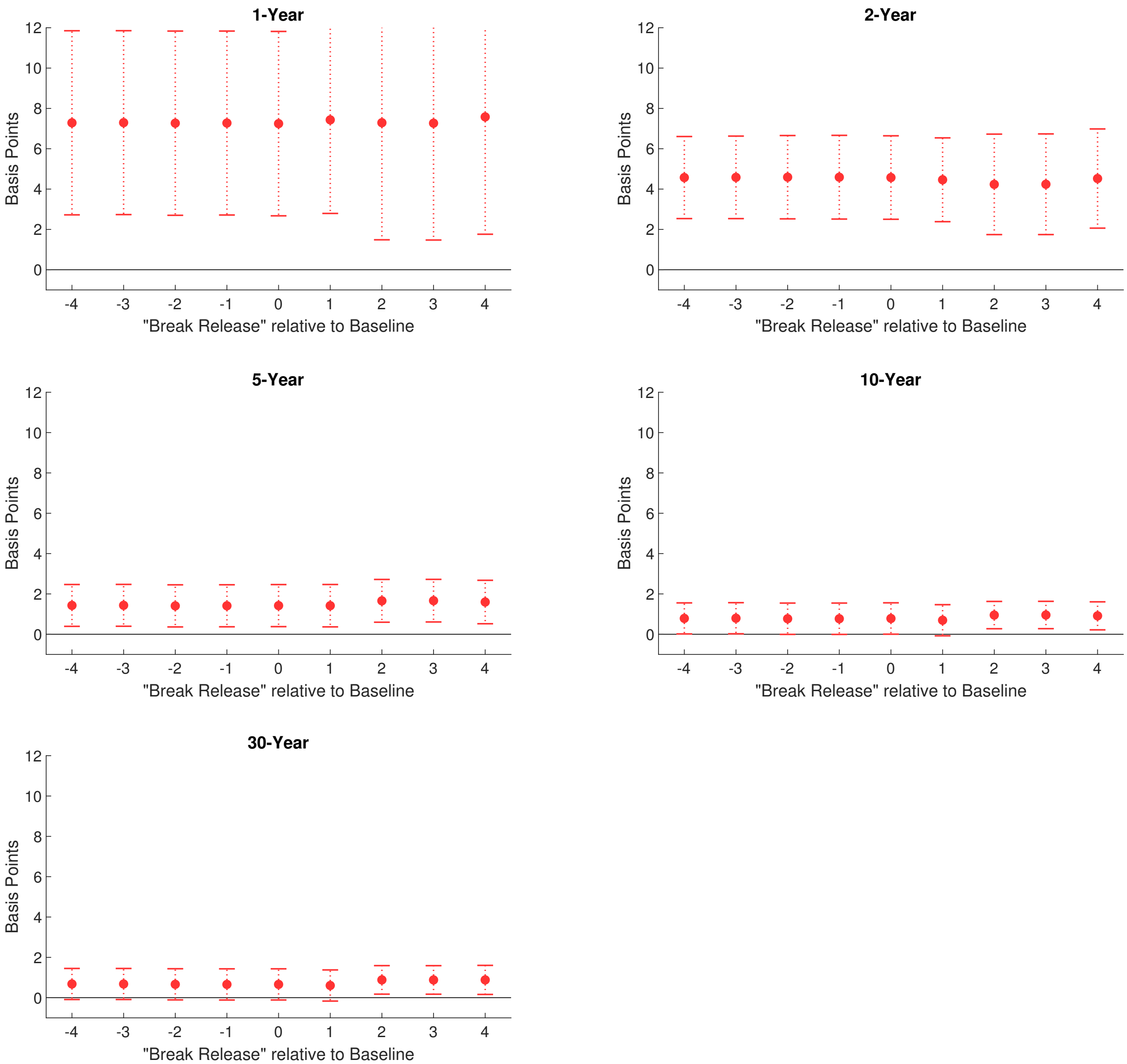
Notes: This figure shows the responses of inflation swap rates to CPI news for different specifications. Each panel displays the results for a given specification and Appendix C.3 provides the details on each. Inflation swap rate changes are expressed in basis points and announcements surprises are normalized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

Figure C7: Increased Sensitivity for CPI releases—Robustness



Notes: The figure displays estimates of the increased sensitivity of interest rates to CPI news under high inflation for alternative "break months". For a given asset price, each circle indicates the estimate of coefficient $\delta_H^{y|k}$ of a version of equation (15), for which only the "break month" between the low- and high-inflation sample is changed relative to the baseline. For each estimate, corresponding 95 percent confidence bands are plotted, where heteroskedasticity-robust standard errors are employed.

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

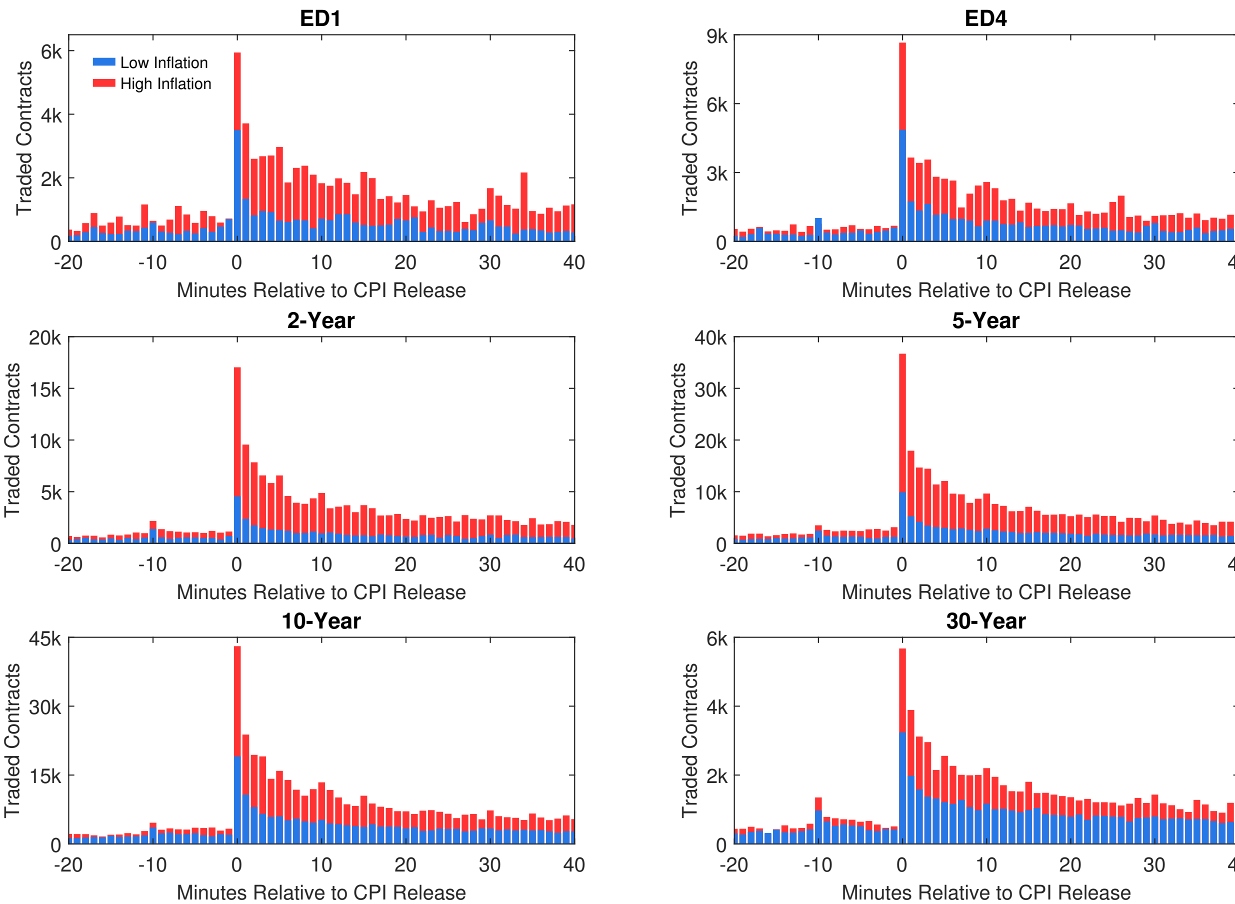


Notes: The figure displays estimates of the increased sensitivity of inflation swap rates to CPI news under high inflation for alternative "break months". For a given asset price, each circle indicates the estimate of coefficient $\delta_H^{\pi|k}$ of a version of equation (15), for which only the "break month" between low- and high-inflation sample is changed relative to the baseline. For each estimate, corresponding 95 percent confidence bands are plotted, where heteroskedasticity-robust standard errors are employed.

D Additional Results for Section 5

D.1 Trading Volume

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



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

D.2 Google Searches

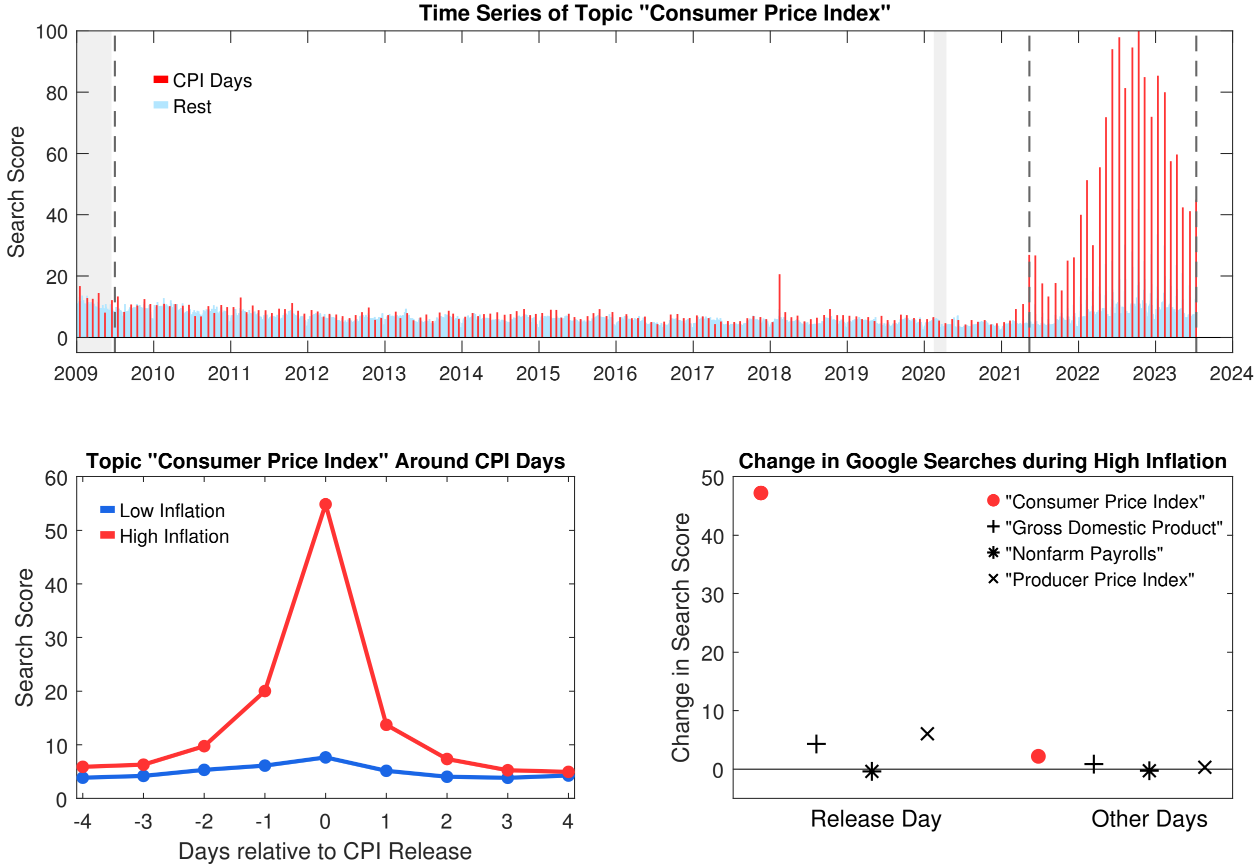
The top panel of Figure D2 shows the resulting daily series for topic "Consumer Price Index." As the figure shows, the searches on days with no CPI release (Rest) are relatively constant throughout the sample. In contrast, for days with a CPI release, the amount of searches rises drastically during the high-inflation period. While during low inflation, the search interest is very similar across days, the search interest on release days spikes up with the start of the high-inflation period.

The bottom-left panel of Figure D2 plots the average Google searches around CPI releases, both during the low-inflation period (blue) and the high-inflation period (red). Consistent with the time series, the figure shows a large upward spike on the day of the release during the recent sample.

Importantly, searches start rising even prior to the release. As I cannot observe the specific timing of searches on the release day, the increase prior to the release rules out that the Google searches solely capture ex-post instead of ex-ante attention to the release. Reassuringly, the averages across both periods are almost identical when moving away from the release.

To further connect the Google search data to my earlier findings, I also look at other topics that are linked to macro releases. In particular, I construct daily series for topics "Producer Price Index," "Nonfarm Payrolls," and "Gross Domestic Product," which map directly to the corresponding data release. The bottom-right panel of Figure D2 shows how the average search score changed on the days of the corresponding release and other days during the high-inflation period. As figure illustrates the increase for the topic "Consumer Price Index" on CPI release days is exceptional compared to other releases. In summary, the evidence based on Google searches further strengthens the case that attention plays a key part in the increased sensitivity of financial markets to CPI releases.

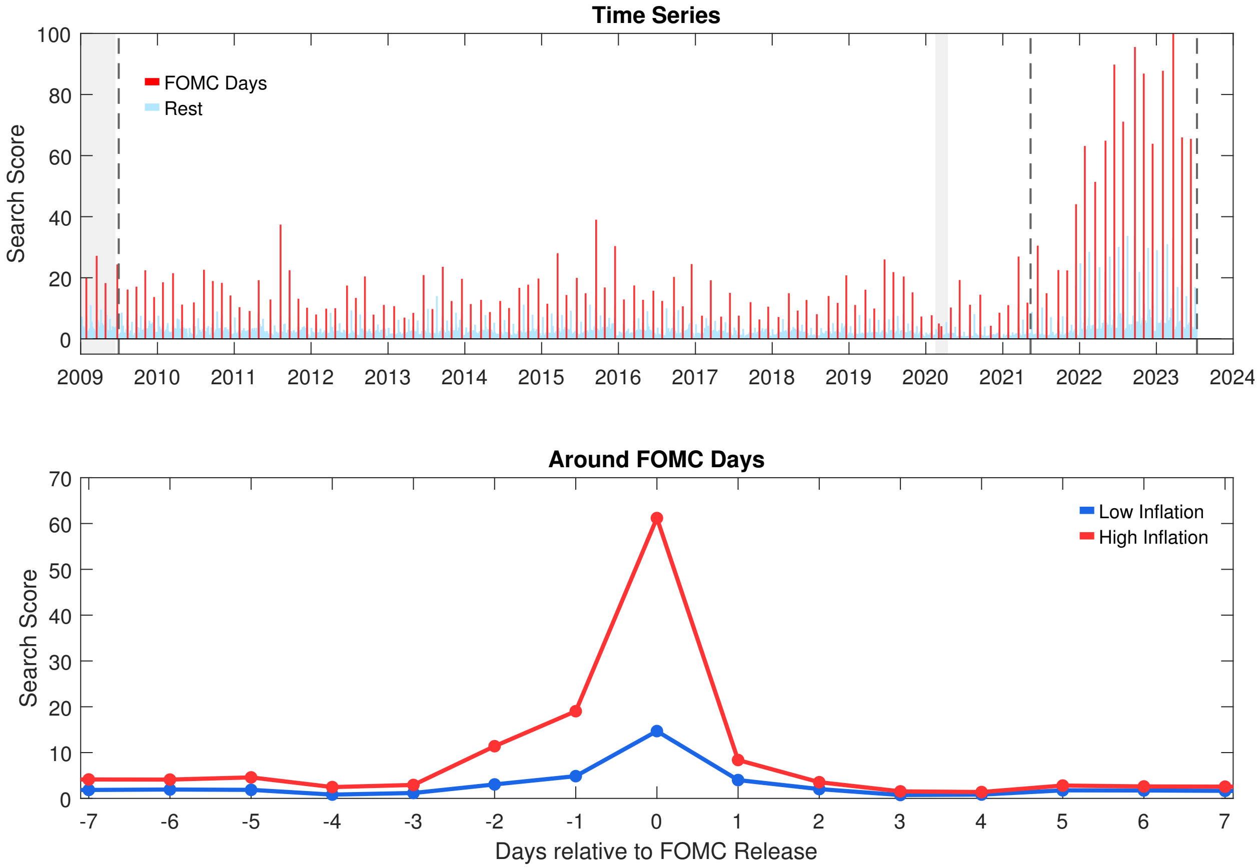
Figure D2: Results from Google Searches



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

D.3 FOMC Announcements

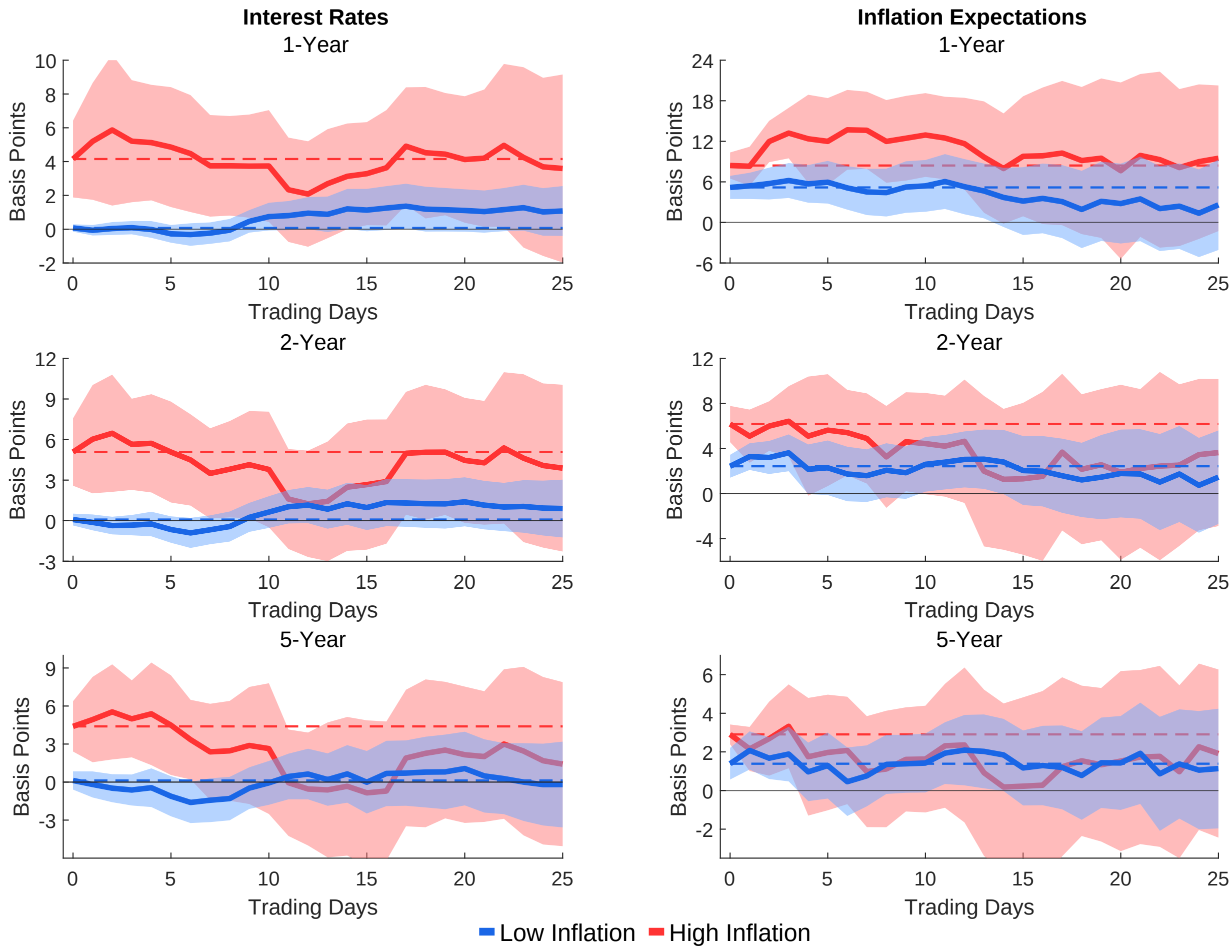
Figure D3: Google Searches for Topic "Federal Open Market Committee"



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

D.4 Lower Frequency Effects

Figure D4: Daily Impulse Responses to CPI News



Notes:

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

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

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