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How Markets Process Macro News: The Importance of Investor Attention*

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Abstract

I provide evidence that investors' attention allocation plays a critical role in how financial markets incorporate macroeconomic news. Using intraday data, I document a sharp increase in the market reaction to Consumer Price Index (CPI) releases during the 2021–2023 inflation surge. Bond yields, market-implied inflation expectations, and other asset prices exhibit significantly stronger responses to CPI surprises, while reactions to other macroeconomic announcements remain largely unchanged. The joint reactions of these asset prices point to an attention-based explanation—an interpretation I corroborate throughout the rest of the paper. Specifically, I construct a measure of CPI investor attention and find that: (1) attention was exceptionally elevated around CPI announcements during the inflation surge, and (2) higher pre-announcement attention robustly leads to stronger market reactions. Studying investor attention in the context of Employment Report releases and Federal Reserve announcements, I document a similar importance of attention allocation for market reactions. Lastly, I find that markets tend to overreact to announcements that attract high levels of attention.

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

Keywords: Macroeconomic News Announcements, Investor Attention, Financial Markets, Inflation, Federal Reserve, High-frequency event study

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1 Introduction

The question of how financial markets incorporate macroeconomic information is crucial for both macroeconomics and finance. Financial economists study it to understand market functioning and the factors determining asset prices, while macroeconomists are interested because they rely on financial data to gauge the state of the economy and construct macroeconomic shocks.[1] One prominent strand of finance—behavioral finance—has highlighted the importance of investors' attention allocation in understanding financial markets.[2] When it comes to the link between markets and the macroeconomy, however, the role of investor attention has received relatively little focus, largely due to the limited empirical evidence demonstrating its importance in this matter.[3]

In this paper, I provide robust evidence that investor attention is crucial for how macroeconomic information is priced in financial markets. I do so by analyzing the market reactions to major macroeconomic news announcements, such as the CPI and Nonfarm Payrolls (NFP), both of which are published monthly by the Bureau of Labor Statistics. Since these announcements are pre-scheduled, they offer a unique setting to study the interplay between investor attention and the incorporation of macroeconomic news. Theories on attention allocation suggest that investors should pay closer attention to inflation-related news during inflationary periods (e.g., Kahneman, 1973). Hence, if investor attention has any meaningful impact on macro-financial dynamics, we should observe a shift in market reactions to CPI news during the 2021–2023 inflation surge compared to the preceding low-inflation period.

To formalize this intuition and guide my empirical analysis, I set up a simple model of information acquisition, building on prior work. At its core, the model features a macroeconomic news announcement—modeled as a public noisy signal about a fundamental—and a set of investors who make trading decisions upon receiving the signal. The model incorporates various channels that can affect the market reaction to the announcement, one of which is investor attention. Following DellaVigna and Pollet (2009), I model attention as the share of investors who immediately incorporate the new information. The model predicts that greater investor attention to a CPI release leads to a stronger immediate impact on market-implied inflation expectations and interest rates, with the latter arising through a

[1] For example, see Cochrane (2008, 2011) for discussions on why financial economists study the macroeconomy, and Bernanke (2004) and Nakamura and Steinsson (2018) for discussions on why macroeconomists study financial markets.

[2] See, for example, Hirshleifer (2015) for a review or the references below in the related literature.

[3] Behavioral frictions have, of course, been explored to understand macro-financial fluctuations (see references below when I discuss the related literature). Nonetheless, the role of investors' attention allocation remains comparatively underexplored.

Taylor-type monetary policy rule. At the same time, sensitivity to other macroeconomic news announcements should not increase, as we do not expect investors to raise their attention to them.

To test these predictions, I estimate the effects of surprises in the headline numbers of 16 major macroeconomic news announcements on asset price returns, measured within a 60-minute window around the releases. Specifically, I compare the effects across two periods: a low-inflation period (mid-2009 to May 2021) and a subsequent high-inflation period (ending in July 2023). Consistent with the model's predictions, I find that CPI inflation surprises have an impact on yields that is more than an order of magnitude stronger in the high-inflation period. Similarly, inflation expectations—measured by inflation swap rates—are far more responsive, particularly at the 1- and 2-year horizons. The differences in sensitivities across periods are highly significant at the 1 or 5 percent level and economically meaningful. In contrast, no other macroeconomic announcement exhibits a comparable rise in market impact during the high-inflation period. The heightened sensitivity to CPI inflation news is not only robust to a range of sensitivity analyses but also extends to other asset classes, including stocks, commodities, corporate bonds, and exchange rates.

Attributing the increased sensitivity to CPI news to heightened investor attention is, of course, far from obvious. Alternative explanations could be that investors believe the Federal Reserve's policy response to inflation has increased, as argued by Bauer, Pflueger, and Sunderam (2024), or that their perceptions of inflation shocks have changed—for example, from demand- to supply-driven.[4] My framework allows me to formalize the empirical implications of these mechanisms for my high-frequency event study analysis. For instance, the model shows that an increase in the perceived policy response to inflation aligns with the heightened sensitivity of interest rates to CPI news. However, it is inconsistent with the observed increase in inflation swap rate sensitivity to CPI news. It also does not align with the relatively unchanged sensitivity of interest rates to other macroeconomic announcements that generally affect inflation swap rates. Similarly, if CPI news reveals supply- rather than demand-driven inflation, the model would predict a weaker (not stronger) sensitivity of interest rates to CPI surprises, as the expected policy response to output partly offsets the inflation response. While these findings do not imply that both mechanisms are entirely absent, they do suggest that they are unlikely to be the primary drivers of the increased sensitivity to CPI news.

[4] Modi and Zaratiegui (2024) argue that supply shocks have become more important for understanding CPI inflation news in the post-COVID period. That being said, they still find demand shocks to be the dominant drivers.

To further corroborate my attention-based explanation, I also examine proxies of investor attention. Using trading volume—a classic proxy for investor attention (e.g., Barber and Odean, 2008)—I find an exceptional increase around CPI announcements during the high-inflation period, while volumes surrounding other releases remain relatively stable. Following more recent work (e.g., Ben-Rephael, Da, and Israelsen, 2017), I further construct a measure of CPI investor attention based on news coverage on the Bloomberg Terminal. This measure exhibits significantly higher levels around CPI announcements during the inflation surge compared to the preceding period.[5] Importantly, attention levels are elevated not only on and after announcement days, but also in the days prior. Using these CPI attention levels prior to the CPI release, I construct a measure of pre-announcement attention (CPI-IA), with one observation per CPI announcement.

The resulting CPI-IA series allows me to conduct a horse-race against a variety of uncertainty measures. Specifically, I can rule out the alternative explanation that CPI releases became more informative during the high-inflation environment. Due to the higher inflation volatility and uncertainty—i.e., higher signal variance—investors may update their priors more based on the CPI release. While this explanation does not necessarily account for the evidence on attention measures, it is consistent with the increased sensitivity to CPI news. To rule out this alternative, I show that my CPI-IA series predicts stronger reactions to CPI news even when allowing a variety of uncertainty measures to affect the reaction as well.

My CPI-IA series also enables me to examine the role of investor attention for the lower-frequency effects of CPI news. A key question is whether markets underreact in low-attention periods or overreact in high-attention periods. Since my framework accommodates the possibility that investors overreact to macroeconomic news announcements via diagnostic expectations (e.g., Bordalo et al., 2020), it can in principle rationalize both of these cases. Estimating a daily local projection, I find that both interest rates and inflation swap rates tend to overreact in the first days following CPI releases when levels of attention are high.

Lastly, I document that the importance of investor attention for macroeconomic news announcements is a broader phenomenon. Specifically, I examine how the market reactions to NFP releases and Federal Reserve announcements depend on investor attention historically. To do so, I construct—analogously to the CPI-IA variable—measures of pre-announcement attention for both announcement series. With these measures in hand, I first show that they predict significantly stronger high-frequency reactions to their respective news announce-

[5] I find very similar patterns when using an investor attention measure based on news coverage on the Dow Jones Newswires, as well as broader attention proxies constructed from Google searches and mainstream media coverage.

ments. Second, I find evidence of overreaction in the lower-frequency effects when attention levels are high. That being said, there is also some evidence of underreaction during periods when investor attention is low.

Related literature My paper relates to the extensive literature on macro-financial dynamics. Seminal contributions include Shiller (1981), Bernanke (1983), Fama and French (1989), Campbell and Cochrane (1999), and Bansal and Yaron (2004), among others. One prominent strand of this literature focuses on behavioral frictions among investors, aiming to rationalize empirical "puzzles" and provide insights into financial crises.[6] This paper contributes to this line of work by demonstrating that investors' attention allocation is a critical but previously underexplored factor in understanding the interplay between financial markets and the macroeconomy. My findings suggest that investors allocate their attention in a manner broadly consistent with the concept of "rational inattention" (Sims, 2003), which has proven instrumental in explaining various macroeconomic phenomena.[7] At the same time, my findings align with recent studies highlighting extrapolative beliefs among investors (Bordalo, Gennaioli, and Shleifer, 2018; Bordalo et al., 2019, 2024; Maxted, 2024). Specifically, I find that heightened attention tends to amplify overreactions to news announcements. These results suggest that integrating attention allocation and extrapolative beliefs into a unified framework could offer a promising avenue for future research.

Another body of work—closely related to my paper—examines the importance of investors' attention for asset pricing. One set of studies provides empirical evidence demonstrating the critical role of investor attention in asset pricing (e.g., Huberman and Regev, 2001; Barber and Odean, 2008; DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009; Da, Engelberg, and Gao, 2011; Ben-Rephael, Da, and Israelsen, 2017, among many others). Another set explores the implications of incorporating varying investor attention into asset pricing models (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). The most closely related paper is Benamar, Foucault, and Vega (2021), which demonstrates that interest rates respond more strongly to macroeconomic announcements when investor attention is higher prior to the announcement.[8] I contribute to the existing work in the following ways. First, I provide a wide range of new empirical

[6] Seminal contributions encompass De Long et al. (1990), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999), among others, while more recent works include Barberis et al. (2015), Adam, Marcet, and Beutel (2017), Bordalo, Gennaioli, and Shleifer (2018), Bordalo et al. (2019, 2024), and Maxted (2024).

[7] For a review of rational inattention in macroeconomics, see Maćkowiak, Matějka, and Wiederholt (2023).

[8] Additional recent studies on the importance of investor attention include Boguth, Grégoire, and Martineau (2019), Hirshleifer and Sheng (2022), Fisher, Martineau, and Sheng (2022), and Andrei, Friedman, and Ozel (2023).

results with respect to macroeconomic news announcements which—as argued above—allow me to single out an attention-based explanation among alternatives. Second, my evidence shows that investor attention is not only affecting the incorporation of macroeconomic news, but is of first-order importance in understanding the link between financial markets and the macroeconomy. Lastly, my results emphasize the macroeconomic environment for understanding investors' attention to macroeconomic news, similar to the evidence documented for firms and households.[9]

The paper also relates to the extensive body of research utilizing high-frequency financial market event studies to enhance our understanding of macroeconomics and finance.[10] Recently, Hanson, Lucca, and Wright (2021) raised concerns about the straightforward interpretation of event study evidence for macroeconomics. They demonstrate that longer-term interest rates tend to overreact to changes in short rates, suggesting that the effects on longer-term rates estimated from event studies are likely biased estimates of the longer-term effects on short rates. My findings indicate that event study estimates may generally be biased if one fails to properly account for the allocation of investor attention to the event.

Lastly, several recent studies employ financial market data to examine the relationship between monetary policy and inflation (Cieslak, McMahon, and Pang, 2024; Andrei and Hasler, 2024; Bauer, Pflueger, and Sunderam, 2024; Bocola et al., 2024; Bundick, Smith, and Van der Meer, 2024).[11] While I argue that the heightened sensitivity to CPI news is primarily driven by shifts in investor attention (rather than by changes in the perceived monetary policy rule), many of my findings align with those of these studies. For instance, consistent with Bundick, Smith, and Van der Meer (2024), my results indicate that investors' long-run inflation expectations remained fairly anchored following COVID. Similarly, in line with Bocola et al. (2024), I find evidence of a weakened relationship between interest rates and inflation in 2020 and 2021.

Roadmap The remainder of the paper is structured as follows. In the next section, I discuss my empirical approach and the theoretical framework that informs it. Section 3

[9] For example, a set of recent papers document the importance of the inflation environment for firms' and households' attention to inflation and their expectation formation (Cavallo, Cruces, and Perez-Truglia, 2017; Weber et al., 2023; Korenok, Munro, and Chen, 2023; Pfäuti, 2023, 2024; Bracha and Tang, 2024). Braggion, Von Meyerinck, and Schaub (2023) document the importance of the inflation environment for investors' behavior by studying the German Hyperinflation in the 1920s.

[10] This is a voluminous literature. See Gürkaynak and Wright (2013) or Nakamura and Steinsson (2018) for discussions of some of the existing work.

[11] Amid renewed interest in inflation, a number of recent papers also investigate the high-frequency effects of CPI releases to explore how inflation is priced in financial markets (Chaudhary and Marrow, 2022; Fang, Liu, and Roussanov, 2022; Gil de Rubio Cruz et al., 2022; Knox and Timmer, 2023; Bonelli, Palazzo, and Yamarthy, 2024; Modi and Zaratiegui, 2024).

introduces the data, while Section 4 presents the main results on the high-frequency effects of macroeconomic news announcements under low and high inflation. In Section 5, I argue for an attention-based explanation of the findings. Section 6 extends the discussion, highlighting the broader importance of investor attention for the effects of macroeconomic news announcements. Finally, Section 7 concludes.

2 Research Design

I aim to assess the role of investor attention in shaping financial market reactions to macroeconomic news announcements. Drawing on classic attention theories (e.g., Kahneman, 1973), I hypothesize that if investor attention holds any relevance, market reactions during the 2021–2023 inflation surge should reflect a shift in focus toward inflation-related news. To formalize this idea and to guide my empirical analysis, I begin by introducing a simple model in this section which creates predictions of how the financial market impact of macroeconomic news announcements varies across different scenarios. Building on these predictions, I then formulate the empirical strategy in the second part of this section, which informs the analyses in the remainder of the paper.

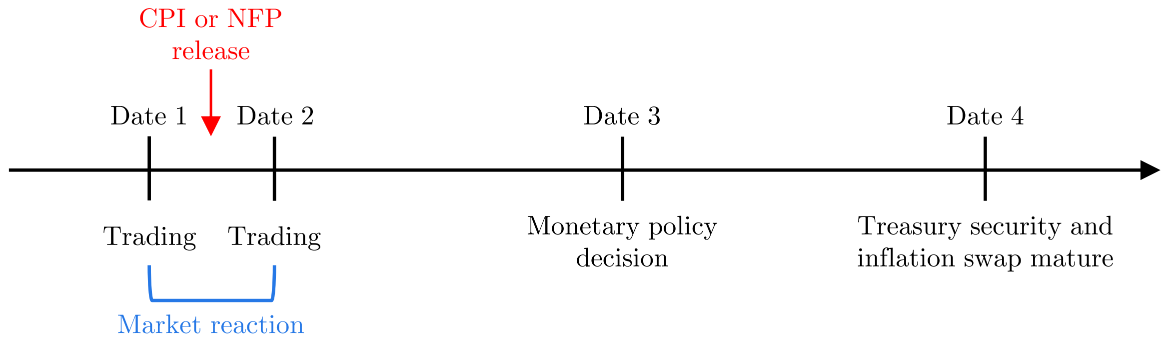
2.1 Market Reaction to Macroeconomic News under different Scenarios

I now briefly outline the model's key components, before presenting the model predictions. Details are relegated to Online Appendix A. The framework follows the tradition of portfolio choice models under noisy information, and is, in many respects, standard and grounded in prior work.[12] The model has four dates and three periods. Figure 1 outlines the timeline of the model.

The economy comprises a continuum of investors, each solving a mean-variance portfolio problem at date 1 and 2. Investors can buy a Treasury security or/and an inflation swap at date 1 and 2. Both assets mature at date 4. Whereas the Treasury security pays out one dollar, the inflation swap pays out the average inflation rate between dates 2 and 4. The fundamentals, inflation and output growth, are linked through coefficient ϱ which is a reduced-form way of capturing demand-driven or supply-driven dynamics. In my baseline, which can be thought of the period of the 2010s, I assume that the economy is demand-driven, $\varrho > 0$, consistent with prior work (see Cieslak and Pflueger, 2023, for a discussion). That being said, this assumption is not crucial for the model's key implications, as will

[12] Classic references include Grossman and Stiglitz (1980), Verrecchia (1982), Kim and Verrecchia (1991), Kandel and Pearson (1995), and Veronesi (2000). The timing of my model is inspired by Benamar, Foucault, and Vega (2021) and references therein.

Figure 1: Model Timeline



Notes: This figure illustrates the four dates in the model, with a summary headline for each. Dates 1 and 2 correspond to the trading periods around a given macroeconomic news announcement, whereas dates 3 and 4 correspond to the events on which the investor problem is focused on. Details are provided in the text and in Online Appendix A.

become clearer below.

Investors cannot observe the change in inflation between dates 2 and 3 which is normally distributed. However, between dates 1 and 2, they either observe a CPI or an NFP release. The CPI release is a public noisy signal about inflation (s^{CPI}), whereas NFP about output growth (s^{NFP}). The signal-to-noise ratio ξ^k governs the informativeness of signal $k \in \{\text{CPI}, \text{NFP}\}$. Following DellaVigna and Pollet (2009), I model *investor attention* as a share of investors, μ^k, paying attention to the release k. That is, attentive investors incorporate the signal k into their inflation expectations using the Kalman filter, while inattentive investors do not. Consistent with recent evidence (e.g., Bordalo et al., 2019), I also allow for the possibility that investors overreact to news due to *diagnostic expectations* allowing the Kalman gain to be larger than one (Bordalo et al., 2020). An important consequence of this is that the presence of limited attention, $\mu^k < 1$, does not automatically imply an initial underreaction of markets to macroeconomic news in the model. I come back to this point in Section 5.

The formation of inflation expectations is central to the market reactions of asset prices between dates 1 and 2. While the link to inflation swap price, i.e., the inflation swap rate, is direct, the yield of the Treasury security reacts due to investors' expectations of the monetary policy rate. In contrast to investors, the monetary policy authority can perfectly observe the change in the inflation rate. Following a Taylor rule with an inflation coefficient ϕ, it sets the the risk-free rate at date 3 accordingly.[13] As a result, the Treasury yield will be a function of the monetary policy rule as well as investors' expected inflation.

[13]The total inflation coefficient ϕ is a function of the direct inflation coefficient (ϕ^{π}), the output growth coefficient (ϕ^{z}), and the co-movement between inflation and output growth (ϱ).

In equilibrium, the model provides closed-form solutions for the immediate market reactions of the Treasury yield and the inflation swap rate to the CPI or the NFP signal. The derivations are provided in Online Appendix A.2. Let y $(= y_2 - y_1)$ be the reaction of the Treasury yield and π $(= \pi_2 - \pi_1)$ of the inflation swap rate. The *market reactions to CPI news and NFP news* can be then written as:

$$y = \beta^{y|k} s^k \quad \text{and} \quad \pi = \beta^{\pi|k} s^k \qquad\qquad \text{for } k \in \{\text{CPI}, \text{NFP}\}, \tag{1}$$

where the coefficients $\beta^{y|k}$ and $\beta^{\pi|k}$ are functions of the model parameters. The restrictions in the baseline imply that the sensitivities are strictly positive, i.e., $\beta^{y|k} > 0$ and $\beta^{\pi|k} > 0$. This is consistent with empirical evidence of prior work and will be confirmed below in Section 4.

Model predictions under different scenarios Based on the model solution in (1), I can now discuss how different scenarios would affect the market reactions. In particular, the framework allows me to illustrate the distinct predictions of increased investor attention to CPI releases during a high-inflation period compared to other ex-ante likely shifts in the economic environment during such a period. In particular, I consider four scenarios which are summarized together with their model implications in Table 1. Online Appendix A.3 provides the details underlying the discussion here.

For easier comparison to the empirical analysis, the baseline parameters will be denoted by subscript L, corresponding to the low-inflation period, and the new parameters by subscript H, corresponding to the high-inflation period. The four scenarios I consider, each with a change in one parameter while keeping the others constant, are as follows: 1) an increase in attention to the CPI release, $\mu_H^{\text{CPI}} > \mu_L^{\text{CPI}}$; 2) an increase in the monetary policy's response to inflation, $\phi_H > \phi_L$; 3) a shift from demand to supply shocks, $\varrho_H < 0 < \varrho_L$; and 4) an increase in the informativeness of the CPI release, $\xi_H^{\text{CPI}} > \xi_L^{\text{CPI}}$.

I begin with the scenario in which *investor attention to the CPI release increases* under high inflation, i.e., $\mu_H^{\text{CPI}} > \mu_L^{\text{CPI}}$.[14] The first row in Table 1 summarizes the implications of this scenario. As more investors immediately incorporate the CPI signal into their expectations, both the interest rate and inflation swap rate exhibit a stronger response on impact, i.e., $\beta_H^{y|\text{CPI}} > \beta_L^{y|\text{CPI}}$ and $\beta_H^{\pi|\text{CPI}} > \beta_L^{\pi|\text{CPI}}$, while the responses to the NFP release remain unchanged.[15] Further, the scenario predicts that measures of investor attention rise around

[14]Both the CPI and the NFP release are equally informative about inflation in the model. In reality, almost all macroeconomic releases contain some information about inflation. However, if information acquisition is costly, the CPI release is—ex-ante—the one most likely to attract greater investor attention during periods of high inflation. I will return to this point below when I discuss the empirical strategy.

[15]The CPI release provides new information about inflation that was not publicly available beforehand. Hence,

Table 1: Model Predictions under Different Scenarios

Scenario	Macro Release	Immediate Market Reaction		Investor Attention Around Release
		Interest Rates	Inflation Swap Rates	
Attention to CPI Release ↑	CPI	↑	↑	↑
	NFP	→	→	→
Monetary Policy Inflation Response ↑	CPI	↑	→	→
	NFP	↑	→	→
From Demand to Supply Shocks	CPI	↓	→	→
	NFP	↓	↓	→
Informativeness of CPI Release ↑	CPI	↑	↑	→
	NFP	→	→	→

Notes: This table summarizes the model predictions in terms of market reactions and investor attention across four different scenarios. The first column describes each scenario, while the second column indicates the type of macroeconomic announcement (CPI or NFP). The third and fourth columns display the changes in the effects on interest rates and inflation swap rates, respectively, while the fifth column shows the changes in investor attention. The specific scenarios are discussed in the text, and the calculations underlying the results are presented in Online Appendix A.3.

CPI releases during high inflation while showing no change around NFP releases.

The second scenario I consider is that *monetary policy's response to inflation increases* under high inflation, i.e., $\phi_H > \phi_L$.[16] The second row of Table 1 summarizes the implications of this scenario. As investors expect a stronger monetary policy response to inflation, the market reactions of the Treasury yield to both the CPI and the NFP release rise, while the reactions of the inflation swap rate remain unchanged. Hence, the key distinction from Scenario 1 is the shift in interest rate reactions without a corresponding change in the reactions of the inflation swap rate.[17] Moreover, measures of investor attention are expected to remain unchanged around releases.

The third scenario I consider is that the inflation surge is associated with a structural shift in the economy from being *demand- to supply-driven*.[18] In the framework, this shift can

attentive individuals should update their expectations following the release. However, these individuals should not be responsive when the same information is presented to them again at a later stage. This behavior is documented by studies that use information treatments with publicly available data (Cavallo, Cruces, and Perez-Truglia, 2017; Weber et al., 2023).

[16] Bauer, Pflueger, and Sunderam (2024) argue that this was the case during the 2021–2023 inflation surge.

[17] Note that the baseline assumes a demand-driven economy ($\varrho > 0$), in which a positive NFP signal is perceived as inflationary. However, even in a supply-driven case ($\varrho < 0$), Scenario 2 generates predictions distinct from Scenario 1, as inflation swap rates would still remain unaffected.

[18] While there is no consensus in the literature on whether supply shocks were the dominant cause of the inflation

be modeled by shifting the relationship between inflation and output growth from positive to negative, i.e., $\varrho_H < 0 < \varrho_L$. Under this scenario, the Treasury yield becomes less sensitive to CPI news, while the inflation swap rate sensitivity remains unaffected. Furthermore, market reactions to NFP news weaken and flip from positive to negative. Once again, measures of investor attention are expected to remain unchanged around releases.

In the last scenario, I consider the case where CPI releases become more informative under high inflation, i.e., $\xi_H^{\text{CPI}} > \xi_L^{\text{CPI}}$. Since higher inflation might also be associated with higher inflation volatility, the CPI's signal variance might increase, leading to a higher CPI signal-to-noise ratio.[19] As shown in the last column of Table 1, the market reaction to CPI releases increases under this scenario as investors update their expectations more based on the signal, i.e., $\beta_H^{y|\text{CPI}} > \beta_L^{y|\text{CPI}}$ and $\beta_H^{\pi|\text{CPI}} > \beta_L^{\pi|\text{CPI}}$, while the responses to the NFP release remain unchanged. Hence, in terms of market reactions, this scenario is observationally equivalent to the first scenario of increased investor attention. However, differently to the first scenario, there is no change in how many investors pay attention to the CPI release. Therefore, investor attention remains unchanged around CPI releases in scenario four.

In summary, the framework provides—as visualized in Table 1—a set of empirical predictions to distinguish an attention-based scenario from plausible alternatives during a high-inflation period. It is very likely that the data presents a mixture of the scenarios outlined here. Hence, most of the subsequent empirical analysis should be understood as finding evidence for a dominant investor attention mechanism, rather than ruling out the presence of other channels that might affect the market reactions to macroeconomic news during high inflation.

2.2 Empirical Strategy

With the model predictions in hand, I now outline the empirical strategy to assess whether investor attention affects the market reactions to CPI news during the 2021–2023 inflation surge. Specifically, I estimate a specification motivated by the market reactions in (1). This requires constructing empirical analogs to the announcement signals in the model. Consider the release of macroeconomic variable k at time t. I construct the surprise (news)

surge (see Kryvtsov, MacGee, and Uzeda, 2023, for a review), I find it worthwhile to consider this possibility.

[19] Note that since the CPI and the NFP release reveal information about the same fundamentals, the only way to increase the CPI signal-to-noise ratio in the model (without increasing the NFP one) is by reducing the CPI noise variance. In reality, however, it is more likely that the signal variance increases. I discuss this point further in Section 5.

by subtracting from the macroeconomic series k its forecast, that is,

$$s_t^k = \frac{k_t - \mathrm{E}[k_t|\mathcal{I}_{t-\Delta^-}]}{\hat{\sigma}^k}, \tag{2}$$

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 $k_t - \mathrm{E}[k_t|\mathcal{I}_{t-\Delta^-}]$, denoted by $\hat{\sigma}^k$.

Having constructed the macroeconomic surprises, I can now turn to the main specification. To allow the market sensitivity to macroeconomic news announcements to vary across periods of low and high inflation, I estimate the following equation:

$$x_t = \beta_L^{x|k} s_t^k \mathbb{1}_{t\in L} + \beta_H^{x|k} s_t^k \mathbb{1}_{t\in H} + \varepsilon_t^k, \tag{3}$$

where x_t denotes the change in an interest rate or inflation swap rate, $x \in \{y, \pi\}$, within a narrow window around the announcement time t. Further, s_t^k represents the news about macroeconomic series k, while $\mathbb{1}_{t\in L}$ and $\mathbb{1}_{t\in H}$ are indicator functions denoting whether the announcement t occurs during the low- or the high-inflation period, which I define below in Section 3. The coefficients of interest, $\beta_L^{x|k}$ and $\beta_H^{x|k}$, capture the sensitivity of asset price x_t to macroeconomic surprise s_t^k in each period. 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 an identical unit of surprise s_t^k, i.e., they reflect the response to the same amount of news. Further, both coefficients can be consistently estimated by ordinary least squares 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 maintain this assumption 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, meaning the estimates can unambiguously attribute systematic changes in the asset price to the surprises. However, differences between $\beta_L^{x|k}$ and $\beta_H^{x|k}$ cannot be easily interpreted without providing more structure, as done in this section.

Besides CPI and NFP releases, I also consider other major macroeconomic releases in the empirical analysis. While this allows for a cleaner identification of systematic patterns across both inflation periods, it also introduces potential complications by including releases, such as the Producer Price Index (PPI), which may also attract increased investor attention during high inflation. That being said, the CPI release should still be by far the most affected by an attention shift towards inflation-related news. The headline CPI number is not only the most cited inflation measure in the press (e.g., Bullard, 2022), but also uniquely important for investors, as it is used to index both inflation swaps and Treasury inflation-protected securities (TIPS). Moreover, the CPI release is relatively timely compared to other common inflation measures. For example, the personal consumption expenditures (PCE) price index, the Federal Reserve's preferred inflation measure, is typically released about two weeks after the CPI.[20] Ultimately, while other releases may also attract greater investor attention during periods of high inflation, the CPI release should, a priori, be the one 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 during periods of high inflation, the market reactions of interest rates and inflation swap rates to CPI news should be stronger. In contrast, the market reactions to other macroeconomic releases should be less affected by inflation-induced attention. This implies the following predictions for the coefficient estimates of equation (3):*

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

where $\neg CPI$ describes the set of non-CPI releases, i.e., $\neg CPI = \{k \mid k \neq CPI\}$. An additional prediction is that measures of investor attention should show an exceptional increase in attention to CPI releases.

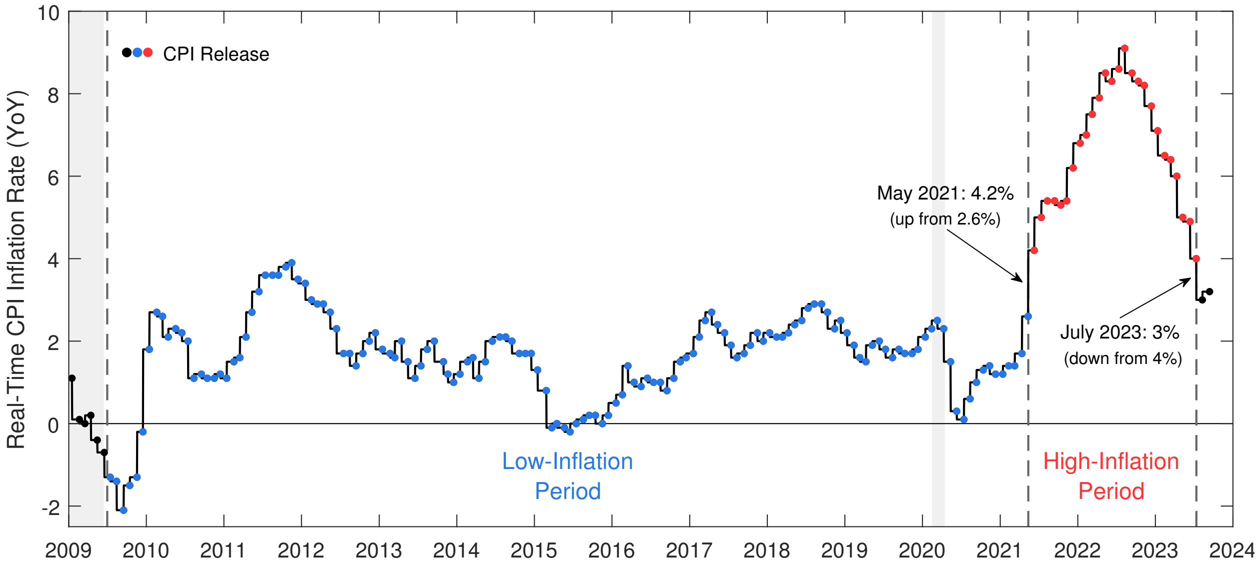
The remainder of the paper is structured around Hypothesis 1. In the next section, I describe the data used to estimate equation (3), followed by the main results in Section 4, where I present strong evidence supporting Hypothesis 1. In Section 5, I provide evidence that investor attention indeed increased around CPI releases and discuss why alternative explanations are inconsistent with the findings. Finally, in Section 6, I show that the importance of investor attention extends beyond CPI releases by presenting similar evidence for NFP and Federal Reserve announcements.

3 Data

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

[20] The PCE release is generally found to elicit weak financial market reactions, a result I will confirm in my analysis below.

Figure 2: Inflation Periods based on the CPI



Notes: This figure shows the real-time CPI inflation rate, measured as the year-over-year (YoY) percentage change, at the beginning of each day from January 2009 to September 2023. Dots represent the days of CPI releases, with blue dots indicating observations during the low-inflation period and red dots during the high-inflation period. Shaded areas highlight NBER recession periods.

3.1 Inflation Periods

The baseline sample begins on July 1, 2009—after the Great Recession—and ends on July 12, 2023, when inflation falls below 4 percent. The starting point is chosen to avoid documented financial market anomalies during the Great Recession and to ensure sufficient liquidity in the inflation swap market. Figure 2 displays the real-time CPI inflation rate at the beginning of each day over the sample period. Hence, the dots—indicating CPI release days—are positioned at the prevailing inflation rate prior to the CPI release, rather than the newly announced rate, as the pre-release rate more accurately reflects the inflation environment at the time of the announcement. As the figure shows, there is a clear split into a period of low inflation and a period of high inflation. I define the period from July 1, 2009, until May 12, 2021 as the *low-inflation period*. Here, I use an inflation threshold of 4 percent, consistent with other recent work.[21] Therefore, the last day of the low-inflation period is the April CPI release on May 12, 2021, which announced a 4.2 percent inflation rate, up from 2.6 percent in March. Consequently, the *high-inflation period* starts on May 13, 2021, and ends on July 12, 2023, when the inflation rate is announced to be 3 percent, down from 4 percent in the

[21] Korenok, Munro, and Chen (2023) and Pfäuti (2023) estimate inflation levels above which people pay attention to inflation. They find thresholds for the U.S. of 3.6 and 4 percent, respectively.

Table 2: Overview of Major Macroeconomic News Announcements

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

Notes: This table displays the 8 macroeconomic news announcements analyzed in most of the paper. The sample ranges from July 2009 to July 2023, with all series published at the monthly frequency. *Announcement* refers to the name of the data release, with its abbreviation (if applicable) provided in brackets. *Observations* indicates the number of observations (surprises) in the sample. *Unit* specifies the unit in which the data release and survey are originally reported. *Surprise (+1 SD)* provides the mapping of a one-standard-deviation positive surprise to the original reporting unit of the release. Online Appendix Table B1 provides the full set of series considered in the paper. Abbreviations: CB—Chicago Board; ISM—Institute for Supply Management; PMI—Purchasing Managers' Index; MoM—month-over-month; QoQ—quarter-over-quarter; ann.—annualized.

prior month.

3.2 Macroeconomic News

I use Bloomberg's U.S. Economic Calendar to obtain data on macroeconomic news releases. Bloomberg provides all necessary information for my analysis, including the release date and time, the announced value, and market expectations prior to the release. I consider 16 major macroeconomic releases, primarily selected based on their documented importance in prior studies (e.g., Rigobon and Sack, 2008; Gürkaynak, Kısacıkoğlu, and Wright, 2020; Boehm and Kroner, 2023). To maintain a concise exposition, I often present results for only 8 of the 16 releases in the main text. Table 2 summarizes these 8 releases, while Online Appendix Table B1 lists the full set.[22] As discussed above, the headline CPI number will serve as the primary release to test Hypothesis 1.

For each release, I construct surprises based on equation (2). Specifically, I use the mean market expectation of the release as the measure of $\mathrm{E}[k_t|\mathcal{I}_{t-\Delta^-}]$. Bloomberg allows forecasters to update their predictions until the release time. Hence, these forecasts should incorporate all publicly available information at the time. Surprises are standardized so that the coefficients $\beta_L^{x|k}$ and $\beta_H^{x|k}$ measure the effects of a one standard deviation surprise across the entire sample. I use Bloomberg's mean forecast rather than the median to construct the

[22] I combine the three GDP releases for a given quarter into a single monthly series. This ensures a sufficient number of observations for each inflation period.

surprises. While both are typically almost perfectly correlated (e.g., 0.96 for the CPI and 1.00 for the NFP release), the CPI surprise based on mean forecasts offers more variation to exploit (as shown in Online Appendix Figure B1), allowing me to conduct a wider range of robustness checks. That said, I will demonstrate in Section 4 that my results remain robust when using Bloomberg's median forecast. Online Appendix Table B1 reports the correlation between mean-forecast surprises and median-forecast surprises for all series.

Online Appendix Figure C1 displays the resulting time series for each of the 8 macro releases used in the main text. To mitigate concerns about extreme outliers (especially at the start of the COVID-19 pandemic), I exclude surprises larger than four standard deviations for all series. For the CPI surprises, this results in the exclusion of the May 2021 release. Unsurprisingly, the volatility of the resulting CPI surprise series is still higher during the high-inflation period. As I will show in the sensitivity analysis in Section 4, however, the larger surprises during the 2021–2023 inflation surge are not the drivers of my findings.

3.3 Financial Data

The intraday data on asset prices comes from the *London Stock Exchange Group (LSEG) Tick History* dataset (formerly known as Thomson Reuters or Refinitiv Tick History). A key advantage of using intraday data is its ability to provide more precise estimates in event studies by reducing noise in the outcome variable. This, in turn, enhances the statistical power to detect systemic differences in financial market responses across periods, which is particular important in my setting given the relatively short high-inflation period with less than 30 observations. In the following, I discuss the intraday data on interest rates and inflation swap rates, which are used throughout most of the paper. Online Appendix Table B2 provides an overview of all intraday financial instruments employed in the main text. Additionally, I utilize other financial data, which I discuss in the relevant sections below.

Interest Rates Building on prior work, I use interest rate futures to measure interest rate responses to macroeconomic news announcements. Specifically, I utilize the first and fourth quarterly Eurodollar futures contracts (*ED1* and *ED4*) to capture shorter horizons. *ED1* reflects expected short-term rates over the next quarter at the end of the current quarter, while *ED4* captures expected short-term rates over the next quarter approximately one year ahead. With the cessation of the LIBOR, I transition to the Secured Overnight Financing Rate (SOFR) futures contracts from April 2022 onward, as these are the successor contracts at the Chicago Mercantile Exchange (CME).[23] For longer maturities, I rely on *2*-, *5*-, *10*-, and

[23] April 2022 marks the first month when trading volumes of SOFR futures surpassed those of the corresponding Eurodollar futures.

30-year Treasury futures contracts. Following Gürkaynak, Kısacıkoğlu, and Wright (2020), I calculate implied yield changes from Treasury futures by dividing price changes by the approximate modified duration and taking their negative. In total, I include six interest rates in my analysis.

Inflation Swap Rates To measure inflation expectations, I use (zero-coupon) inflation swaps, which are based on the CPI. At a given point in time, the swap buyer agrees to pay a predetermined fixed rate—the swap rate—in exchange for a floating payment based on the realized CPI over the inflation period of the swap. Online Appendix Figure B2 illustrates the timing of the payoffs. Accordingly, the h-year inflation swap rate represents the risk-neutral expectation of the annual CPI inflation over next h-years. For my analysis, I employ five inflation swap rates: *1-*, *2-*, *5-*, *10-*, and *30-year*. Each swap rate is calculated as the midpoint of the bid and ask price.[24]

Inflation swap rates are preferred over breakeven inflation rates derived from inflation-indexed Treasury securities (TIPS) for two main reasons: First, inflation swap rates are less affected by liquidity issues, making them more reliable measures of inflation expectations (e.g., Fleckenstein, Longstaff, and Lustig, 2014). Second, they are readily available and reliable for shorter horizons, such as the 1- and 2-year.[25] In contrast, TIPS breakeven inflation rates are less reliable at shorter horizons, as TIPS are only issued at maturities of 5 years or more (Bauer and McCarthy, 2015). As a result, I use inflation swap rates throughout my baseline analysis. However, I will demonstrate in the sensitivity analysis in Section 4 that the main findings are robust to using breakeven rates.

Event Window Throughout my analysis, I construct price changes using a window that spans from 5 minutes before a macroeconomic release to 60 minutes after. I refer to this as the *60-minute window* or *60-minute change* hereafter. While narrower windows are generally preferred to minimize background noise, they must also be long enough for asset prices to fully incorporate the new information. I select the 60-minute window based on preliminary checks, ensuring that, compared to shorter windows, inflation swaps have sufficient time to absorb the information from the release.[26]

[24] An inspection of the inflation swap data revealed the need to remove high-frequency misquotes, which I addressed using the procedure outlined by Brownlees and Gallo (2006).

[25] Diercks et al. (2023) demonstrates that the 1-year inflation swap rate performs well in forecasting inflation compared to alternative measures.

[26] Online Appendix Figure C2 presents the impulse responses of interest rates and inflation swap rates to CPI news over the sample period. While interest rate futures incorporate the new information almost instantaneously, inflation swap rates exhibit a slightly slower adjustment.

Investor Type As I aim to understand investor behavior, it is crucial to identify the types of investors active in the interest rate futures and inflation swap markets. While I do not have detailed data on investor composition, prior research and public information make it clear that retail traders are generally not active in these markets, meaning that institutional investors are essentially the sole participants. I discuss this point in more detail in Online Appendix B.2 and will return to the role of institutional investors in Section 5, where I measure investor attention.

4 High-frequency Effects of Macro News under Low and High Inflation

In this section, I implement the high-frequency event study and estimate the effects of macroeconomic news announcements on asset prices during the low-inflation period and the high-inflation period. I first outline the estimation specifications before documenting the exceptional increase in the sensitivity of interest rates and inflation swap rates to CPI news during the high-inflation period, consistent with Hypothesis 1. I then show—among other things—that these findings are robust to a wide range of sensitivity tests and extend to a broad set of asset prices.

4.1 Specifications

To estimate the effects of macroeconomic news announcements during both inflation periods (as specified in equation (3)), I run the following regression for each announcement series k:

$$x_t = \alpha_L^k + \alpha_H^k + \beta_L^{x|k} s_t^k \mathbb{1}_{t\in L} + \beta_H^{x|k} s_t^k \mathbb{1}_{t\in H} + \varepsilon_t^k, \tag{4}$$

where the dependent variable is the 60-minute change in either an interest rate or an inflation swap rate, $x \in \{y, \pi\}$. The indicator function $\mathbb{1}_{t\in L}$ equals one if announcement t occurs during the low-inflation period and zero otherwise, while $\mathbb{1}_{t\in H}$ is defined analogously. Since $\mathbb{1}_{t\in L}$ and $\mathbb{1}_{t\in H}$ partition the sample, it follows 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.

To better visualize the differences across periods, I also estimate the change in sensitivity between the low-inflation period and the high-inflation period for announcement series k, denoted as $\delta_H^{x|k}$, from the following regression:

$$x_t = \alpha_L^k + \alpha_H^k + \beta_L^{x|k} s_t^k + \delta_H^{x|k} s_t^k \mathbb{1}_{t\in H} + \varepsilon_t^k, \tag{5}$$

where the dependent variable is the 60-minute change in either an interest rate or an inflation swap rate, $x \in \{y, \pi\}$. Note that $\delta_H^{x|k} = \beta_H^{x|k} - \beta_L^{x|k}$ and testing the null hypothesis $\delta_H^{x|k} = 0$ is equivalent to testing $\beta_L^{x|k} = \beta_H^{x|k}$ in equation (4).

4.2 Effects on Interest Rates

Figure 3 presents the results for equation (4), using the six interest rates discussed in Section 3 as the dependent variables. The blue bars show the estimates in the low-inflation period ($\beta_L^{y|k}$), and the red bars display the estimates in the high-inflation period ($\beta_H^{y|k}$). Equation (4) also allows me to directly test the equivalence of $\beta_L^{y|k}$ and $\beta_H^{y|k}$, thereby checking for a structural break in the effect of the surprise.[27] For each left-hand side variable, the test's p-value is reported below the interest rate abbreviation in the figure. Based on the significance level of the test, bars are shown in darker shades if the differences in the coefficients $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are more significant.

With respect to the CPI release, Figure 3 provides the following key takeaways. First, a higher-than-expected CPI surprise generally leads to an increase in interest rates, consistent with the framework in Section 2 and prior evidence. More importantly for this paper, positive CPI news leads to much larger reactions along the yield curve during the 2021–2023 inflation surge. The differences between the coefficients $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are highly statistically significant, allowing me to reject the null hypothesis of their equivalence across both inflation periods at the one- or five-percent level. Overall, the evidence is consistent with increased investor attention to CPI releases, and thus with Hypothesis 1.

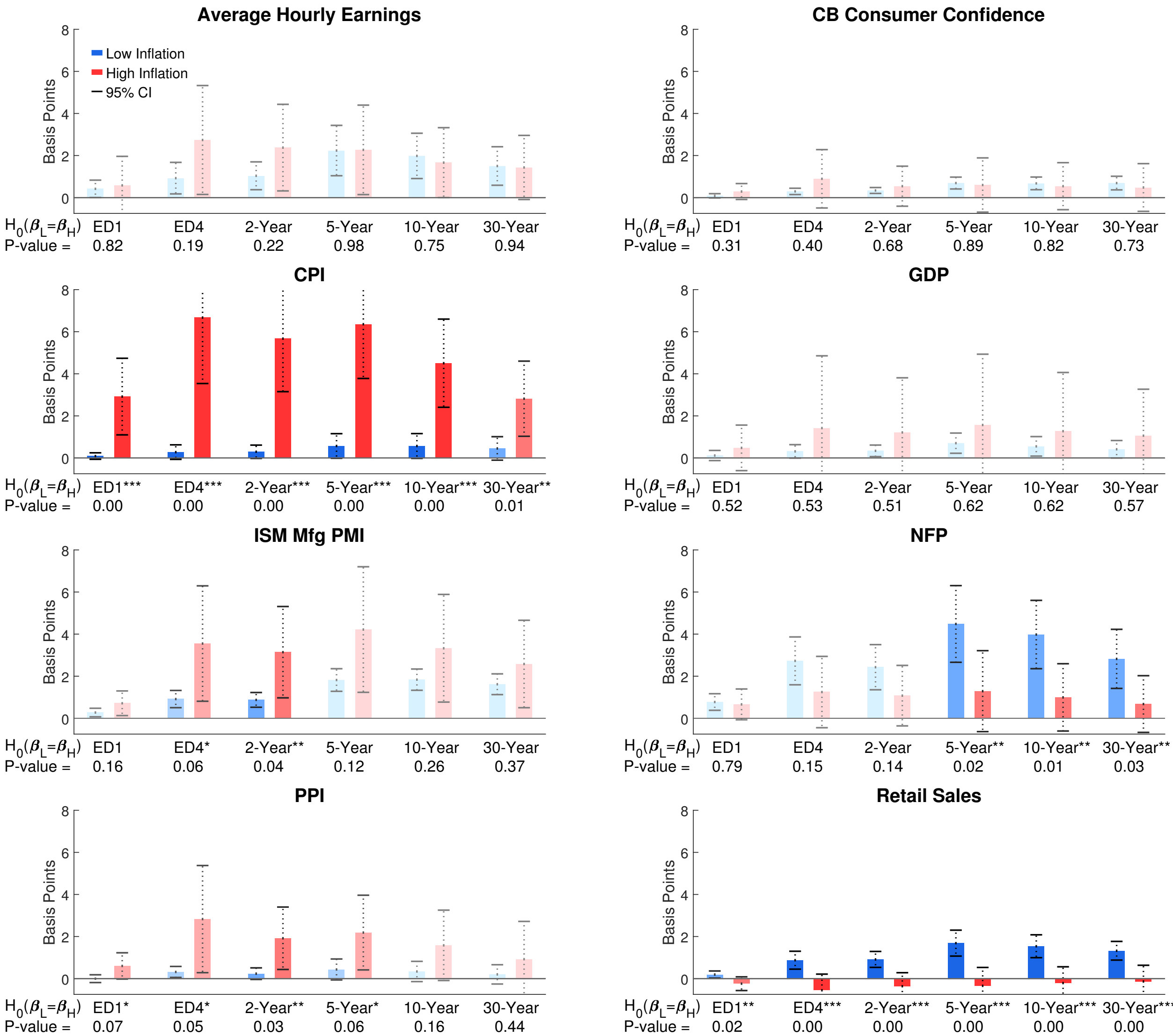
Turning to the other announcements, Figure 3 shows that none exhibit an increase in sensitivity comparable to that of the CPI release. For the ISM Mfg PMI and the PPI, there is some evidence of heightened sensitivity, but it is much less pronounced and considerably noisier. Given that the PPI is itself a price index and that the ISM Mfg PMI provides insights into supply chain disruptions (one of the primary drivers of the inflation surge),[28] the somewhat increased market reaction to both releases could also reflect heightened investor attention. For NFP and Retail Sales—typically among the most important macroeconomic releases—I find a significant decline in their market impact on interest rates. Several factors could explain this, such as investors focusing less on these releases or finding them harder to interpret in the post-COVID environment.[29] However, since this result is not central to my

[27] This is similar to a Chow test, except that I do not include the intercepts for the two inflation periods in the test.

[28] For example, Golle (2022) discusses supply chain issues in the context of the ISM Mfg PMI release.

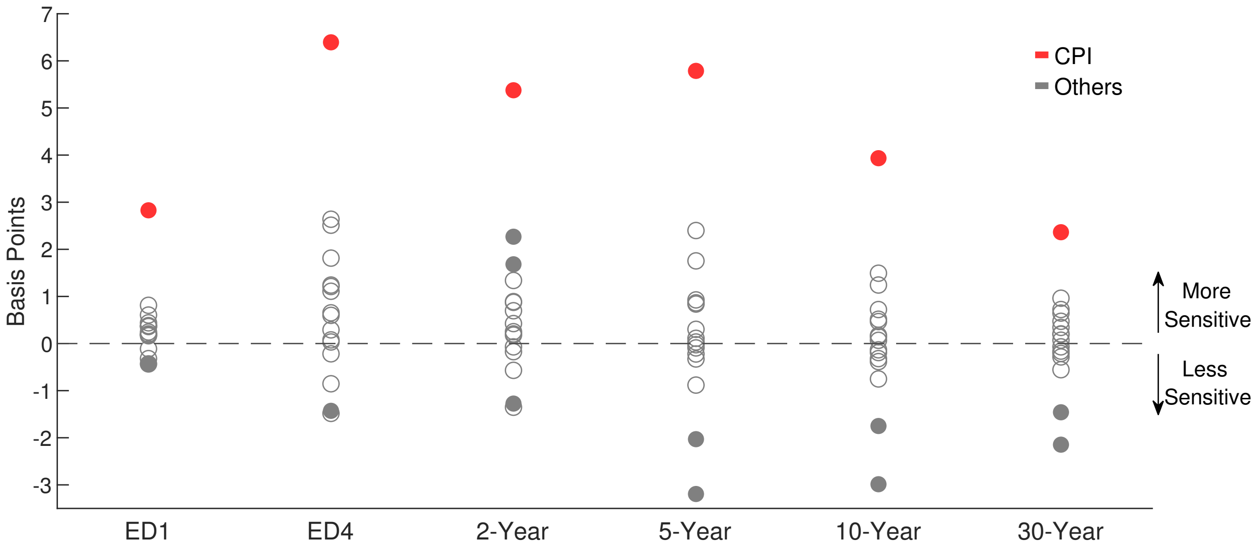
[29] See Saraiva (2023a) for an article mentioning the challenges in interpreting Retail Sales due to high inflation and Saraiva (2023b) for one on the complexities of assessing the employment report in the post-COVID period.

Figure 3: Effects of Macro News on Interest Rates under Low and High Inflation



Notes: This figure shows the responses of interest rates to each of the 8 main macroeconomic news announcements. Interest rate changes are expressed in basis points, and announcement surprises are normalized to standard deviations. Blue bars represent the effects during the low-inflation period (i.e., estimates of $\beta_L^{y|k}$ from equation (4)), while red bars represent the effects during the high-inflation period (i.e., estimates of $\beta_H^{y|k}$ from equation (4)). Black error bands show the 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level in rejecting the null hypothesis that $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are equal. The p-value for 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 throughout the analysis. Online Appendix Figure C3 shows the results for the other 8 macroeconomic announcements.

Figure 4: Changes in Interest Rate Sensitivity to Macro News under High Inflation



Notes: The figure displays the changes in interest rate sensitivity to macroeconomic news announcements from the low-inflation period to the high-inflation period. Circles represent the estimates of $\delta_H^{y|k} = \beta_H^{y|k} - \beta_L^{y|k}$ from equation (5). Filled circles indicate significance at the 5 percent level, while empty circles indicate insignificant effects. Heteroskedasticity-robust standard errors are employed throughout the analysis. *Others* includes the following 15 releases: Average Hourly Earnings, Capacity Utilization, CB Consumer Confidence, Durable Goods Orders, GDP, Initial Jobless Claims, ISM Mfg PMI, New Home Sales, NFP, PCE Price Index, Philadelphia Fed Index, PPI, Retail Sales, UM Consumer Sentiment P, and Unemployment Rate. See Online Appendix Table B1 for details on the releases.

analysis, I do not explore it further. Overall, the lack of strong increases in market reactions to non-CPI releases aligns with Hypothesis 1.

While Figure 3 indicates the unparalleled increase in sensitivity to CPI releases during the high-inflation period, Figure 4 provides a clearer visualization of this pattern. Specifically, the figure shows the change in sensitivity across both inflation periods—the estimates $\delta_H^{y|k}$ from (5)—for all 16 macroeconomic news announcements. Changes for the CPI release are displayed in red, while those for the other announcements are shown in gray. Filled dots represent statistically significant differences at the 5 percent level. The figure clearly highlights the CPI release as unique in how its impact on interest rates increased during the high-inflation period. None of the other 15 macroeconomic releases show a comparable rise in market reaction.

4.3 Effects on Inflation Swap Rates

Figure 5 presents the results for equation (4), using the five inflation swap rates discussed in Section 3 as dependent variables. The figure parallels Figure 3 for interest rates. Regarding the CPI release, Figure 5 provides several insights. First, consistent with the framework and arguments in Section 2, a higher-than-expected CPI release leads to the largest increases in inflation swap rates. Second, and more importantly, the effect of CPI news on inflation swap rates is substantially stronger during the high-inflation period. The differences between the coefficients $\beta_L^{\pi|k}$ and $\beta_H^{\pi|k}$ are highly statistically significant, allowing me—except for the 30-year maturity—to reject the null hypothesis of their equivalence across both inflation periods at the one- or five-percent level. The downward-sloping pattern of increased sensitivity in inflation swap rates suggests that markets expect the Federal Reserve to bring inflation down in the medium to long run. Put differently, long-run inflation expectations appear well-anchored, consistent with Bundick, Smith, and Van der Meer (2024).

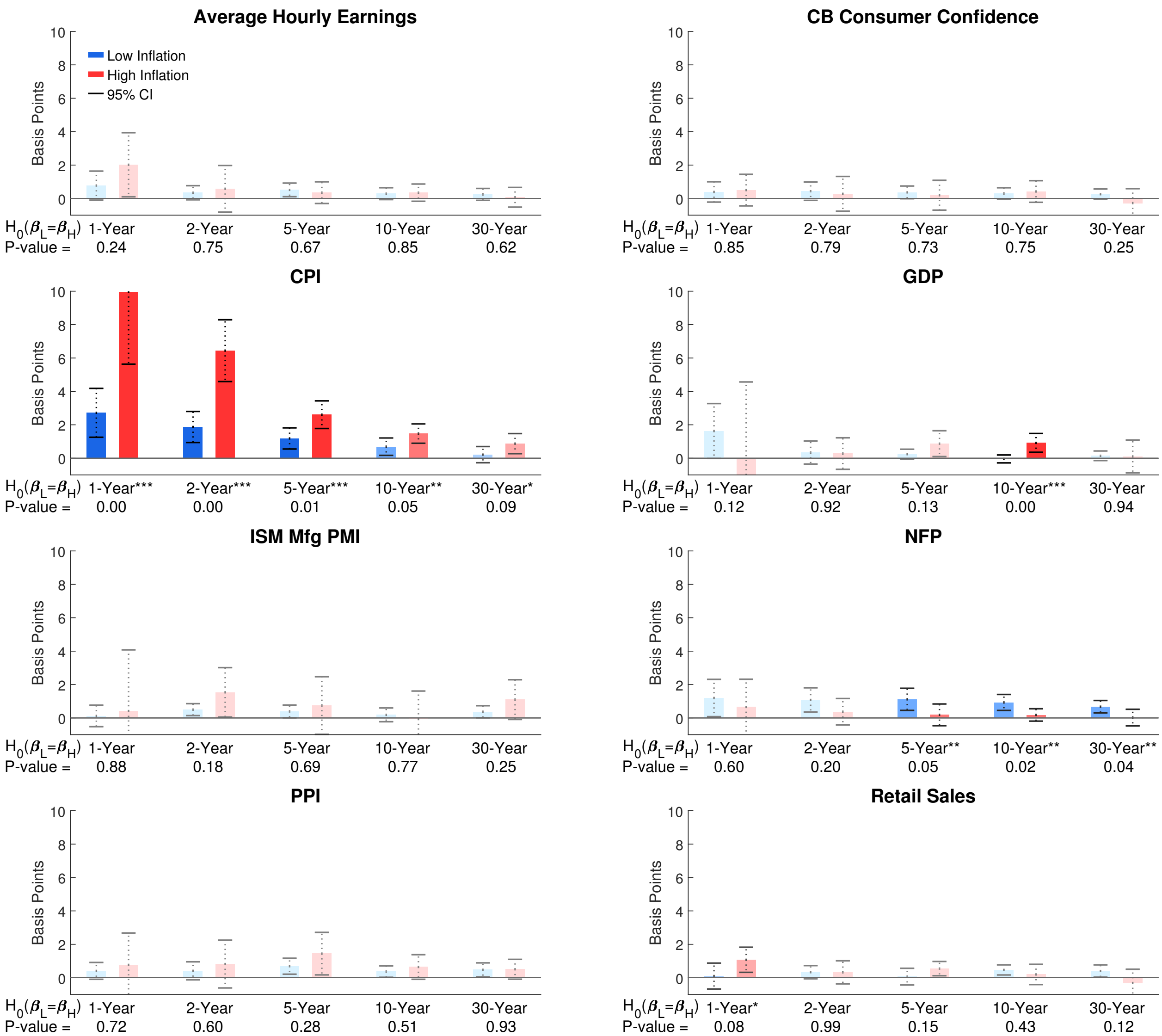
With respect to other releases, the effects are much smaller and noisier. That said, a few releases still exhibit significant effects, where positive surprises lead to higher inflation swap rates, aligning with the assumptions in Section 2's framework. Consistent with the interest rate results, the sensitivity of inflation swap rates is somewhat elevated for the ISM Mfg PMI and the PPI, while it declines for NFP. However, no other release shows an increase in sensitivity comparable to that for the CPI. Overall, the heightened responsiveness of inflation swap rates to CPI releases—and the lack thereof for non-CPI releases—supports the notion of increased investor attention to CPI news, in line with Hypothesis 1.

As with interest rates, Figure 6 provides a clearer visualization of this pattern. Specifically, the figure shows the change in sensitivity across both inflation periods—the estimates $\delta_H^{\pi|k}$ from (5)—for all 16 macroeconomic news announcements. The figure highlights the exceptional increase in the CPI's market impact on inflation swap rates during the 2021–2023 inflation surge. None of the other 15 macroeconomic releases exhibit a comparable rise in market reaction.

4.4 Sensitivity Analysis

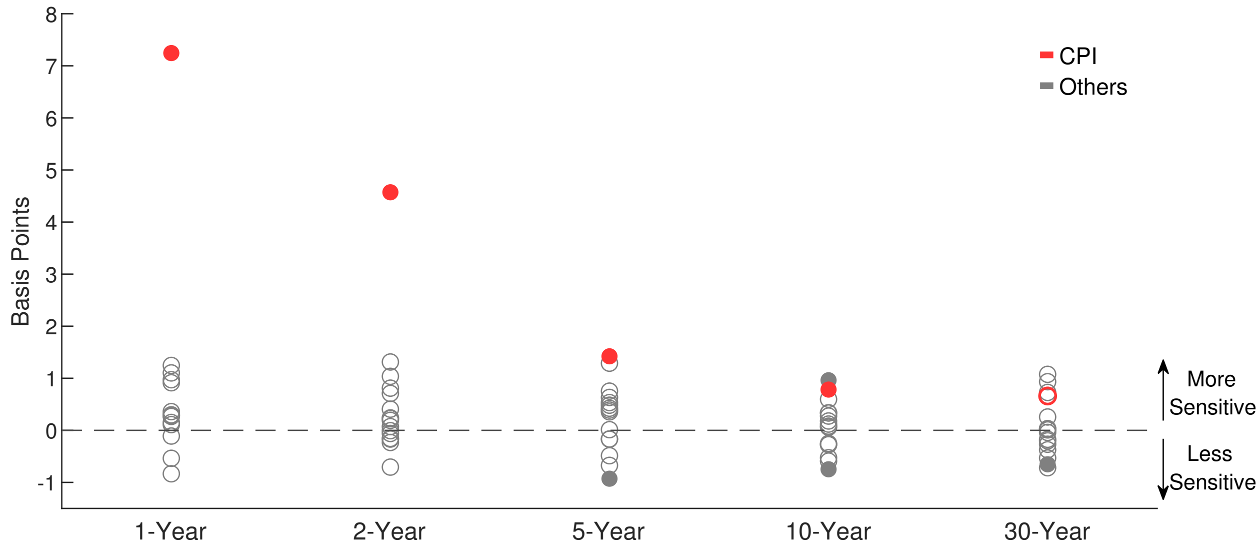
I now summarize the evidence demonstrating that the stark increases in interest rate and inflation swap rate sensitivity to CPI releases—found in this section—are a robust feature of the data. Results for robustness checks on interest rates are shown in Online Appendix Figure C5, and for inflation swap rates in Online Appendix Figure C6. The top rows of the figures show that the results are essentially unchanged when using surprises about core CPI (*Core*) or YoY CPI (*YoY*) inflation instead of the MoM CPI inflation used in the baseline. In the second rows, I show that the results are almost identical when using surprises based on the median forecast (*Median Forecast Surprise*) rather than the mean forecast.

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



Notes: This figure shows the responses of inflation swap rates to each of the 8 main macroeconomic news announcements. Inflation swap rate changes are expressed in basis points, and announcement surprises are normalized to standard deviations. Blue bars represent the effects during the low-inflation period (i.e., estimates of $\beta_L^{\pi|k}$ from equation (4)), while red bars represent the effects during the high-inflation period (i.e., estimates of $\beta_H^{\pi|k}$ from equation (4)). Black error bands show the 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level in rejecting the null hypothesis that $\beta_L^{\pi|k}$ and $\beta_H^{\pi|k}$ are equal. The p-value for 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 throughout the analysis. Online Appendix Figure C4 shows the results for the other 8 macroeconomic announcements.

Figure 6: Changes in Inflation Swap Rate Sensitivity to Macro News under High Inflation



Notes: The figure displays the changes in inflation swap rate sensitivity to macroeconomic news announcements from the low-inflation period to the high-inflation period. Circles represent the estimates of $\delta_H^{\pi|k} = \beta_H^{\pi|k} - \beta_L^{\pi|k}$ from equation (5). Filled circles indicate significance at the 5 percent level, while empty circles indicate insignificant effects. Heteroskedasticity-robust standard errors are employed throughout the analysis. *Others* includes the following 15 releases: Average Hourly Earnings, Capacity Utilization, CB Consumer Confidence, Durable Goods Orders, GDP, Initial Jobless Claims, ISM Mfg PMI, New Home Sales, NFP, PCE Price Index, Philadelphia Fed Index, PPI, Retail Sales, UM Consumer Sentiment P, and Unemployment Rate. See Online Appendix Table B1 for details on the releases.

Further, I investigate how sensitive the results are to two statistical properties of CPI surprises that may be of concern. First, as noted in Section 3, there are a few large surprises in the sample, particularly during the high-inflation period. The second rows of Online Appendix Figures C5 and C6 show that the results are robust to excluding these large surprises (*Excluding Large Surprises*), where I drop surprises greater than two standard deviations. In fact, the effects of CPI news during the high-inflation period actually become stronger compared to the baseline. The figures also show that the main findings remain essentially unchanged when I remove the autocorrelation from the CPI surprise series by residualizing the series with respect to its last 12 observations (*Residualized Surprises*).

I check several other specifications, which are shown in the last rows of the figures. I find that the results remain robust to including a single intercept in specification 4 (*One Intercept*) and to including the large surprise from May 2021 (*Including May 2021*). For interest rates, I also verify the robustness of the results when starting the low-inflation sample in 1996 instead of 2009 (*Sample starting in 1996*), which is not feasible for the inflation swap data. For inflation swap rates, I demonstrate that the results remain robust when using TIPS breakeven inflation rates (*Breakeven Inflation*).[30] Finally, I examine the robustness of my analysis with respect to the break date between the low-inflation period and the high-inflation period, with results shown in Online Appendix Figure C7. Overall, the main findings remain robust when selecting alternative break months around the baseline.

4.5 Additional Results

To understand the increased market sensitivity to CPI news, I conduct a variety of additional analyses, which I summarize in the following.

Other Asset Classes While interest rates and inflation swap rates have the most straightforward predictions from the model, I test whether the increased sensitivity to CPI news during the high-inflation period extends more broadly. To do this, I re-estimate equation (4) using a variety of asset prices as dependent variables. The results are shown in Table 3. As the table demonstrates, CPI surprises have significantly stronger effects across asset classes, both economically and statistically. A positive CPI surprise leads to a sharper decline in the S&P 500, as well as in commodity and corporate bond prices. It also causes a larger increase in the VIX and a greater depreciation of the Euro and Bitcoin against the U.S. Dollar. All of these effects are consistent with the stronger interest rate reaction documented above. The findings on the S&P 500 echo Gil de Rubio Cruz et al. (2022), who also observe an increased stock market sensitivity to inflation surprises since 2021. Overall, the heightened sensitivity to CPI news across asset classes during the 2021–2023 inflation surge is consistent with increased investor attention.

Role of Risk Premia So far, I have ignored the role of risk premia in my analysis, as they are difficult to measure and challenging to incorporate into a simple framework like the one in Section 2. To gauge their importance, I use daily yield curve decompositions from Adrian, Crump, and Moench (2013) and Kim and Wright (2005) for interest rates and d'Amico, Kim, and Wei (2018) for inflation compensation. Online Appendix Figure C10 shows that around two-thirds of the increased sensitivity to CPI news is driven by expected short rates and inflation expectations.[31] While these decompositions have limitations, they suggest that expectations drive most of the increased sensitivity, in line with the framework. That said, risk premia sensitivity also rises. Although beyond the model's scope, increased

[30] Intraday breakeven inflation rates come from the Federal Reserve Board and are estimated using intraday data from the New York Fed, following the methodology outlined in Gürkaynak, Sack, and Wright (2010).

[31] While I lack direct evidence on inflation compensation at shorter maturities, evidence from other studies—as discussed by Dierckx et al. (2023)—suggests that inflation risk premia play a lesser role at these horizons.

Table 3: Effects of CPI News on Different Asset Classes

Basis Points	S&P 500		VIX		Commodities	
	Low Inflation	High Inflation	Low Inflation	High Inflation	Low Inflation	High Inflation
News	-4.98*	-66.09***	27.75*	188.53***	-0.30	-22.99***
	(2.60)	(18.46)	(15.62)	(35.50)	(2.49)	(6.43)
P-value for $H_0: \beta_L = \beta_H$	0.00		0.00		0.00	
Basis Points	Corporate Bonds		Euro		Bitcoin	
	Low Inflation	High Inflation	Low Inflation	High Inflation	Low Inflation	High Inflation
News	1.33	-38.01***	-1.77	-30.83***	-3.87	-114.25***
	(2.06)	(11.22)	(2.25)	(7.65)	(11.13)	(40.41)
P-value for $H_0: \beta_L = \beta_H$	0.00		0.00		0.01	

Notes: This table presents estimates of $\beta_L^{x|\text{CPI}}$ and $\beta_H^{x|\text{CPI}}$ for specifications analogous to (4), where the dependent variables are now 60-minute log-changes of different asset prices, each expressed in basis points. The table also reports the p-value for the null hypothesis that $\beta_L^{x|\text{CPI}}$ and $\beta_H^{x|\text{CPI}}$ are equal. *S&P 500* refers to the front-month E-mini S&P 500 futures contract, *VIX* to the front-month VIX futures contract, *Commodities* to the S&P GS Commodity Index, and *Corporate Bonds* to the iShares iBoxx $ Investment Grade Corporate Bond ETF (LQD). *Euro* and *Bitcoin* refer to their respective spot rates against the U.S. Dollar. Values are denoted in U.S. dollars so that a decline reflects depreciation against the U.S. dollar. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

investor attention is generally consistent with higher risk premia (e.g., Andrei and Hasler, 2015). As investors observe a stronger market reaction to the CPI release, they may demand a higher compensation in anticipation of increased volatility around future releases. The increased sensitivity of term premia also echoes findings by Cieslak, McMahon, and Pang (2024), who argue that uncertainty about the Federal Reserve's response to inflation has risen between 2020 and 2022. I will examine the role of monetary policy uncertainty in more detail in Section 5.

International Spillovers Boehm and Kroner (2023) document the importance of U.S. macroeconomic news announcements for global financial markets. In Supplementary Appendix S2, I investigate whether the increased sensitivity to CPI news also applies to international spillovers. Specifically, I consider a range of international yields, stock indexes, and dollar exchange rates. The results, as shown in Supplementary Appendix Figure S2.1, reveal that the international spillovers of CPI news also significantly increased during the high-inflation period. The general pattern following a positive CPI surprise is that foreign interest rates rise, foreign stock prices decline, and the U.S. dollar appreciates against foreign currencies. In summary, the evidence suggests that investor attention plays a role in the international transmission of U.S. macroeconomic news announcements. See Supplementary Appendix S2 for more details.

Time-Varying Coefficient Approach While I show that the main findings are robust—among other things—to variations in the break date, one might still be concerned about underlying time-variation in the market impact of CPI news. To address this, I estimate a time-varying coefficient model in Supplementary Appendix S3. While such a framework has its limitations, it allows for changes in sensitivity to CPI news without taking a stance on when or why these changes occur. As shown in Supplementary Appendix Figure S3.1, the results are consistent with my previous findings. The figure illustrates that the effects of CPI news on interest rates, inflation swap rates, and stocks were relatively stable and muted following the Great Recession. Starting in 2021, the figure shows an increase in sensitivities to CPI news, peaking in 2023. See Supplementary Appendix S3 for more details.

5 An Attention-Based Explanation

In this section, I seek to provide direct evidence that the increased sensitivity to CPI releases—documented in Section 4—is indeed driven by investor's attention allocation towards CPI releases. I first present evidence from trading volumes before employing more direct measures of investor attention. I then address alternative explanations and examine the role of investor attention in the lower-frequency effects of CPI news.

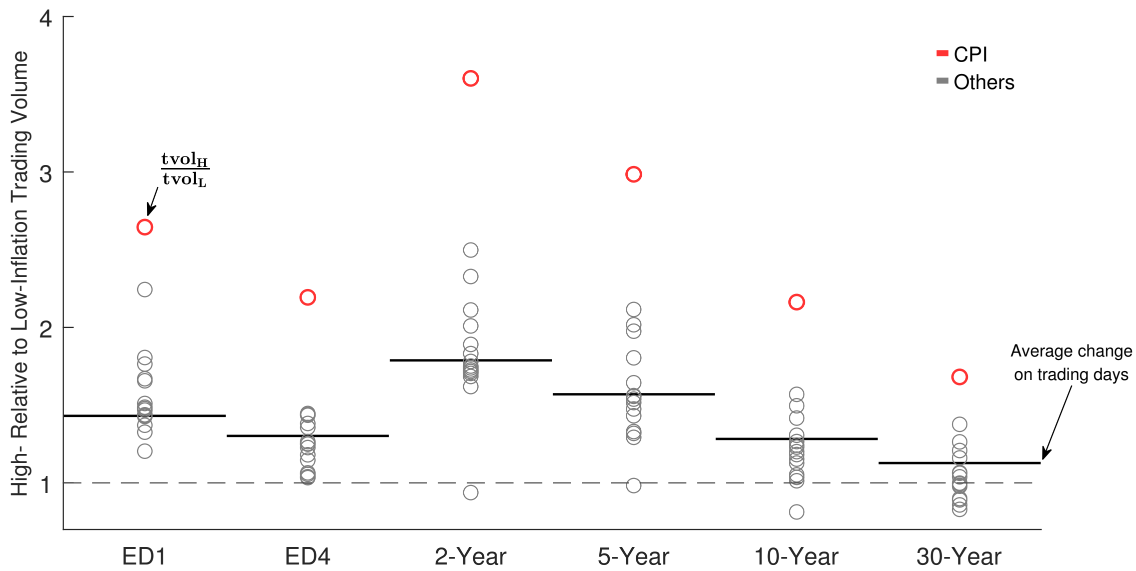
5.1 Trading Volume

As investor attention is generally difficult to measure, I begin by analyzing trading volume—a widely used proxy for investor attention (e.g., Huberman and Regev, 2001; Barber and Odean, 2008; DellaVigna and Pollet, 2009). While beyond the scope of the simple framework outlined in Section 2, one would theoretically expect significantly higher trading volumes around CPI releases if the increased market impact stems from more investors paying attention (Kim and Verrecchia, 1994). To test this prediction, I analyze trading volumes of the interest rate futures used in my analysis so far.[32] Specifically, I measure the number of contracts traded in the 60-minute window surrounding each release and compute the average for each announcement series separately in the low-inflation and the high-inflation period.

Figure 7 displays the results. For a given interest rate, a circle corresponds to a macroeconomic release and shows the ratio of the average trading volume during the high-inflation period to that during the low-inflation period. As a benchmark, the solid black lines display the ratio of the average trading volumes across both inflation periods. A circle above the

[32]The data comes directly from *LSEG Tick History*. Unfortunately, I do not observe trades for inflation swap rates, so trading volume is not available for them.

Figure 7: Changes in Trading Volume around Macro News



Notes: This figure displays the changes in trading volumes of interest rate futures around macroeconomic news announcements from the low-inflation period to the high-inflation period. Each circle corresponds to the ratio of the average trading volume around the release during the high-inflation period ($\mathrm{tvol_H}$) to that during the low-inflation period ($\mathrm{tvol_L}$), with volumes constructed using 60-minute windows around releases. Horizontal lines show the ratio of the average trading volumes across both inflation periods. *Others* includes the following 15 releases: Average Hourly Earnings, Capacity Utilization, CB Consumer Confidence, Durable Goods Orders, GDP, Initial Jobless Claims, ISM Mfg PMI, New Home Sales, NFP, PCE Price Index, Philadelphia Fed Index, PPI, Retail Sales, UM Consumer Sentiment P, and Unemployment Rate. See Online Appendix Table B1 for details on the releases.

corresponding line can then be interpreted as an abnormal increase in trading volume around the specific macroeconomic release. As the figure illustrates, trading volume increased exceptionally around CPI releases during the high-inflation period (red circles), both relative to other releases (gray circles) and the general rise in trading volume (black lines). In Online Appendix Figure C8, I also present the average minute-by-minute volumes, which confirm that the abnormal increase around CPI announcements is driven by trading following the releases.

At this point, one might be concerned that the rise in trading volume results from greater disagreement among investors regarding the release (Kim and Verrecchia, 1991), rather than increased attention. In Online Appendix Table C1, I show that the increased trading volumes around CPI releases are primarily driven by increased investor attention. To establish this, I regress the trading volumes around CPI releases on an investor attention measure (which I introduce below), as well as various disagreement and uncertainty measures. As shown in the table, investor attention is by far the most significant and robust predictor of trading volumes around CPI releases. In sum, the evidence on trading volume supports the idea that a rise in investor attention to inflation news drives the increased market impact of CPI releases, consistent with Hypothesis 1.

5.2 Measuring Investor Attention

Investor Attention around Macro Releases After focusing on trading volume, I now turn to more direct measures of investor attention. As noted in Section 3, institutional investors are essentially the sole participants in interest rate futures and inflation swap markets, and therefore the primary drivers of my findings in Section 4. Consequently, I focus now on directly measuring *institutional investor attention* around macroeconomic announcements. To do so, I follow the previous literature and construct measures based on news providers for professional investors (e.g., Ben-Rephael, Da, and Israelsen, 2017; Boguth, Grégoire, and Martineau, 2019).

My main measure is based on the news coverage from the *Bloomberg Terminal*, the most widely used professional financial news service.[33] The large majority of Bloomberg terminal users are institutional investors (Ben-Rephael, Da, and Israelsen, 2017). Previous research has shown that Bloomberg Terminal news coverage matters for investors (e.g., Fedyk, 2024). For a given trading day d, I obtain the number of relevant articles for announcement series k (N_d^k), and the number of published articles on the terminal (N_d). I then construct my daily investor attention measure for announcement series k as follows:

$$\mathrm{IA}_d^k = \frac{N_d^k}{\overline{N}_d}, \tag{6}$$

where $\overline{N}_d$ is the average number of articles published per day over the last year. Dividing by this average makes the attention measure less susceptible to structural shifts in the platform's news coverage, ensuring a more consistent measurement over time. The resulting attention measure reflects the intensity of news coverage on day d for announcement series k.

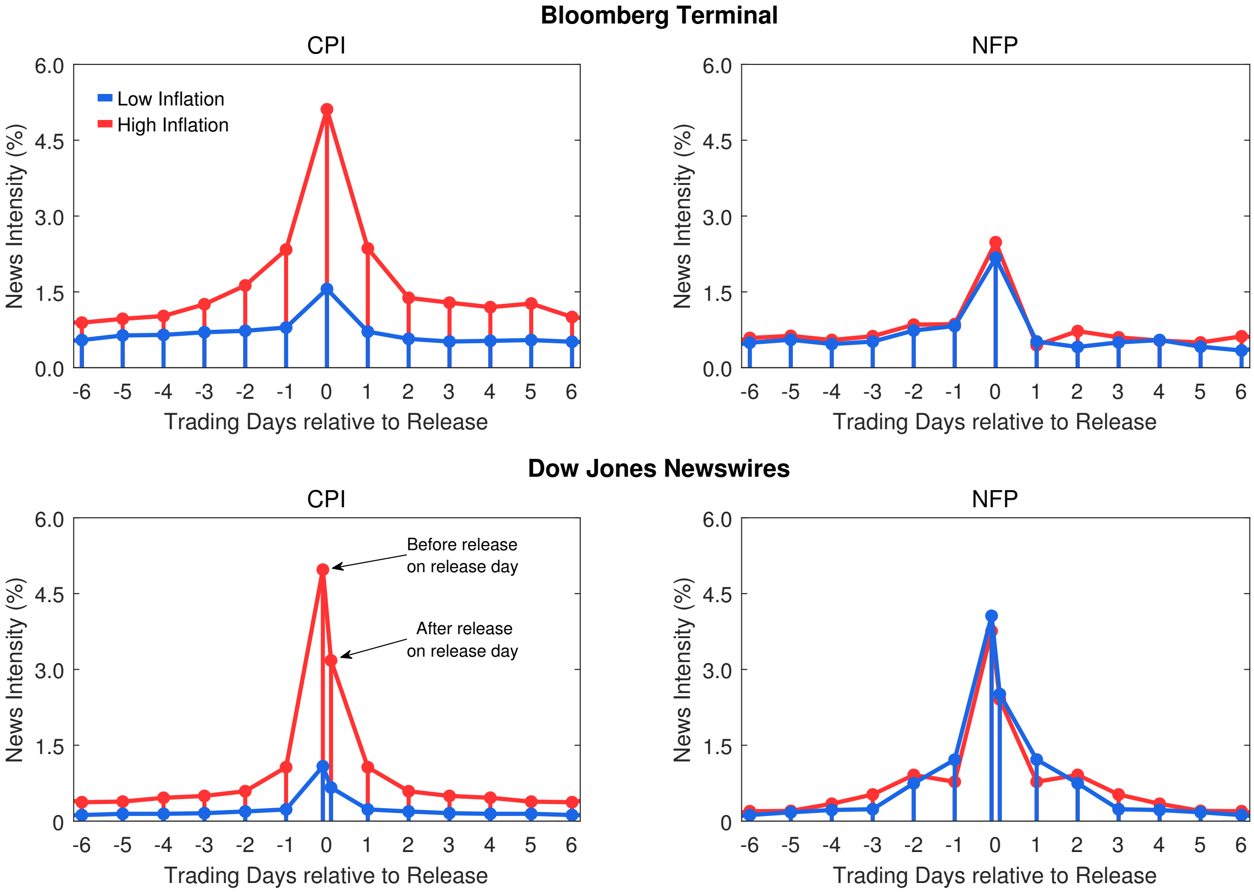
Based on (6), I construct a CPI attention measure and, for comparison, also an NFP one.[34] For robustness, I repeat the construction using news articles from the *Dow Jones Newswires*, an alternative professional financial news service. While it is less widely used by investors,[35] Dow Jones Newswires is still a popular proxy for investor attention (e.g., Ai et al., 2023).

[33] The Bloomberg Terminal had an estimated market share of 33 percent in 2021 (Wigglesworth, 2022).

[34] I choose NFP as it is considered the most important macroeconomic release. Given that my attention measures are only proxies, this implies a relatively high signal-to-noise ratio. Additionally, identifying relevant articles is easier for NFP compared to other macroeconomic releases due to distinct keywords.

[35] The Dow Jones Newswires had an estimated independent market share of 0.6 percent in 2021 (Wigglesworth, 2022). However, it became accessible through the Bloomberg Terminal starting in 2019 (Bloomberg, 2019).

Figure 8: Investor Attention around CPI and NFP Releases



Notes: The figure plots the CPI and NFP attention measures, as defined in (6), around their respective releases. Blue lines show the average values during the low-inflation period, while red lines show the average values during the high-inflation period. Measures represent the share of relevant articles on a given day, expressed as a percentage. They are based on news articles from the Bloomberg Terminal (top row) or the Dow Jones Newswires (bottom row). See the text for details on the construction.

Online Appendix B.3 provides details on the construction of all measures.

Figure 8 plots the average path of the CPI and NFP attention measures around the respective news releases, both based on the Bloomberg Terminal (top row) and the Dow Jones Newswires (bottom row). Blue lines correspond the low-inflation period, while red lines represent the high-inflation period. The figure reveals a significant increase in investor attention to CPI releases during the inflation surge. In contrast, attention to NFP releases remains largely unchanged. These findings are consistent with increased investor attention being the primary driver of the results in Section 4, thereby supporting Hypothesis 1. Lastly, note that the investor attention measures always rise around release days and that the paths across inflation periods converge when moving away from the release. Both patterns validate the construction of the measures.

Public Attention around Macro Releases While institutional investors are almost surely driving the results reported so far, I also look at two broader attention measures to capture the attention of retail investors and non-investors. The first measure is based on *Google Searches* which have been widely used as an attention proxy in recent years (e.g., Da, Engelberg, and Gao, 2011). Compared to previous papers, I construct a measure at the daily frequency. The second measure is based on news coverage by *Mainstream Media* (e.g., Fang and Peress, 2009), and is constructed using news articles from major news sources in the U.S. The details on the construction of both measures are provided in the Online Appendix B.3.

Similar to Figure 8, Online Appendix Figure C9 plots CPI and NFP attention for both of these broader measures around the respective releases. As the figure illustrates, the dynamics of the attention proxies based on *Google Searches* as well as *Mainstream Media* are qualitatively very similar to the dynamics shown in Figure 8. Hence, the results indicate that the public's attention to CPI releases also increased during the high-inflation period. This is consistent with evidence on inflation attention documented by other recent papers (e.g., Korenok, Munro, and Chen, 2023).

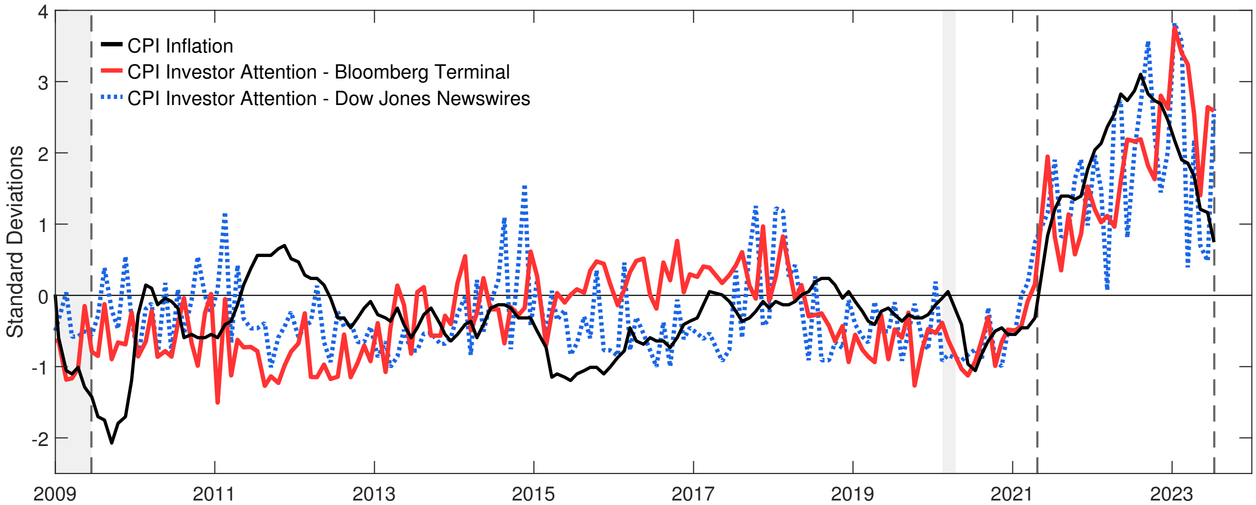
CPI Pre-Announcement Investor Attention After documenting above how the daily CPI investor attention measure moves around the CPI announcement, I now construct a measure which aims to capture the attention to a specific CPI announcement. To rule out reverse causality (e.g., larger CPI surprises might cause increased attention), I will base the measure entirely on the investor attention in the days prior to the release. Let d_t be the day of announcement k at time t, then the pre-announcement investor attention for announcement series k (k-IA hereafter) is constructed as:

$$\mathrm{IA}_t^k = \frac{\sum_{j=1}^{5} N_{d_t-j}^k}{\sum_{j=1}^{5} \overline{N}_{d_t-j}}. \tag{7}$$

I choose the 5-day window prior to the release compared to a shorter window as a find evidence (in unreported results) that the daily investor attention starts often to slightly picking up 5 trading days prior to releases.

Figure 9 plots the resulting series for the CPI (CPI-IA), both based on the Bloomberg Terminal and the Dow Jones Newswires. For comparison, the figure also displays the inflation

Figure 9: CPI Pre-Announcement Investor Attention and Inflation



Notes: The figure plots the CPI pre-announcement investor attention (CPI-IA) series, as defined in (7). The red line represents the series based on Bloomberg Terminal coverage, while the blue dotted line represents the series based on Dow Jones Newswires coverage. The solid black line denotes the real-time YoY CPI inflation rate at the time of the CPI announcement. Shaded areas indicate NBER recession periods, and vertical dotted lines mark the inflation periods, as defined in Section 3.1.

level at the time of each CPI release. All series are normalized to standard deviations. As the figure shows, the inflation level is a good proxy for investors' attention to inflation. This is in line with other recent papers which find that the level of the inflation rate is a key variable to understand household and firm attention to inflation (Korenok, Munro, and Chen, 2023; Weber et al., 2023).

5.3 Ruling out Alternative Explanations

So far in this section, I have provided evidence in support of an attention-based explanation. I now discuss plausible alternative explanations in the context of my findings.

Perceived Monetary Policy Response to Inflation As discussed in Section 2, a change in the perceived monetary response to inflation would theoretically imply a shift in interest rates without a corresponding shift in inflation swap rates in response to CPI news. It would also predict a similar shift in interest rates for non-CPI releases that affect inflation swap rates. However, as shown in Section 4, neither pattern appears in the data. Moreover, the increases in investor attention to CPI releases—documented in this section—should not occur under this explanation. Taken together, these findings suggest that changes in the perceived monetary policy rule are not the primary driver of my results. That being said, I cannot fully rule out that some shift in the policy rule occurred over this period, as argued by Bauer, Pflueger, and Sunderam (2024).

Perceived Sources of Inflation A change in the perceived sources of CPI inflation could also serve as an alternative explanation for the findings. One possibility is that supply shocks became relatively more important during the recent high-inflation period.[36] However, my model in Section 2 suggests that such a channel would reduce interest rate sensitivity to CPI news, as the expected policy response to output growth would offset the expected inflation response relatively more. This is at odds with the results in Section 4. Further, this narrative would not predict any changes in investor attention around CPI releases.

Another possibility—beyond the scope of my framework in Section 2—is that inflation remained demand-driven but was being perceived as more persistent during the high-inflation period. If investors also believed that the Federal Reserve only responds to the persistent part of inflation, this could potentially explain the findings. However, this narrative faces several challenges in light of the evidence: First, it would not predict any changes in investor attention around CPI releases. Second, the shift in perceived inflation persistence does not align with the fact that the sensitivity of the 1-year inflation swap increased the most, as shown in Figure 6. Finally, it is unclear why changes in perceived inflation persistence would apply specifically to CPI releases and not to other macroeconomic announcements that affect inflation swap rates.

In summary, while the perceived sources of CPI inflation likely shifted during the 2021–2023 inflation surge, the findings suggest that this is not the primary driver of the results. It is important to note that the scenarios I consider here are designed to not include any attention channels that might arise from shifts in the perceived inflation sources. In fact, my evidence suggests that the change in the inflation environment is the main factor driving the shifts in investor attention to CPI releases. However, the evidence also suggests that it is the resulting shift in investor attention that leads to the documented changes in market reactions.

Informativeness of CPI Release As shown Section 2, there is an alternative explanation which can rationalize the increased sensitivity to CPI news. This explanation assumes that CPI releases became more informative during the current high-inflation period, as summarized by a higher signal-to-noise ratio and consequently a higher Kalman gain in the model. Ex-ante, this is an intuitive story. As a high-inflation environment is associated with higher inflation volatility and uncertainty, i.e., higher signal variance, investors might just update

[36]For example, Modi and Zaratiegui (2024) argue that supply shocks have gained prominence in explaining CPI inflation news during the post-COVID period.

their prior more based on the CPI release—without any change in their attention.[37] And while this explanation cannot necessarily rationalize the evidence on trading volume and attention measures presented above, one might still wonder if such a simpler Bayesian updating story is not sufficient to rationalize the evidence.

In the following, I aim to differentiate the attention-based explanation from a simple Bayesian updating one. Specifically, I conduct a horse race between my CPI-IA series and various measures of uncertainty to better understand the increased sensitivity to CPI releases. To do so, I estimate the following specification:

$$x_t = \alpha + \beta^x s_t^{\text{CPI}} + \gamma^x \left(s_t^{\text{CPI}} \times \text{IA}_t^{\text{CPI}}\right) + \Gamma^x \left(s_t^{\text{CPI}} \times Z_t\right) + \theta^x \, \text{IA}_t^{\text{CPI}} + \Theta^x Z_t + \varepsilon_t, \tag{8}$$

where the dependent variable is either the 60-minute change in interest rates or inflation swap rates, $x \in \{y, \pi\}$. Here, IA_t^{CPI} denotes the CPI-IA series based on Bloomberg Terminal coverage, as constructed in equation (7), and Z_t is a vector of control variables. For ease of interpretation, I standardize both the IA_t^{CPI} and the measures in Z_t by first subtracting the sample mean and then dividing by the sample standard deviation. Thus, γ^x represents the differential effect of a CPI surprise when investor attention (IA_t^{CPI}) is one standard deviation higher than average. The coefficients θ^x can be interpreted similarly.

I estimate specification (8) with two different sets of controls Z_t. The first set includes only a recession and zero lower bound (ZLB) dummy. That is, this specification allows the effects of CPI surprises to vary during recession and ZLB periods.[38] The second specification additionally includes five uncertainty measures as controls: (1) *Inflation Volatility* refers to the realized volatility of CPI inflation over the previous year; (2) *Inflation Uncertainty—Consumer Survey* measures the expected inflation uncertainty over the next year based on consumer surveys by the University of Michigan and the New York Fed; (3) *Inflation Disagreement—Bloomberg Survey* captures the dispersion of forecasters' estimates for a given CPI release in the Bloomberg survey; (4) *Monetary Policy Uncertainty* denotes the Kansas City Fed's measure of option-implied policy rate uncertainty over the next year; and (5) *VIX* is the 30-day option-implied volatility index of the S&P 500. To avoid simultaneity concerns, I use lagged values—either from the day or the month prior to the release—for all

[37] Of course, a reduction in the noise variance would also increase the signal-to-noise ratio. However, the evidence seems to suggest that noise in macroeconomic news announcements rather increased in the post-COVID period (Sløk, 2023).

[38] NBER recession periods are used, and the ZLB periods are based on the effective federal funds rate. The first ZLB period in my sample spans from December 16, 2008, to December 15, 2015, and the second spans from March 15, 2020, to March 15, 2022.

controls, except for the disagreement measure, which is based on the current release. Online Appendix B.4 provides details on the uncertainty measures.

Table 4 presents the estimates. First, and consistent with the findings so far, the sensitivity of interest rates (top panel) and inflation swap rates (bottom panel) to CPI news substantially increases on days with higher investor attention. For example, the estimates of the specification with fewer controls imply that the 2-year Treasury yield responded by 0.7 basis points during the low-inflation period, while by 5.2 basis points during the high-inflation period.[39] These estimates closely align with those shown in Figure 3, where I estimate the sensitivity separately by period. Second, and more important for this section, the table shows that the effects of investor attention remain robust even when interactions of CPI news with measures of uncertainty are included. Although the coefficients on investor attention become somewhat smaller, they remain highly significant in most cases. Finally, the results are very similar when investor attention is constructed from the Dow Jones Newswires, as shown in Online Appendix Table C2.

The results in Table 4—when the uncertainty measures are included—should be seen as conservative. As shown by prior papers, economic uncertainty and investor attention are closely connected with each other (Benamar, Foucault, and Vega, 2021; Andrei, Friedman, and Ozel, 2023). Hence, increased uncertainty might drive some of the increase in investor attention—consistent with the estimates of the second specification. However, the sensitivity to CPI news may still rise only to the extent that uncertainty translates into investor attention. Even if one disagrees with this interpretation, the key takeaway from this analysis is that existing uncertainty measures cannot explain away the importance of the investor attention measure. In other words, the CPI-IA series contains variation that is independent of the uncertainty measures. This is not entirely surprising, given the strong co-movement with the CPI inflation level, as shown in Figure 9. While investor attention remains robust even with the inclusion of uncertainty measures, the interaction term with monetary policy uncertainty is notably significant for interest rates. This finding echoes recent works by Andrei and Hasler (2024) and Cieslak, McMahon, and Pang (2024), which highlight the importance of uncertainty about the Federal Reserve's reaction function during the 2021–2023 inflation surge.

[39]The average of the CPI-IA series is -0.34 standard deviations during the low-inflation period and 1.85 standard deviations during the high-inflation period. As a result, the sensitivity during the low-inflation period is 0.72 basis points ($= 1.42 - 0.34 \times 2.06$), while it increases to 5.2 basis points ($= 1.42 + 1.85 \times 2.06$) during the high-inflation period.

Table 4: Effects of CPI News: Role of Investor Attention versus Uncertainty

Interest Rates (bp)	ED1		ED4		2-Year		5-Year		10-Year		30-Year	
News	0.75***	0.61***	1.65***	1.72***	1.42***	1.47***	1.73***	1.90***	1.35***	1.51***	0.95***	1.05***
	(0.23)	(0.15)	(0.38)	(0.28)	(0.31)	(0.23)	(0.36)	(0.31)	(0.31)	(0.27)	(0.27)	(0.26)
News × Investor Attention	1.02***	0.33*	2.48***	1.56***	2.06***	1.37***	2.33***	1.83***	1.63***	1.37***	0.97***	0.92**
	(0.27)	(0.20)	(0.42)	(0.37)	(0.34)	(0.30)	(0.37)	(0.39)	(0.32)	(0.36)	(0.31)	(0.37)
News × Inflation Volatility		-0.28		0.01		-0.05		0.24		0.00		-0.26
		(0.27)		(0.50)		(0.41)		(0.54)		(0.46)		(0.44)
News × Inflation Uncertainty —Consumer Survey		0.69**		0.65		0.54		0.27		0.16		0.15
		(0.31)		(0.56)		(0.48)		(0.56)		(0.47)		(0.44)
News × Inflation Disagreement —Bloomberg Survey		0.22		-0.48		-0.36		-0.47		-0.38		-0.23
		(0.20)		(0.36)		(0.28)		(0.37)		(0.34)		(0.30)
News × Monetary Policy Uncertainty		0.69***		1.27***		0.87***		0.67*		0.57*		0.38
		(0.20)		(0.36)		(0.28)		(0.35)		(0.30)		(0.28)
News × VIX		0.02		0.20		0.35		0.46		0.42		0.47*
		(0.16)		(0.30)		(0.26)		(0.33)		(0.29)		(0.28)
Recession & ZLB Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.50	0.64	0.60	0.68	0.60	0.69	0.54	0.61	0.46	0.55	0.32	0.42
Observations	166	166	166	166	166	166	166	166	166	166	166	166
Inflation Swap Rates (bp)	1-Year		2-Year		5-Year		10-Year		30-Year			
News	4.00***	4.20***	2.74***	2.83***	1.39***	1.80***	0.80***	0.99***	0.32*	0.43**		
	(0.69)	(0.75)	(0.43)	(0.39)	(0.29)	(0.27)	(0.21)	(0.23)	(0.18)	(0.18)		
News × Investor Attention	3.02***	2.25**	1.86***	1.34**	0.66**	0.35	0.41**	0.20	0.38**	0.46*		
	(1.08)	(1.01)	(0.51)	(0.63)	(0.30)	(0.38)	(0.21)	(0.32)	(0.16)	(0.25)		
News × Inflation Volatility		2.46		0.89		0.97**		0.36		-0.06		
		(2.57)		(0.65)		(0.43)		(0.35)		(0.31)		
News × Inflation Uncertainty —Consumer Survey		0.88		0.54		0.18		0.31		-0.02		
		(1.31)		(0.72)		(0.58)		(0.42)		(0.36)		
News × Inflation Disagreement —Bloomberg Survey		-2.07***		-0.52		-0.63**		-0.19		0.14		
		(0.76)		(0.47)		(0.29)		(0.25)		(0.24)		
News × Monetary Policy Uncertainty		-1.68*		-0.30		0.19		0.01		0.15		
		(0.97)		(0.60)		(0.35)		(0.29)		(0.27)		
News × VIX		0.17		0.39		-0.50		-0.41		-0.30		
		(0.83)		(0.40)		(0.39)		(0.28)		(0.22)		
Recession & ZLB Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
R^2	0.42	0.51	0.43	0.52	0.22	0.36	0.18	0.27	0.14	0.20		
Observations	166	166	166	166	166	166	166	166	166	166		

Notes: The table presents estimates of β^x, γ^x, and Γ^x from equation (8), where investor attention denotes the CPI-IA series as defined in (7) and constructed from Bloomberg Terminal data. The top panel reports estimates for changes in interest rates as the dependent variables, while the bottom panel reports estimates for inflation swap rates. Changes in both interest rates and inflation swap rates are expressed in basis points. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Online Appendix Table C2 reports the corresponding estimates when investor attention is constructed from Dow Jones Newswires data.

5.4 Lower-frequency Effects

One question I have not addressed so far is whether macroeconomic news announcements that face high investor attention are associated with market overreaction or announcements that face low investor attention with market underreaction. As briefly mentioned in Section 2, my framework does not have a clear prediction on this. As the model includes both investor underreaction due to limited attention and overreaction due to diagnostic expectations, it can in principle rationalize both of these cases. Hence, to inform this question, I now estimate daily impulse responses to CPI news when investor attention is low or high. To increase the statistical power of my analysis, I will extend the sample to include CPI releases from 1996 onwards and pool across interest rates and across inflation swap rates.

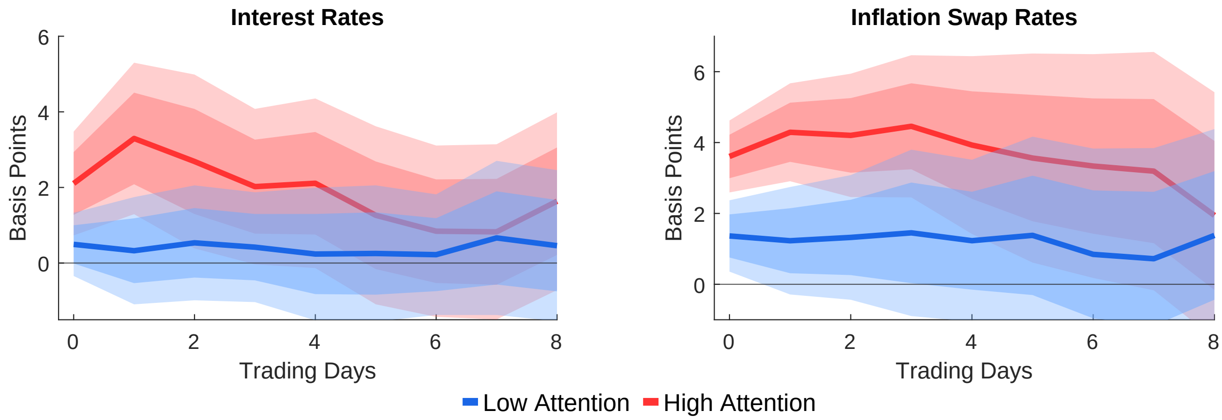
In particular, I run the following daily pooled local projection specification:

$$x_{m,d}^{(h)} = \alpha_m^{(h)} + \beta^{(h)} s_d^{\text{CPI}} + \gamma^{(h)} \times \text{IA}_d^{\text{CPI}} + \delta^{(h)} \text{IA}_d^{\text{CPI}} + \varepsilon_{m,d}^{(h)}, \tag{9}$$

where $x_{m,d}^{(h)}$ is the h-day change of the m-year interest rate or inflation swap rate, i.e., $x_{m,d}^{(h)} = x_{m,d+h} - x_{m,d-1}$. I consider daily data on 1-,2-,5-,10- and 30-year maturities, i.e., $m \in \{1, 2, 5, 10, 30\}$. The data on Treasury yields comes from the updated Gürkaynak, Sack, and Wright (2007) database, while the data on inflation swap rates is from *Bloomberg*. I demean investor attention IA_d^{CPI} and normalize it to standard deviations. Hence, the pooled effect $\beta^{(h)}$ captures the *average* effect of a one standard deviation positive surprise s_d^{CPI} on interest rates, whereas pooled interaction effect $\gamma^{(h)}$ captures s_d^{CPI}'s additional effect under a one standard deviation increase in investor attention IA_d^{CPI}. I employ Driscoll and Kraay (1998) standard errors which are robust to heteroskedasticity, autocorrelation, and cross-sectional dependence.

Figure 10 presents the impulse responses based on the estimates of equation (9). I focus on a horizon of 8 trading days (one and a half weeks), beyond which standard errors become too large to draw informative conclusions. As the figure illustrates, when attention is high, interest rates and inflation swap rates exhibit a significantly stronger response on the first two days following the release. After that, the response under high attention converges to that under low attention. Hence, the evidence suggests that higher attention leads to overreaction in both interest rates and inflation swap rates. Moreover, this documented overreaction validates that my investor attention measure captures a behavioral mechanism, as structural shifts—such as changes in the monetary policy coefficient or the sources of inflation—would predict neither underreaction nor overreaction.

Figure 10: Daily Impulse Responses to CPI News



Notes: The figure displays the daily impulse response of interest rates (left) and inflation swap rates (right) to a one-standard-deviation positive CPI surprise. Both panels are based on estimates of $\beta^{(h)}$ and $\gamma^{(h)}$ from pooled specification (9). *Low Attention* (blue) corresponds to the effect of CPI news at the 5th percentile of the investor attention distribution, whereas *High Attention* (red) corresponds to the effect at the 95th percentile. Investor attention denotes the CPI-IA series, as defined in (7) and constructed from Bloomberg Terminal data. The sample period for interest rates starts in 1996, while for inflation swap rates it begins in 2004. Dark and light shaded areas show 68 percent and 90 percent confidence bands, respectively. All standard errors are based on Driscoll and Kraay (1998).

6 Beyond Inflation: Macro News and Investor Attention

In this section, I provide evidence that the pivotal role of investor attention—documented so far in the context of the CPI release—also extends to other macroeconomic news announcements. To do so, I study two other major announcement series: NFP and Federal Open Market Committee (FOMC) announcements. Specifically, I construct—analogous to the CPI-IA series—investor attention measures for NFP and FOMC announcements, using the news coverage from the Bloomberg Terminal. Online Appendix B.3 provides the details. For this analysis, I extend the sample period to include announcements from 1996 onwards and focus on the effects on interest rates, which are typically the most precisely estimable.

While I can continue using the same surprise series for NFP announcements, I need to construct a suitable news measure for FOMC announcements. I ultimately use an indicator variable based on the Gürkaynak, Sack, and Swanson (2005) path factor, which utilizes 30-minute changes in Federal Funds and Eurodollar futures and which I update based on data from Boehm and Kroner (2024).[40] My news measure is then an indicator variable taking the value of 1 if the path factor is positive, 0 if the path factor is zero, and -1 if the path factor

[40]My path factor has a 97 percent correlation with Acosta's (2022) updated path factor for the overlapping sample.

Table 5: Role of Investor Attention in High-Frequency Effects of Macro News

Interest Rates (bp)	ED1	ED4	2-Year	5-Year	10-Year	30-Year
CPI Announcement						
News	0.43***	1.14***	0.95***	1.17***	0.85***	0.57***
	(0.16)	(0.31)	(0.25)	(0.31)	(0.26)	(0.20)
News × Investor Attention	0.42**	1.06**	0.83**	0.94**	0.67**	0.48*
	(0.19)	(0.43)	(0.36)	(0.44)	(0.33)	(0.25)
Recession & ZLB Interactions	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.12	0.15	0.14	0.12	0.10	0.08
Observations	315	315	315	315	315	315
NFP Announcement						
News	1.25***	3.70***	3.11***	3.86***	3.06***	2.06***
	(0.17)	(0.42)	(0.37)	(0.48)	(0.40)	(0.31)
News × Investor Attention	0.31**	1.29**	0.73*	1.00**	0.81**	0.35
	(0.15)	(0.51)	(0.37)	(0.47)	(0.40)	(0.30)
Recession & ZLB Interactions	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.27	0.34	0.31	0.27	0.26	0.20
Observations	302	302	302	302	302	302
FOMC Announcement						
News	2.13***	4.41***	3.57***	4.40***	3.27***	1.51***
	(0.31)	(0.40)	(0.44)	(0.50)	(0.45)	(0.34)
News × Investor Attention	0.52	1.44***	0.86	1.20**	0.80**	0.46*
	(0.36)	(0.45)	(0.56)	(0.47)	(0.38)	(0.27)
Recession & ZLB Interactions	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.24	0.41	0.27	0.30	0.24	0.13
Observations	213	213	213	213	213	213

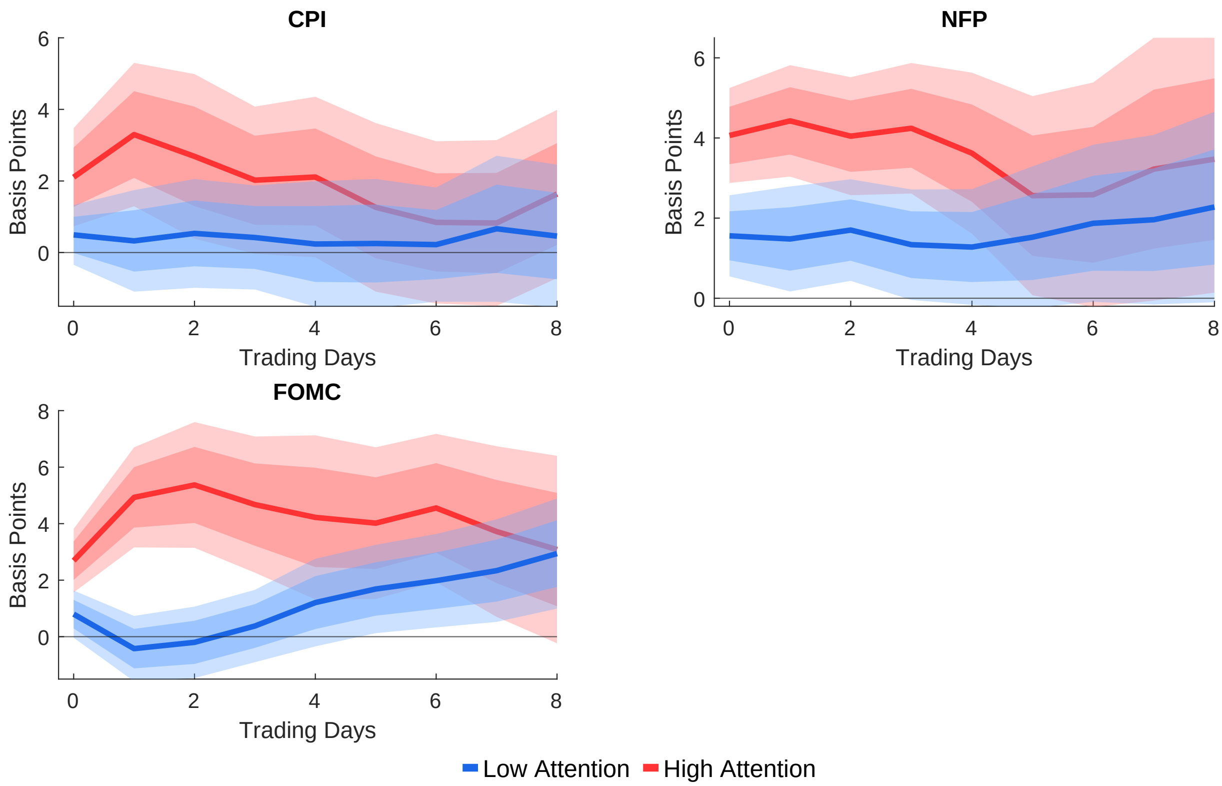
Notes: The table shows the estimates β^x and γ^x from the corresponding versions of equation (8). Investor attention denotes the k-IA series, as defined in (7) and constructed from Bloomberg Terminal data. The dependent variables are changes in interest rates, expressed in basis points, and the sample period starts in 1996. Announcement news is in units of standard deviations. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

is negative.[41] The rationale behind this construction is to create a news measure capable of predicting the direction of interest rate responses to FOMC announcements while not including any response magnitudes, which could be affected by investor attention and thus bias the analysis.

High-frequency Evidence I begin by providing evidence on the role of investor attention for the high-frequency effects. Specifically, I re-estimate specification (8) for CPI, NFP, and FOMC announcements over the extended sample period. The results are presented in Table 5. First, the table shows that, for all three announcement series, a positive surprise leads to an

[41] The FOMC news measure turns out to have a standard deviation of one over the sample period, which facilitates direct comparison with the other two surprise measures which are expressed in units of standard deviations.

Figure 11: Daily Impulse Responses of Interest Rates to Macro News



Notes: The figure displays the daily impulse response of interest rates to a one-standard-deviation positive surprise for CPI (top left), NFP (top right), and FOMC announcements (bottom left). All panels are based on estimates of $\beta^{(h)}$ and $\gamma^{(h)}$ from the corresponding versions of pooled specification (9). *Low Attention* (blue) corresponds to the effect of news at the 5th percentile of the investor attention distribution, whereas *High Attention* (red) corresponds to the effect at the 95th percentile. Investor attention denotes the k-IA series, as defined in (7) and constructed from Bloomberg Terminal data. The sample period for interest rates starts in 1996. Dark and light shaded areas show 68 percent and 90 percent confidence bands, respectively. All standard errors are based on Driscoll and Kraay (1998).

increase in interest rates, consistent with the earlier results and prior research. Second, and more importantly, the table indicates that investor attention has qualitatively similar effects across all three announcement series: announcements that attract more investor attention have stronger impact effects on interest rates.

Lower-frequency Evidence After documenting the importance of investor attention for the high-frequency effects, I now turn to the lower-frequency effects. To do so, I re-estimate panel specification (9) for all three announcement series, where I now focus solely on interest rates. Figure 11 displays the impulse responses based on the estimates. Several points are worth highlighting. First, for all three announcement series, higher investor attention is associated with a stronger reaction in the first few days, in line with the evidence on the high-frequency effects. Second, announcements with higher attention appear to be linked to overreaction. That is, the reaction reverses after a few days. Finally, there is also some evidence of underreaction to NFP and FOMC announcements when investor attention is comparatively low.

7 Conclusion

In this paper, I demonstrate that investors' attention allocation plays a critical role in how financial markets process macroeconomic news. Using a high-frequency event study design, I document a significant increase in market reactions to CPI releases during the 2021–2023 inflation surge. At the same time, reactions to other macroeconomic news announcements remain largely unchanged. Through the lens of a simple information acquisition model, the documented market reactions suggest that increased investor attention is the primary driver. I corroborate this interpretation by providing a range of evidence based on measures of investor attention and carefully ruling out alternative explanations. Lastly, I show that this attention-based channel extends beyond CPI releases and that markets tend to overreact to announcements that attract significant investor attention.

My findings suggest that investor attention plays a crucial role in understanding the link between financial markets and the macroeconomy. One promising avenue for future research, highlighted by my findings, is to integrate investors' attention allocation alongside extrapolative beliefs into a unified model. Additionally, my results indicate that high-frequency event study estimates may be systematically biased if the allocation of investor attention to the event of interest is not properly accounted for. For example, it could be valuable to explore whether so-called high-frequency monetary policy shocks can be refined by controlling for ex-ante investor attention.

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Online Appendix

for

How Markets Process Macro News: The Importance of Investor Attention*

T. Niklas Kroner

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

In this appendix, I lay out the model described in Section 2. I start by discussing the model environment before I turn to the model solution. To preserve space, I relegate more complex mathematical derivations to Supplementary Appendix S1.

A.1 Environment

The model has *four dates*, i.e., $\tau = \{1, 2, 3, 4\}$, and consequently three periods. Figure 1 displays the timeline of the model. At date 1 and 2, investors trade their assets. Between these dates, a macroeconomic announcement occurs which is a public signal about an economic fundamental. At date 3, the monetary policy authority announces their decision based on the economic fundamentals, and at date 4 the assets mature. As the period from date 1 to 2 corresponds to the intraday window defined below in the empirical analysis, it should be interpreted as very short. In contrast, the other two periods should be understood as substantially longer as depicted in the figure.

Investors There is a *continuum of investors* in the model, $i \in [0, 1]$. Each investor has a quadratic utility function with risk aversion parameter γ.[1] At date 1, each investor solves her portfolio choice problem to determine her demands for a Treasury security, λ_1^i and λ_2^i, and for an inflation swap, ω_1^i and ω_2^i. At date 2, each investor reoptimizes her portfolio to determine her demand $\tilde{\lambda}_2^i$ for a Treasury security and $\tilde{\omega}_2^i$ for an inflation swap. At dates 3 and 4, portfolio optimization does not occur, as investors' wealth is assumed to be held entirely in the risk-free asset. Investors are identical except for how they process the macroeconomic announcement.

Fundamentals The model has two fundamentals: *inflation* $\bar{\pi}_\tau$ and *output growth* $\bar{z}_\tau$. Inflation $\bar{\pi}_\tau$ is the change in the price level between τ and $\tau - 1$ and output growth $\bar{z}_\tau$ is the change in output between τ and $\tau - 1$. Since the period between 1 and 2 is very short, I assume $\bar{\pi}_2 = 0$ and $\bar{z}_2 = 0$. The inflation rate for the remaining two periods is given by:

$$\bar{\pi}_4 = \bar{\pi}_3 = \Delta\bar{\pi} + \bar{\pi}_{-1},$$

with the change in inflation being defined as:

$$\Delta\bar{\pi} = \Delta\bar{\pi}_{-1} + \varepsilon_\pi, \text{ with } \varepsilon_\pi \sim N\left(0, \sigma_\pi^2\right),$$

where $\bar{\pi}_{-1}$ and $\Delta\bar{\pi}_{-1}$ are taken as given and reflect the inflation and change in inflation prior to date 1. The output growth for dates 3 and 4 is given by:

$$\bar{z}_4 = \bar{z}_3 = \Delta\bar{z} + \bar{z}_{-1},$$

with the change in output growth being defined as:

$$\Delta\bar{z} = \varrho\Delta\bar{\pi},$$

[1] Since investor's wealth will be normally distributed, a quadratic utility function is equivalent to a negative exponential utility function in this setting.

where $\bar{z}_{-1}$ reflects the output growth prior to date 1 and ϱ governs the relationship between inflation and output growth. A positive ϱ can be interpreted as a demand-driven environment, while a negative ϱ suggests a supply-driven environment.

Assets There are three assets available: (1) a riskless asset (a cash account), (2) a *Treasury security* (a government bond), and (3) an *inflation swap*. The riskless asset returns R_τ each period, where R_τ is the risk-free rate earned between dates τ and $\tau - 1$. Since the first period (from date 1 to date 2) should be interpreted as very short, I assume there is no return on the cash account earned during this period and hence no discounting in the model for that period, $R_2 = 0$. Further, $R_3 = R_{-1}$, where R_{-1} is taken as given and reflects the risk-free rate prior to date 1. The risk-free rate earned between dates 4 and 3, R_4, is defined as:

$$R_4 = \Delta R + R_3,$$

which simplifies to

$$R_4 = \Delta R + R_{-1},$$

where ΔR is the change in the risk-free rate announced by the monetary policy authority. The Treasury security matures at date 4, pays a coupon of one dollar at maturity, and is in zero net supply. The inflation swap is slightly more complex in this setting. I assume it is also in zero net supply, matures at date 4, and pays out the average inflation rate between dates 2 and 4 in terms of period 2 units, $\frac{1}{2}\left(\bar{\pi}_3 + \bar{\pi}_4\right)\left(1 + R_3\right)\left(1 + R_4\right)$. This ensures that there is no discounting mismatch between the price of the swap (i.e., the inflation swap rate) and the payoff of the swap (i.e., the average inflation rate). This is consistent with inflation swaps in practice, where no cash flows are exchanged at the time of the trade, but only at maturity.

Monetary Policy The monetary policy authority announces the change in the risk-free rate, ΔR, at date 3, which it sets according to the following *Taylor rule*:

$$\Delta R = \phi^\pi \Delta\bar{\pi} + \phi^z \Delta\bar{z}.$$

I 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 rises.

Information Structure Investors cannot observe the change in inflation, $\Delta\bar{\pi}$, or output growth, $\Delta\bar{z}$, prior to the monetary policy decision at date 3. However, before date 2, investors receive a public noisy signal (the macroeconomic new release), which is either about $\Delta\bar{\pi}$ through the CPI release or about $\Delta\bar{z}$ through the NFP release. The signals are given by

$$s^{\mathrm{CPI}} = \Delta\bar{\pi} + \eta, \text{ with } \eta \sim N\!\left(0, \sigma_\eta^2\right),$$

and

$$s^{\mathrm{NFP}} = \Delta\bar{z} + \nu, \text{ with } \nu \sim N\!\left(0, \varrho^2\sigma_\nu^2\right).$$

Following DellaVigna and Pollet (2009), I assume that for each signal s^k, where $k \in \{\mathrm{CPI}, \mathrm{NFP}\}$, only μ^k investors (*attentive investors*) incorporate it into their expectations, while $1 - \mu^k$ investors (*inattentive investors*) ignore it.[2] Additionally, attentive investors update their expectations using a diagnostic Kalman filter (Bordalo et al., 2020), which allows for *investor overreaction* to signals. Parameter $\kappa \geq 0$ governs the extent of overreaction. As a result of the diagnostic expectations, the presence of inattentive investors ($\mu^k < 1$) does not necessarily imply an average underreaction to the signals.

Simplifying Assumptions Note that the level of inflation, output growth, or the risk-free rate is not critical for the model mechanism. Therefore, I will assume $\bar{\pi}_{-1} = 0$, $\bar{z}_{-1} = 0$, and $R_{-1} = 0$, when I solve the model. I will also assume that there is no change in the inflation rate in the prior period, $\Delta\bar{\pi}_{-1} = 0$. These assumptions make the model very tractable. Of course, in reality, parameters such as μ^k (which I vary in my comparative statics) are likely functions of $\Delta\bar{\pi}_{-1}$, $\Delta\bar{z}_{-1}$, and R_{-1}.

A.2 Solution

I now outline the model solution. I first solve the investors' portfolio choice and signal extraction problems, before I derive the equilibrium prices.

A.2.1 Portfolio Choice Problem

To setup investor i's portfolio choice problem, it is useful to employ the intertemporal budget constraint, which I derive in the following. Let π_τ denote the price of the inflation swap at date τ and b_τ the price of Treasury security at date τ. Investor i's budget constraint at each date is given by:

$$\begin{aligned}
\tilde{W}_1^i &= \tilde{W}_0^i - b_1\lambda_1^i - \pi_1\omega_1^i, \\
\tilde{W}_2^i &= \left(\lambda_1^i - \lambda_2^i\right) b_2 + \left(\omega_1^i - \omega_2^i\right) \pi_2 + \tilde{W}_1^i, \\
\tilde{W}_3^i &= \tilde{W}_2^i \left(1 + R_3\right), \\
\tilde{W}_4^i &= \lambda_2^i + \omega_2^i \frac{\bar{\pi}_3 + \bar{\pi}_4}{2} \left(1 + R_3\right)\left(1 + R_4\right) + \tilde{W}_3^i \left(1 + R_4\right),
\end{aligned}$$

where $\tilde{W}_\tau^i$ denotes investor i's wealth as of date τ. Hence, the intertemporal budget constraint is given by:

$$\tilde{W}_4^i = \lambda_2^i + \left(\omega_2^i \frac{\bar{\pi}_3 + \bar{\pi}_4}{2} + \left(\lambda_1^i - \lambda_2^i\right) b_2 + \left(\omega_1^i - \omega_2^i\right) \pi_2 + \tilde{W}_0^i - b_1\lambda_1^i - \pi_1\omega_1^i\right) \left(1 + R_3\right)\left(1 + R_4\right). \tag{A1}$$

Let W_t^i represent investor i's wealth in terms of date 1's present value. Then W_0^i and W_4^i can be written as:

$$W_4^i = \frac{\tilde{W}_4^i}{\left(1 + R_3\right)\left(1 + R_4\right)} \quad \text{and} \quad W_0^i = \tilde{W}_0^i. \tag{A2}$$

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

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

of date 1's or 2's present value:

$$W_4^i = \lambda_2^i (V_b - b_2) + \lambda_1^i (b_2 - b_1) + \omega_2^i (V_\pi - \pi_2) + \omega_1^i (\pi_2 - \pi_1) + W_0^i, \tag{A3}$$

where I define $V_b = \frac{1}{(1+R_3)(1+R_4)}$ and $V_\pi = \frac{\bar{\pi}_3+\bar{\pi}_4}{2}$ as the present values of the Treasury security and the inflation swap, respectively.

Date 1 At date 1, investor i solves the following problem:

$$\begin{aligned} & \max_{\lambda_1^i,\lambda_2^i,\omega_1^i,\omega_2^i} E_1^i \left[W_4^i\right] - \frac{\gamma}{2} Var_1^i \left[W_4^i\right] \\ \text{s.t. } W_4^i &= \lambda_2^i (V_b - b_2) + \lambda_1^i (b_2 - b_1) + \omega_2^i (V_\pi - \pi_2) + \omega_1^i (\pi_2 - \pi_1) + W_0^i. \end{aligned}$$

Substituting the expression for W_4^i into the objective function, the problem can be rewritten as:

$$\begin{aligned} \max_{\lambda_1^i,\lambda_2^i,\omega_1^i,\omega_2^i} & \lambda_2^i \left(E_1^i [V_b] - E_1^i [b_2]\right) + \lambda_1^i \left(E_1^i [b_2] - b_1\right) + \omega_2^i \left(E_1^i [V_\pi] - E_1^i [\pi_2]\right) + \omega_1^i \left(E_1^i [\pi_2] - \pi_1\right) + W_0^i \\ & - \frac{\gamma}{2} \left(\left(\lambda_2^i\right)^2 Var_1^i [V_b] + \left(\lambda_1^i\right)^2 Var_1^i [b_2] + \left(\omega_2^i\right)^2 Var_1^i [V_\pi] + \left(\omega_1^i\right)^2 Var_1^i [\pi_2] \right). \end{aligned}$$

The first-order conditions with respect to λ_1^i and λ_2^i are then given by:

$$E_1^i [b_2] - b_1 - \gamma \lambda_1^i Var_1^i [b_2] = 0 \quad \text{and} \quad E_1^i [V_b] - E_1^i [b_2] - \gamma \lambda_2^i Var_1^i [V_b] = 0,$$

which yield the optimal demands for the Treasury security at dates 1 and 2:

$$\lambda_1^i = \frac{E_1^i [b_2] - b_1}{\gamma Var_1^i [b_2]} \quad \text{and} \quad \lambda_2^i = \frac{E_1^i [V_b] - E_1^i [b_2]}{\gamma Var_1^i [V_b]}. \tag{A4}$$

Similarly, the optimal demands for the inflation swap can be derived as:

$$\omega_1^i = \frac{E_1^i [\pi_2] - \pi_1}{\gamma Var_1^i [\pi_2]} \quad \text{and} \quad \omega_2^i = \frac{E_1^i [V_\pi] - E_1^i [\pi_2]}{\gamma Var_1^i [V_\pi]}. \tag{A5}$$

Date 2 At date 2, investor i solves the following problem:

$$\begin{aligned} \max_{\tilde{\lambda}_2^i,\tilde{\omega}_2^i} & \tilde{\lambda}_2^i \left(E_2^i [V_b] - b_2\right) + \lambda_1^i (b_2 - b_1) + \tilde{\omega}_2^i \left(E_1^i [V_\pi] - E_1^i [\pi_2]\right) + \omega_1^i \left(E_1^i [\pi_2] - \pi_1\right) + W_0^i \\ & - \frac{\gamma}{2} \left(\left(\tilde{\lambda}_2^i\right)^2 Var_2^i [V_b] + \left(\tilde{\omega}_2^i\right)^2 Var_1^i [V_\pi] \right), \end{aligned}$$

which yields the updated optimal demands for the Treasury security and the inflation swap:

$$\tilde{\lambda}_2^i = \frac{E_2^i [V_b] - b_2}{\gamma Var_2^i [V_b]} \quad \text{and} \quad \tilde{\omega}_2^i = \frac{E_2^i [V_\pi] - \pi_2}{\gamma Var_2^i [V_\pi]}. \tag{A6}$$

A.2.2 Signal Extraction Problem

In order to determine their optimal demands, investors need to evaluate the asset values V_b and V_π at date 1 and 2. The value of the Treasury security (V_b) can be written as:

$$V_b = \frac{1}{(1+R_3)(1+R_4)} = \frac{1}{1+\Delta R} \approx 1 - \Delta R = 1 - \phi \Delta \bar{\pi},$$

where I impose $R_{-1} = 0$, use a first order approximation around $\Delta R = 0$, substitute in the Taylor rule $\Delta R = \phi^\pi \Delta \bar{\pi} + \phi^z \Delta \bar{z}$, and define $\phi = (\phi^\pi + \phi^z \varrho)$ for brevity. The value of the inflation swap is given by:

$$V_\pi = \frac{\bar{\pi}_3 + \bar{\pi}_4}{2} = \bar{\pi}_3 = \Delta \bar{\pi} + \bar{\pi}_{-1} = \Delta \bar{\pi},$$

where I use $\bar{\pi}_4 = \bar{\pi}_3$ and $\bar{\pi}_2 = 0$. As a result, the following relationship between V_b and V_π holds:

$$V_b = 1 - \phi V_\pi.$$

Date 1 At date 1, all investors have the same expectations for V_b and V_π,

$$E_1^i [V_\pi] = 0 \quad \text{and} \quad E_1^i [V_b] = 1, \quad \forall i,$$

and the same conditional variances,

$$Var_1^i [V_\pi] = \sigma_\pi^2 \quad \text{and} \quad Var_1^i [V_b] = \phi^2 \sigma_\pi^2, \quad \forall i.$$

Date 2 At date 2, μ^k investors (attentive investors) observe signal s^k, where $k \in \{\text{CPI}, \text{NFP}\}$, while $1 - \mu^k$ investor (inattentive investors) do not. Let $E_\tau^{\mu^k} [\cdot]$ be the expectation of attentive investors at date τ, and let $E_\tau^{1-\mu^k} [\cdot]$ be the expectation of inattentive investors at date τ. Similarly, I define $Var_\tau^{\mu^k} [\cdot]$ and $Var_\tau^{1-\mu^k} [\cdot]$ for the conditional variances. *Inattentive investors* still have the same expectations and conditional variances as at date 1, regardless of the signal k:

$$E_2^i [V_\pi] = E_2^{1-\mu^k} [V_\pi] = 0 \quad \text{and} \quad E_2^i [V_b] = E_2^{1-\mu^k} [V_b] = 1, \tag{A7}$$

and

$$Var_2^i [V_\pi] = Var_2^{1-\mu^k} [V_\pi] = \sigma_\pi^2 \quad \text{and} \quad Var_2^i [V_b] = Var_2^{1-\mu^k} [V_b] = \phi^2 \sigma_\pi^2, \tag{A8}$$

for $i \in (\mu^k, 1]$ and $k \in \{\text{CPI}, \text{NFP}\}$.

Upon observing the CPI release ($s^{\text{CPI}} = \Delta \bar{\pi} + \eta$, with $\eta \sim N\left(0, \sigma_\eta^2\right)$), *attentive investors* update their expectations using the diagnostic density:

$$f\left(\Delta \bar{\pi} | s^{\text{CPI}}\right) = f^{RE}\left(\Delta \bar{\pi} | s^{\text{CPI}}\right) H\left(\Delta \bar{\pi}\right)^\kappa \frac{1}{\Upsilon},$$

where $f^{RE}\left(\Delta \bar{\pi} | s^{\text{CPI}}\right)$ represents the density under rational expectations, Υ is a normalization factor ensuring $f\left(\Delta \bar{\pi} | s^{\text{CPI}}\right)$ integrates to one, $H\left(\Delta \bar{\pi}\right)$ is the representativeness heuristic, and parameter $\kappa \geq 0$ measures the deviation from rational expectations due to representativeness (i.e., the degree of overreaction). For $\kappa = 0$, the model simplifies to the rational expectations framework.

The representativeness heuristic $H(\Delta\bar{\pi})$ is defined as:

$$H(\Delta\bar{\pi}) = \frac{f^{RE}\left(\Delta\bar{\pi}|s^{\text{CPI}}\right)}{f^{RE}\left(\Delta\bar{\pi}|E_1^i\left[\Delta\bar{\pi}\right]\right)}.$$

A realization of $\bar{\pi}$ is deemed more representative if the observed signal s^{CPI} increases its likelihood (as reflected in the numerator) relative to the case where the signal equals the prior expectation (as reflected in the denominator). This formalization, introduced by Gennaioli and Shleifer (2010) and Bordalo et al. (2016), builds on Kahneman and Tversky's (1972) idea of a representativeness heuristic.

As shown in Supplementary Appendix S1.1, each attentive investor, $i \in [0, \mu^k]$, updates its expectation of $\Delta\bar{\pi}$ after observing the CPI signal as:

$$E_2^i\left[\Delta\bar{\pi}|s^{\text{CPI}}\right] = (1+\kappa)\frac{\sigma_\pi^2}{\sigma_\pi^2+\sigma_\eta^2}s^{\text{CPI}}.$$

Defining the signal-to-noise ratio for the CPI release as $\xi^{\text{CPI}} = \frac{\sigma_\pi^2}{\sigma_\pi^2+\sigma_\eta^2}$, the attentive investors' expectations of V_π and V_b are given by:

$$E_2^i\left[V_\pi\right] = E_2^{\mu^{\text{CPI}}}\left[V_\pi\right] = (1+\kappa)\,\xi^{\text{CPI}}s^{\text{CPI}},$$

and

$$E_2^i\left[V_b\right] = E_2^{\mu^{\text{CPI}}}\left[V_b\right] = 1-\phi\,(1+\kappa)\,\xi^{\text{CPI}}s^{\text{CPI}},$$

for $i \in [0, \mu^k]$. The corresponding conditional variances are

$$Var_2^i\left[V_\pi\right] = Var_2^{\mu^{\text{CPI}}}\left[V_\pi\right] = \left(1-\left(1-\kappa^2\right)\xi^{\text{CPI}}\right)\sigma_\pi^2, \tag{A9}$$

and

$$Var_2^i\left[V_b\right] = Var_2^{\mu^{\text{CPI}}}\left[V_b\right] = \phi^2 Var_2^{\mu^{\text{CPI}}}\left[V_\pi\right] = \phi^2\left(1-\left(1-\kappa^2\right)\xi^{\text{CPI}}\right)\sigma_\pi^2. \tag{A10}$$

Similarly, upon observing the NFP release ($s^{\text{NFP}} = \Delta\bar{z}+\nu$, with $\nu \sim N\left(0, \varrho^2\sigma_\nu^2\right)$), attentive investors update their expectations of $\Delta\bar{z}$ as follows (as derived in Supplementary Appendix S1.2):

$$E_2^i\left[\Delta\bar{z}|s^{\text{NFP}}\right] = (1+\kappa)\frac{\sigma_\pi^2}{\sigma_\pi^2+\sigma_\nu^2}s^{\text{NFP}}.$$

Defining the signal-to-noise ratio for the NFP release as $\xi^{\text{NFP}} = \frac{\sigma_\pi^2}{\sigma_\pi^2+\sigma_\nu^2}$ and using $\Delta\bar{\pi} = \frac{1}{\varrho}\Delta\bar{z}$, one obtains the attentive investors' expectations of V_π and V_b:

$$E_2^i\left[V_\pi\right] = E_2^{\mu^{\text{NFP}}}\left[V_\pi\right] = \frac{1}{\varrho}(1+\kappa)\,\xi^{\text{NFP}}s^{\text{NFP}},$$

and

$$E_2^i\left[V_\pi\right]=E_2^{\mu^{\mathrm{NFP}}}\left[V_\pi\right]=1-\frac{\phi}{\varrho}\left(1+\kappa\right)\xi^{\mathrm{NFP}}s^{\mathrm{NFP}},$$

for $i\in[0,\mu^k]$. The corresponding conditional variances are:

$$Var_2^i\left[V_\pi\right]=Var_2^{\mu^{\mathrm{NFP}}}\left[V_\pi\right]=\left(1-\left(1-\kappa^2\right)\xi^{\mathrm{NFP}}\right)\sigma_\pi^2, \tag{A11}$$

and

$$Var_2^i\left[V_b\right]=Var_2^{\mu^{\mathrm{NFP}}}\left[V_b\right]=\phi^2 Var_2^{\mu^{\mathrm{NFP}}}\left[V_\pi\right]=\phi^2\left(1-\left(1-\kappa^2\right)\xi^{\mathrm{NFP}}\right)\sigma_\pi^2. \tag{A12}$$

A.2.3 Equilibrium Prices

With the investors' demands and asset valuations established, I now derive the asset prices. Following DellaVigna and Pollet (2009), the weighted average expectation $E_\tau\left[\cdot\right]$ is defined as:

$$E_\tau\left[\cdot\right]=h_{\tau,\cdot}^k E_\tau^{\mu^k}\left[\cdot\right]+\left(1-h_{\tau,\cdot}^k\right)E_\tau^{1-\mu^k}\left[\cdot\right],$$

where $h_{2,\cdot}^k=\frac{\mu^k g_{2,\cdot}^k}{\gamma Var_2^{\mu^k}\left[\cdot\right]}$ and $g_{2,\cdot}^k=\left(\frac{\mu^k}{\gamma Var_2^{\mu^k}\left[\cdot\right]}+\frac{1-\mu^k}{\gamma Var_2^{1-\mu^k}\left[\cdot\right]}\right)^{-1}$. The weight $h_{\tau,\cdot}^k$ broadly reflects the population share of attentive investors, adjusted for their relative contribution to the conditional variance and their level of risk aversion.

Date 1 At date 1, the market clearing condition for ω_1^i yields:

$$\begin{aligned}\int_0^1\lambda_1^i di &= 0\\ \int_0^1\frac{E_1^i\left[\pi_2\right]-\pi_1}{\gamma Var_1^i\left[\pi_2\right]}di &= 0\\ h_{1,\pi_2}^k E_1^{\mu^k}\left[\pi_2\right]+\left(1-h_{1,\pi_2}^k\right)E_2^{1-\mu^k}\left[\pi_2\right] &= \pi_1\\ E_1\left[\pi_2\right] &= \pi_1.\end{aligned} \tag{A13}$$

Similarly, the market clearing conditions for λ_1^i, ω_2^i and λ_2^i yield:

$$b_1=E_1\left[b_2\right],\quad E_1\left[\pi_2\right]=E_1\left[V_\pi\right],\quad\text{and}\quad E_1\left[b_2\right]=E_1\left[V_b\right]. \tag{A14}$$

Note that $E_1\left[\cdot\right]=E_1^i\left[\cdot\right]$ holds since investors' beliefs are identical, i.e., $E_1^i\left[\cdot\right]=E_1^{\mu^k}\left[\cdot\right]=E_1^{1-\mu^k}\left[\cdot\right]$ and $Var_1^i\left[\cdot\right]=Var_1^{\mu^k}\left[\cdot\right]=Var_1^{1-\mu^k}\left[\cdot\right]$ for all $i\in[0,1]$. Combining (A13) and (A14) gives the asset prices at date 1:

$$\pi_1=E_1\left[V_\pi\right]=0\quad\text{and}\quad b_1=E_1\left[V_b\right]=1. \tag{A15}$$

Date 2 At date 2, the market clearing condition for $\tilde{\omega}_2^i$ determines the price of the inflation swap:

$$\begin{aligned}
\int_0^1 \tilde{\omega}_2^i di &= 0 \\
\int_0^1 \frac{E_2^i\left[V_\pi\right]-\pi_2}{\gamma Var_2^i\left[V_\pi\right]} di &= 0 \\
h_{2,V_\pi}^k E_2^{\mu^k}\left[V_\pi\right]+\left(1-h_{2,V_\pi}^k\right) E_2^{1-\mu^k}\left[V_\pi\right] &= \pi_2 \\
\pi_2 &= E_2\left[V_\pi\right].
\end{aligned}$$

Similarly, the market clearing conditions for $\tilde{\lambda}_2^i$ yields the price of the Treasury security:

$$b_2=E_2\left[V_b\right].$$

The weight $h_{\tau,V_\pi}^{\mathrm{CPI}}$ can be expressed as:

$$h_{\tau,V_\pi}^{\mathrm{CPI}}=\frac{\mu^{\mathrm{CPI}} g_{2,V_\pi}^{\mathrm{CPI}}}{\gamma Var_2^{\mu^{\mathrm{CPI}}}\left[V_\pi\right]}=\frac{\mu^{\mathrm{CPI}}}{1-\left(1-\mu^{\mathrm{CPI}}\right)\left(1-\kappa^2\right)\xi^{\mathrm{CPI}}}.$$

Defining $\Theta(\mu^k,\xi^k)=\frac{\mu^k(1+\kappa)\xi^k}{1-\left(1-\mu^k\right)(1-\kappa^2)\xi^k}$, the asset prices at date 2 in terms of the CPI signal are:

$$\pi_2=\Theta(\mu^{\mathrm{CPI}},\xi^{\mathrm{CPI}})s^{\mathrm{CPI}} \quad \text{and} \quad b_2=1-\phi\Theta(\mu^{\mathrm{CPI}},\xi^{\mathrm{CPI}})s^{\mathrm{CPI}}. \tag{A19}$$

Similarly, the asset prices at date 2 in terms of the NFP signal are:

$$\pi_2=\frac{1}{\varrho}\Theta(\mu^{\mathrm{NFP}},\xi^{\mathrm{NFP}})s^{\mathrm{NFP}} \quad \text{and} \quad b_2=1-\frac{\phi}{\varrho}\Theta(\mu^{\mathrm{NFP}},\xi^{\mathrm{NFP}})s^{\mathrm{NFP}}. \tag{A20}$$

Details on the derivations are provided in Supplementary Appendix S1.3.

A.3 Market Reaction

With the model solution at hand, I now characterize the market reactions to macroeconomic news in the model. As interest rate responses are more commonly referenced in the literature, I focus on the market's response in terms of the Treasury security's yield rather than its price. Let y_τ be the yield of the Treasury security at date 1 and 2, which can be expressed in terms of the prices as follows:

$$b_\tau=\frac{1}{\left(1+y_\tau\right)^2}\approx 1-2y_\tau \Longleftrightarrow y_\tau\approx\frac{1}{2}-\frac{1}{2}b_\tau,$$

where I use a first order approximation around $y_\tau=0$. Note that the maturity of the Treasury security is two periods, as dates 1 and 2 are effectively simultaneous and the bond matures at date 4. That being said, the bond maturity does not affect the main takeaways from the model.

Defining y as the change in the Treasury security's yield between date 1 and 2 ($y=y_2-y_1$), I can write:

$$y=\frac{1}{2}\phi\Theta(\mu^{\mathrm{CPI}},\xi^{\mathrm{CPI}})s^{\mathrm{CPI}} \quad \text{or} \quad y=\frac{1}{2}\frac{\phi}{\varrho}\Theta(\mu^{\mathrm{NFP}},\xi^{\mathrm{NFP}})s^{\mathrm{NFP}}.$$

Similarly, the change in the inflation swap rate between date 1 and 2 ($\pi=\pi_2-\pi_1$) is given by:

$$\pi=\Theta(\mu^{\mathrm{CPI}},\xi^{\mathrm{CPI}})s^{\mathrm{CPI}} \text{ or } \pi=\frac{1}{\varrho}\Theta(\mu^{\mathrm{NFP}},\xi^{\mathrm{NFP}})s^{\mathrm{NFP}}$$

As a result, the interest rate and inflation swap rate sensitivities to CPI and NFP signals are given by:

$$\begin{aligned}\beta^{y|\mathrm{CPI}} &= \phi\Theta\left(\mu^{\mathrm{CPI}},\xi^{\mathrm{CPI}}\right), \quad \beta^{\pi|\mathrm{CPI}}=\Theta\left(\mu^{\mathrm{CPI}},\xi^{\mathrm{CPI}}\right),\\ \beta^{y|\mathrm{NFP}} &= \frac{\phi}{\varrho}\Theta\left(\mu^{\mathrm{NFP}},\xi^{\mathrm{NFP}}\right), \quad \beta^{\pi|\mathrm{NFP}}=\frac{1}{\varrho}\Theta\left(\mu^{\mathrm{NFP}},\xi^{\mathrm{NFP}}\right).\end{aligned} \tag{A16}$$

Before I discuss different scenarios in which I shift certain model parameters, it is useful to go through the parameter restrictions and their implications in the baseline. As mentioned above, I impose that Taylor rule coefficients as well as the overall response to inflation are strictly positive, i.e., ϕ^π, ϕ^z, $\phi>0$, which are standard assumptions. This implies the following restriction on the co-movement between inflation and output growth: $\varrho>-\frac{\phi^\pi}{\phi^z}$. In the baseline, this restriction will be not binding as I assume that the economy is demand-driven, i.e., $\varrho>0$, consistent with prior work documenting that financial markets perceived the U.S. economy to be mostly driven by demand shocks in the 2000s and 2010s (see Cieslak and Pflueger, 2023, for a discussion).

The share of attentive investors μ^k and the signal-to-noise ratio ξ^k are restricted as follows: $0<\mu^k\leq 1$ and $0<\xi^k\leq 1$, for $k\in\{\mathrm{CPI},\mathrm{NFP}\}$. Further, I assume that investors might overreact due to diagnostic expectations, $\kappa\geq 0$. The restrictions on μ^k, ξ^k, and κ imply $\Theta\left(\mu^{\mathrm{k}},\xi^{\mathrm{k}}\right)>0$, which can be seen as follows:

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

which always holds since $1-\frac{1}{(1-\mu^k)\xi^k}<0$ for $0<\mu^k\leq 1$ and $0<\xi^k\leq 1$. As ϕ, $\varrho>0$, the sensitivities in (A16) are strictly positive in the baseline:

$$\beta^{y|\mathrm{CPI}}>0, \quad \beta^{\pi|\mathrm{CPI}}>0, \quad \beta^{y|\mathrm{NFP}}>0, \quad \text{and} \quad \beta^{\pi|\mathrm{NFP}}>0.$$

In the following, I go through four scenarios, each of which involves a change in one parameter relative to the baseline, while keeping the others constant. Let subscript L denote a parameter or sensitivity under the baseline (corresponding to the low-inflation period) and subscript H under the scenario of interest (corresponding to the high-inflation period).

Scenario 1: Increased Attention to CPI Release An increase in investors' attention to the CPI release ($\mu_H^{\text{CPI}} > \mu_L^{\text{CPI}}$) implies ceteris paribus the following changes in sensitivities:

$$\beta_H^{y|\text{CPI}} > \beta_L^{y|\text{CPI}}, \quad \beta_H^{\pi|\text{CPI}} > \beta_L^{\pi|\text{CPI}}, \quad \beta_H^{y|\text{NFP}} = \beta_L^{y|\text{NFP}}, \quad \text{and} \quad \beta_H^{\pi|\text{NFP}} = \beta_L^{\pi|\text{NFP}}. \tag{A17}$$

This result arises from the relationship:

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

which implies

$$\frac{\partial\beta^{y|\text{CPI}}}{\partial\mu^{\text{CPI}}} > 0, \quad \frac{\partial\beta^{\pi|\text{CPI}}}{\partial\mu^{\text{CPI}}} > 0, \quad \frac{\partial\beta^{y|\text{NFP}}}{\partial\mu^{\text{CPI}}} = 0, \quad \text{and} \quad \frac{\partial\beta^{\pi|\text{NFP}}}{\partial\mu^{\text{CPI}}} = 0.$$

Scenario 2: Increased Monetary Policy Inflation Response An increase in the overall responsiveness of monetary policy to inflation ($\phi_H > \phi_L$) leads ceteris paribus to the following changes in sensitivities:

$$\beta_H^{y|\text{CPI}} > \beta_L^{y|\text{CPI}}, \quad \beta_H^{\pi|\text{CPI}} = \beta_L^{\pi|\text{CPI}}, \quad \beta_H^{y|\text{NFP}} > \beta_L^{y|\text{NFP}}, \quad \text{and} \quad \beta_H^{\pi|\text{NFP}} = \beta_L^{\pi|\text{NFP}}. \tag{A18}$$

This result follows from:

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

Observe that an increase in ϕ can arise from a stronger response to inflation ($\phi_H^\pi > \phi_L^\pi$) or to output growth ($\phi_H^z > \phi_L^z$):

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

While the assumption $\varrho > 0$ is the reason that the implications for $\phi_H^\pi > \phi_L^\pi$ and $\phi_H^z > \phi_L^z$ are the same, it is important to highlight that even for $\varrho < 0$, Scenario 2 produces distinct predictions to Scenario 1. Ultimately, this distinction is what matters for the empirical analysis.

Scenario 3: From Demand to Supply Shocks A shift from demand-driven fundamentals to supply-driven ones ($\varrho_H < 0 < \varrho_L$) leads ceteris paribus to the following changes in sensitivities:

$$\beta_H^{y|\text{CPI}} < \beta_L^{y|\text{CPI}}, \quad \beta_H^{\pi|\text{CPI}} = \beta_L^{\pi|\text{CPI}}, \quad \beta_H^{y|\text{NFP}} < 0 < \beta_L^{y|\text{NFP}}, \quad \text{and} \quad \beta_H^{\pi|\text{NFP}} < 0 < \beta_L^{\pi|\text{NFP}}. \tag{A19}$$

First, observe that $0 > \varrho_H > -\frac{\phi^\pi}{\phi^z}$ implies

$$\beta_H^{y|\text{NFP}} < 0 < \beta_L^{y|\text{NFP}} \quad \text{and} \quad \beta_H^{\pi|\text{NFP}} < 0 < \beta_L^{\pi|\text{NFP}}.$$

Second, from ϕ's partial derivative, $\frac{\partial \phi}{\partial \varrho} = \frac{\partial(\phi^{\pi}+\varrho\phi^{z})}{\partial \varrho} = \phi^{z} > 0$, follows that $\frac{\partial \beta^{y|\text{CPI}}}{\partial \varrho} > 0$. Since $\frac{\partial \beta^{\pi|\text{CPI}}}{\partial \varrho} = 0$, one ends up with:

$$0 < \beta_H^{y|\text{CPI}} < \beta_L^{y|\text{CPI}} \quad \text{and} \quad \beta_H^{\pi|\text{CPI}} = \beta_L^{\pi|\text{CPI}} > 0.$$

Scenario 4: Increased Informativeness of CPI release An increase in the CPI's signal-to-noise ratio ($\xi_H^{\text{CPI}} > \xi_L^{\text{CPI}}$) implies ceteris paribus the following changes in sensitivities:

$$\beta_H^{y|\text{CPI}} > \beta_L^{y|\text{CPI}}, \quad \beta_H^{\pi|\text{CPI}} > \beta_L^{\pi|\text{CPI}}, \quad \beta_H^{y|\text{NFP}} = \beta_L^{y|\text{NFP}}, \quad \text{and} \quad \beta_H^{\pi|\text{NFP}} = \beta_L^{\pi|\text{NFP}}. \tag{A20}$$

This result follows from:

$$\frac{\partial \Theta(\mu^{\text{CPI}}, \xi^{\text{CPI}})}{\partial \xi^{\text{CPI}}} = \frac{\partial \left(\frac{\mu^{\text{CPI}}(1+\kappa)\xi^{\text{CPI}}}{1-(1-\mu^{\text{CPI}})(1-\kappa^2)\xi^{\text{CPI}}} \right)}{\partial \xi^{\text{CPI}}} = \frac{\mu^{\text{CPI}}\,(1+\kappa)}{\left(1-\left(1-\mu^{\text{CPI}}\right)\left(1-\kappa^2\right)\xi^{\text{CPI}}\right)^2} > 0,$$

and consequently:

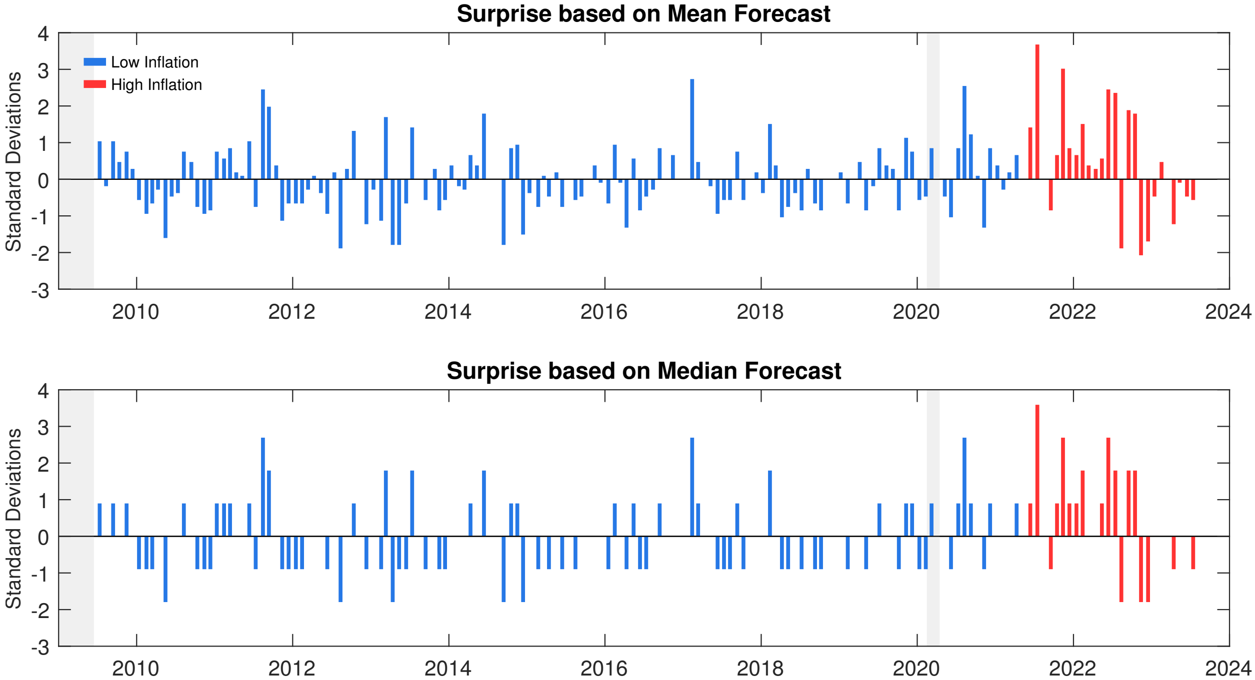
$$\frac{\partial \beta^{y|\text{CPI}}}{\partial \xi^{\text{CPI}}} > 0, \quad \frac{\partial \beta^{\pi|\text{CPI}}}{\partial \xi^{\text{CPI}}} > 0, \quad \frac{\partial \beta^{y|\text{NFP}}}{\partial \xi^{\text{CPI}}} = 0, \quad \text{and} \quad \frac{\partial \beta^{\pi|\text{NFP}}}{\partial \xi^{\text{CPI}}} = 0.$$

Note that an increase in the CPI's signal-to-noise ratio without a corresponding increase in NFP's signal-to-noise ratio implies a reduction in the CPI's signal noise, $\sigma_{H,\eta} < \sigma_{L,\eta}$.

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. Blue and red observations indicate surprises which occurred during the low-inflation period and the high-inflation period, respectively. Shaded areas show NBER recession periods.

Table B1: Overview of All Macroeconomic News Announcements

Announcement	Release Time	Frequency	Observations Total	Observations Low	Observations High	Unit	Surprise (+1 SD)	Mean-Median Correlation
Average Hourly Earnings	8:30	Monthly	160	135	25	% MoM	0.15	0.99
Capacity Utilization	9:15	Monthly	165	140	25	%	0.38	0.99
CB Consumer Confidence	10:00	Monthly	168	142	26	Index	4.99	1.00
Durable Goods Orders	8:30	Monthly	166	140	26	% MoM	1.78	1.00
Consumer Price Index (CPI)								
Headline—Baseline	8:30	Monthly	166	140	26	% MoM	0.11	0.96
Core	8:30	Monthly	164	139	25	% MoM	0.09	0.97
Headline YoY	8:30	Monthly	166	140	26	% YoY	0.12	0.97
Gross Domestic Product (GDP)	8:30	Monthly	164	140	24	% QoQ ann.	0.42	0.98
Initial Jobless Claims	8:30	Weekly	708	595	113	Level	17.51k	0.97
ISM Manufacturing PMI (ISM Mfg PMI)	10:00	Monthly	169	143	26	Index	1.75	1.00
New Home Sales	10:00	Monthly	167	141	26	Level	52.30k	1.00
Nonfarm Payrolls (NFP)	8:30	Monthly	156	133	23	Change	90.15k	1.00
Personal Consumption Expenditures Price Index (PCE Price Index)	8:30	Monthly	162	137	25	% YoY	0.07	0.86
Philadelphia Fed Index	10:00	Monthly	167	141	26	Index	9.88	1.00
Producer Price Index (PPI)	8:30	Monthly	168	142	26	% MoM	0.32	0.99
Retail Sales	8:30	Monthly	161	135	26	% MoM	0.47	0.98
UM Consumer Sentiment P	10:00	Monthly	168	142	26	Index	3.57	1.00
Unemployment Rate	8:30	Monthly	159	134	25	%	0.16	0.98

Notes: This table provides an overview of all macroeconomic announcement series used throughout the paper. The sample ranges from July 2009 to July 2023. *Announcement* refers to the name of the data release, with its abbreviation (if applicable) provided in brackets. *Release Time* denotes the typical time of the release, stated in AM EST. *Frequency* refers to the frequency of the data release. *Observations* indicates the number of observations (surprises) in the sample. *Unit* specifies the unit in which the data release and survey are originally reported. *Surprise (+1 SD)* provides the mapping of a one-standard-deviation positive surprise to the original reporting unit of the release. *Mean-Median Correlation* is the correlation between surprises constructed using Bloomberg's mean and median forecasts. Abbreviations: P—preliminary; CB—Chicago Board; UM—University of Michigan; ISM—Institute for Supply Management; PMI—Purchasing Managers' Index; YoY—year-over-year. MoM—month-over-month; QoQ—quarter-over-quarter; ann.—annualized.

B.2 Financial Data

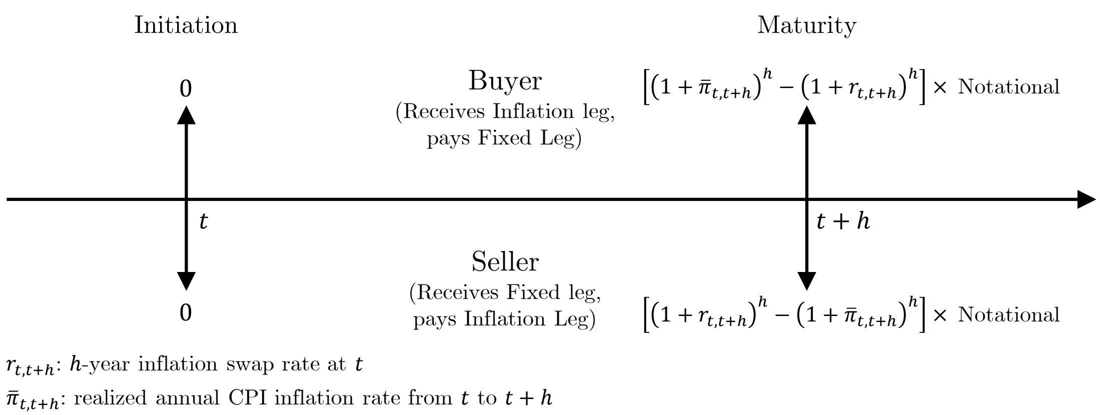
Tables and Figures

Table B2: Overview of Intraday Financial Data from LSEG Tick History

Name	Description	Ticker	Sample
Interest Rates			
ED1	1st Quarterly Eurodollar/SOFR Futures	EDcm1/SRAcm2	2009–2023
ED4	4th Quarterly Eurodollar/SOFR Futures	EDcm4/SRAcm5	2009–2023
2-Year	2-Year Treasury Futures	TUc1/TUc2	2009–2023
5-Year	5-Year Treasury Futures	FVc1/FVc2	2009–2023
10-Year	10-Year Treasury Futures	TYc1/TYc2	2009–2023
30-Year	30-Year Treasury Futures	USc1/USc2	2009–2023
Inflation Swap Rates			
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
Other			
S&P 500	front-month E-mini S&P 500 Futures	ESc1	2009–2023
VIX	front-month VIX Futures	VXc1:VE/VXc1	2011–2023
Commodities	S&P GS Commodity Index	.SPGSCI	2009–2023
Corporate Bonds	iShares iBoxx $ Investment Grade Corporate Bond ETF (LQD)	LQD	2009–2023
Euro	Euro/U.S. Dollar Spot Rate	EUR=	2009–2023
Bitcoin	Bitcoin/U.S. Dollar Spot Rate	BTC=BTSP	2014–2023

Notes: This table lists the asset prices from *LSEG Tick History* used throughout the main text. For all series, the sample period ends in July 2023. *Ticker* refers to the Reuters Instrument Code (RIC). Abbreviations: SOFR—Secured Overnight Financing Rate.

Figure B2: Net Cash Flows of h-Year Inflation Swap



Notes: This figure illustrates the timing of net cash flows of an h-year zero-coupon inflation swap. Inflation swaps have an indexation lag of two to three months, i.e., realized inflation is calculated based on a period that begins and ends two to three months prior to the start and end date of the contract, respectively. See, e.g., Kerkhof (2005) for a more detailed discussion of inflation swaps.

Role of Institutional Investors In the main text, I argue that institutional investors are essentially the sole participants in the interest rate futures and inflation swap markets. In the following, I provide a brief overview of the empirical evidence supporting this claim. The Commodity Futures Trading Commission (CFTC) reports open interest data for futures markets, and certain institutional investors are required to disclose their positions. Consequently, for futures contracts with relatively large contract sizes, such as those used in this paper, the share of non-reportable open interest serves as an upper bound for the proportion of retail investors in the market. In 2023, these shares ranged from 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, retail investors may represent only a small fraction of the overall non-reportable share. While similar data is not available for inflation swap markets, retail investors are likely almost nonexistent, 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 Attention Measures

Bloomberg Terminal The Bloomberg Terminal offers daily historical counts of relevant articles based on specified keywords. Although data from earlier dates is available, it becomes meaningful starting in 1992. According to the Bloomberg Help Desk, the informativeness of these series improves over time, as the Bloomberg Terminal had fewer sources in the past, and historical content removed by sources may no longer be reflected. For the CPI announcement, I download article counts for the specified keywords “Consumer Price Index” or “CPI”. For the NFP announcement, the keywords are “Nonfarm Payrolls”, “Employment Report”, or “Unemployment Rate”. For the FOMC announcement, I use the keywords “Rederal Reserve”, “FOMC”, or “Fed”. Lastly, I download the daily total article count from the Bloomberg terminal. As explained in the main text, I construct my daily attention measure for all three announcements by dividing the count of relevant articles by the daily average of the total article count over the last year.

Dow Jones News Wires I obtain the data on Dow Jones News Wires articles from *RavenPack Analytics*. The dataset includes, among other details, the headline and timestamp of each article and is available starting in 2000. Similar to the Bloomberg Terminal data, the data quality appears relatively noisy in the earlier years. To identify relevant articles, I select those with specific words in their headline. Since these must be exact matches, I use expanded lists based on some manual inspections of headlines. For the CPI announcement, I consider articles with one of following words in their headline: “consumer price index”, “CPI”, “inflation report”, “inflation”, “consumer prices”, “inflationary”, “US Prices”, or “U.S. Prices”. For the NFP announcement, the words are “nonfarm payrolls”, unemployment rate”, “non-farm payrolls”, “employment report” , “employment situation”, “jobs”, “layoffs”, “job”, “employment”, “payrolls’, “labor”, or “payroll”. For the FOMC announcement, the words are “fomc”, “fed”, “federal reserve”, “U.S. rate”, “U.S. rates”, “US rate”, “US rates”, “funds rate”, or “fed”.

Google Searches Google provides data on search interest over time through its platform *Google Trends*. During the sample period, from January 2009 to July 2023, 84 percent of all search queries in the United States were conducted via Google.[3] For my analysis, I focus on searches within the U.S. for release-specific topics. A "topic" is defined by Google as a group of search terms that share the same concept in any language (Google, 2023). Unlike previous research, I construct a daily search score series for each topic. As Google trends provides historical daily data only for short time intervals, several steps are required to create an internally consistent daily series for the entire sample period. Details of this construction, along with additional results, are provided in Supplementary Appendix S4.

Mainstream Media I obtain the data on mainstream media articles from *RavenPack Analytics*. The construction of the announcement attention measures follows the same steps described for the Dow Jones News Wires measures above, except that I now use a set of mainstream media sources instead of the Dow Jones News Wires. Specifically, I include the following newspapers based on their circulation: The Wall Street Journal, The New York Times, The New York Post, The Washington Post, USA Today, and The Los Angeles Times.[4] Additionally, I include articles from CNN, Fox News, and MSN which, along with The New York Times, were among the most visited news websites in the United States as of July 2023.[5]

B.4 Uncertainty Measures

I use five uncertainty measures in Section 5.3 which I describe in detail below. Online Appendix Figure C12 presents the time series of the employed values in my analysis. Note that I use lagged values for my uncertainty measures—either from the day or the month prior to the CPI release, except for the disagreement measure, which is based on the current release.

Inflation Volatility This measure is the realized volatility of the real-time YoY CPI inflation rate over the previous year.

Inflation Uncertainty—Consumer Survey It captures the expected inflation uncertainty over the next year based on the University of Michigan Surveys of Consumers (MSC) and the New York Fed's Survey of Consumer Expectations (SCE). The measure is constructed as the common factor of Binder's (2017) 1-year-ahead inflation uncertainty based on the MSC and the 1-year-ahead inflation uncertainty based on the SCE (Armantier et al., 2017). Since both series do not cover the full sample, I estimate the common factor using a standard expectation-maximization (EM) algorithm (Stock and Watson, 2002). Online Appendix Figure C11 displays the time series of all three series.

Inflation Disagreement—Bloomberg Survey The measure captures the dispersion across Bloomberg's professional forecasters expectations for CPI releases and is calculated as the standard deviation of forecasters' estimates for a given CPI release in the Bloomberg survey.

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

[4] `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).

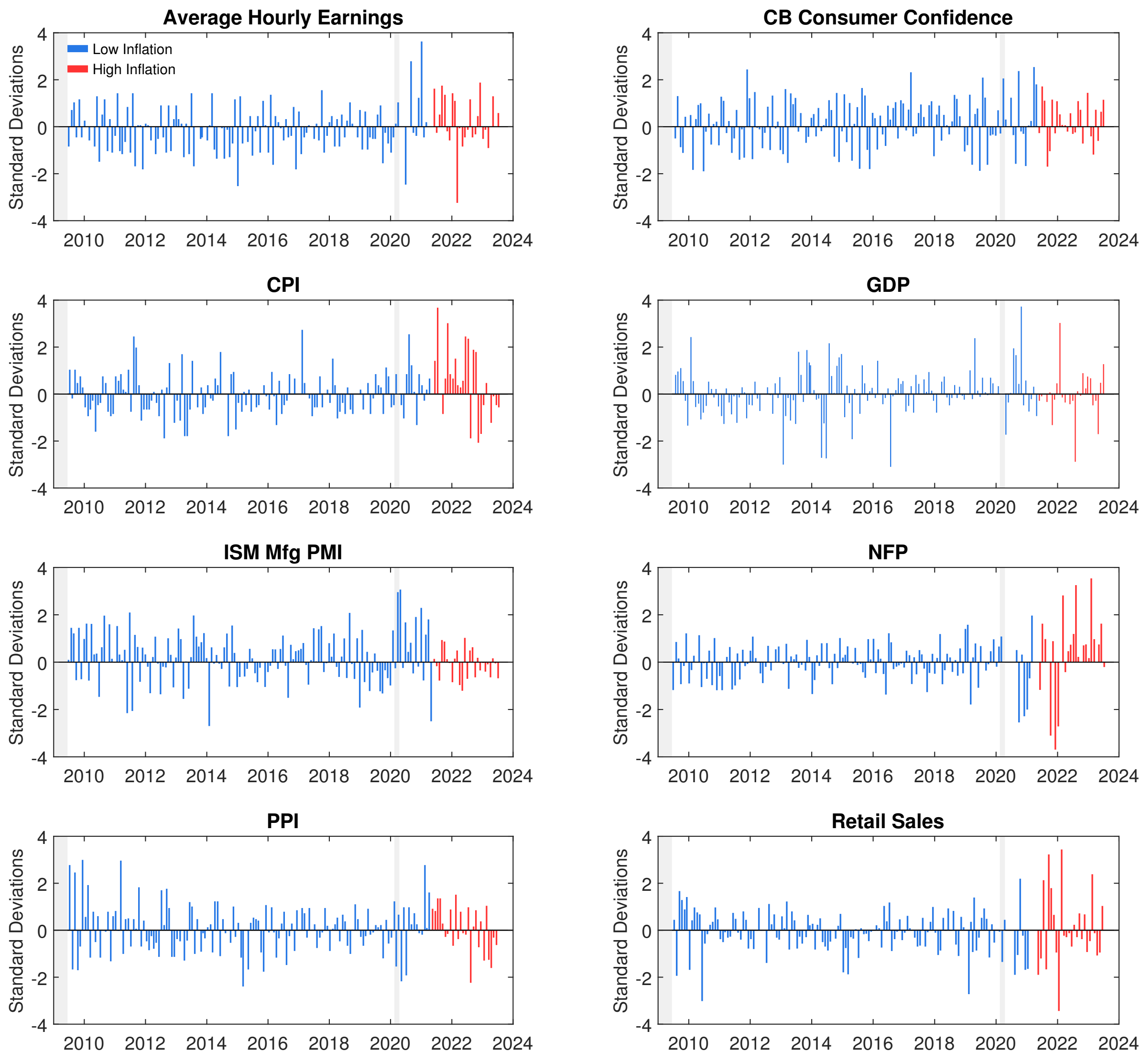
[5] `https://pressgazette.co.uk/media-audience-and-business-data/media_metrics/most-popular-websites-news-us-monthly-3/` (accessed on February 28, 2024).

Monetary Policy Uncertainty This series is the Kansas City Fed's measure of policy rate uncertainty over the next year, constructed from Eurodollar/SOFR options. See Bundick, Smith, and Van der Meer (2024) for details.

VIX This is the 30-day option-implied volatility index of the S&P 500.

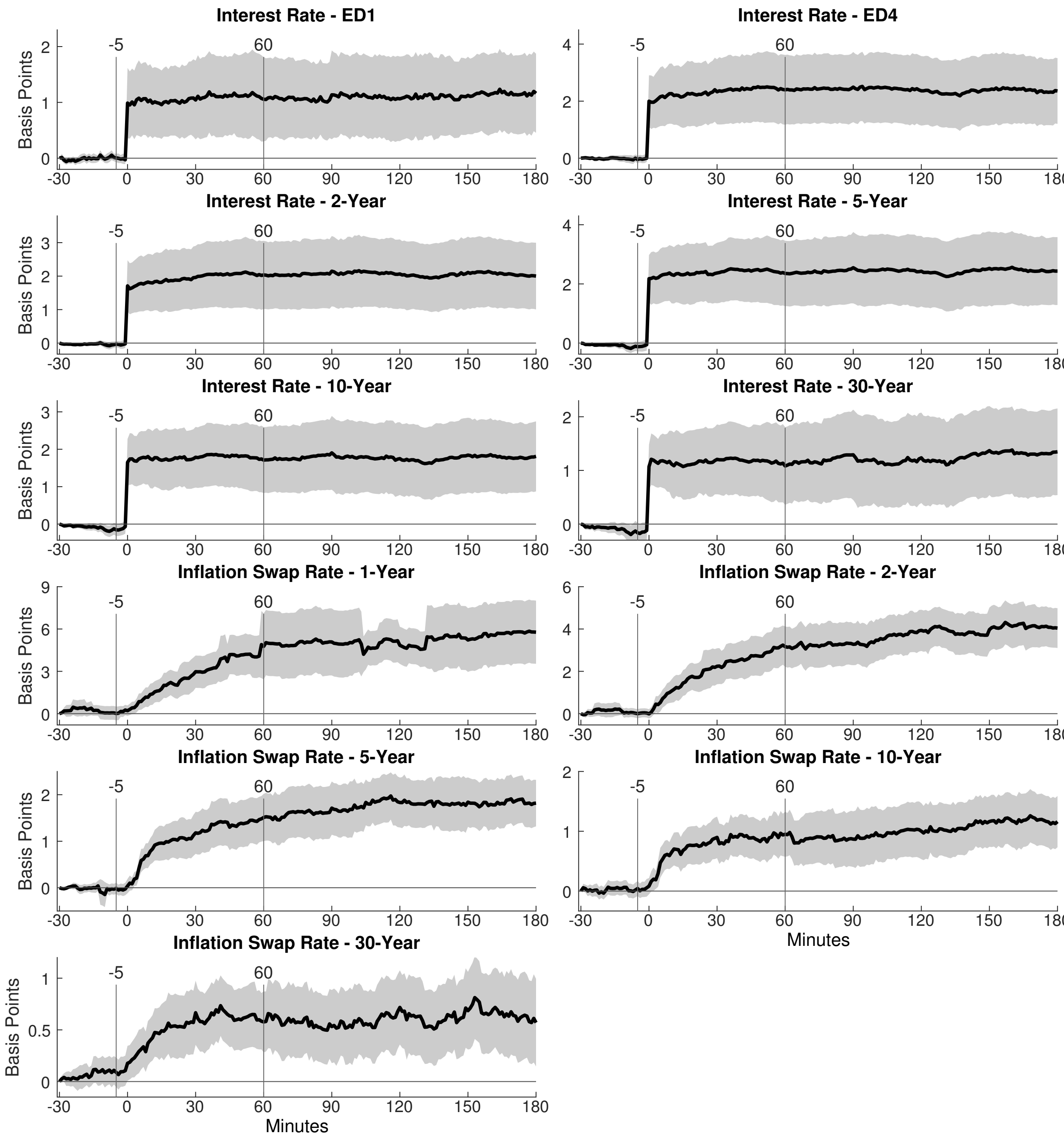
C Additional Results

Figure C1: 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-inflation period and the high-inflation period, respectively, as defined in Section 3.1. Shaded areas show NBER recession periods.

Figure C2: Intraday Impulse Responses to CPI News

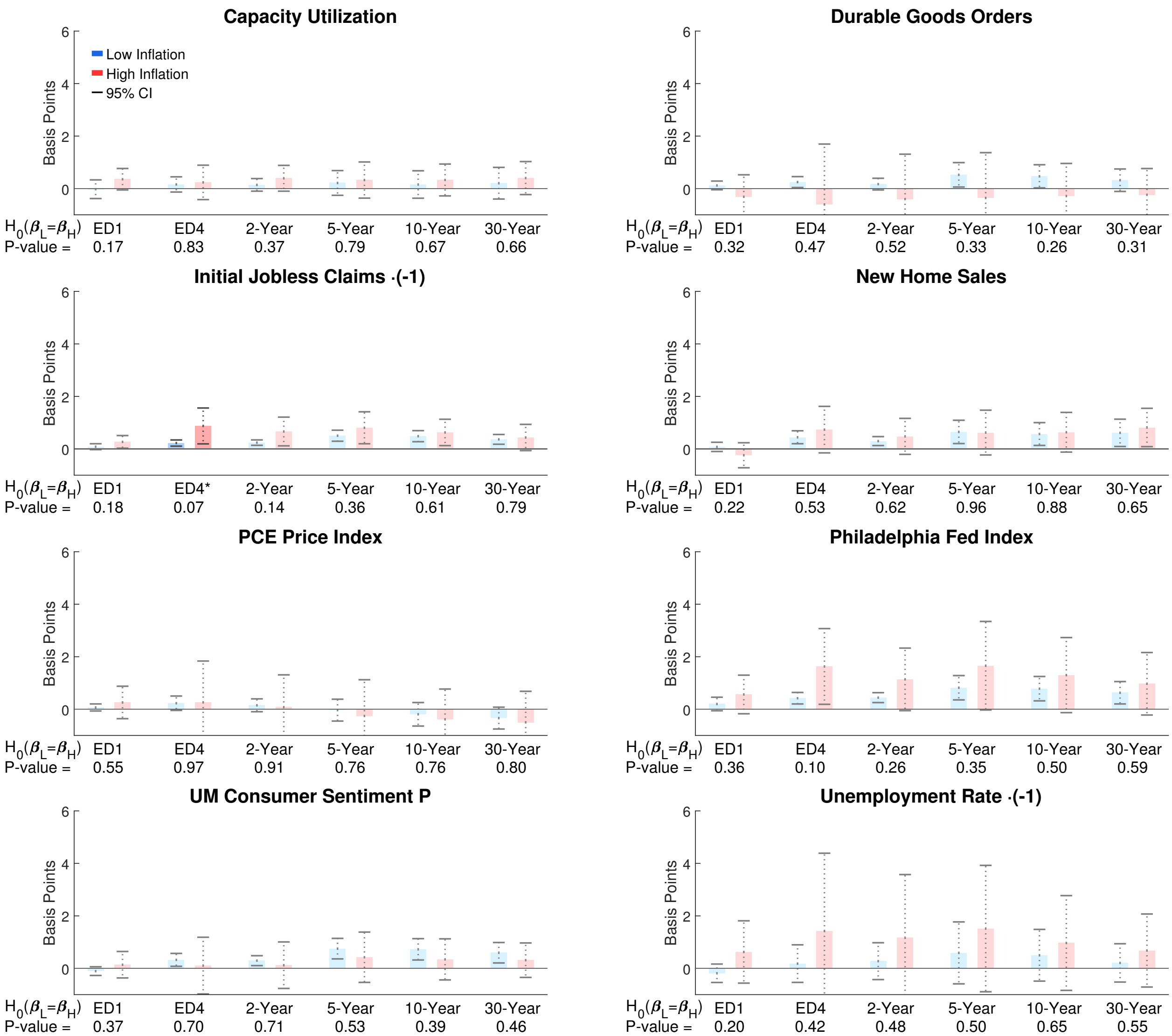


Notes: This figure shows the intraday impulse responses of interest rates and inflation swap rates to CPI news, estimated from the following specification:

$$x_{t+h} - x_{t-30} = \alpha^{(h)} + \beta^{(h)} s_t^{\text{CPI}} + \varepsilon_t^{(h)},$$

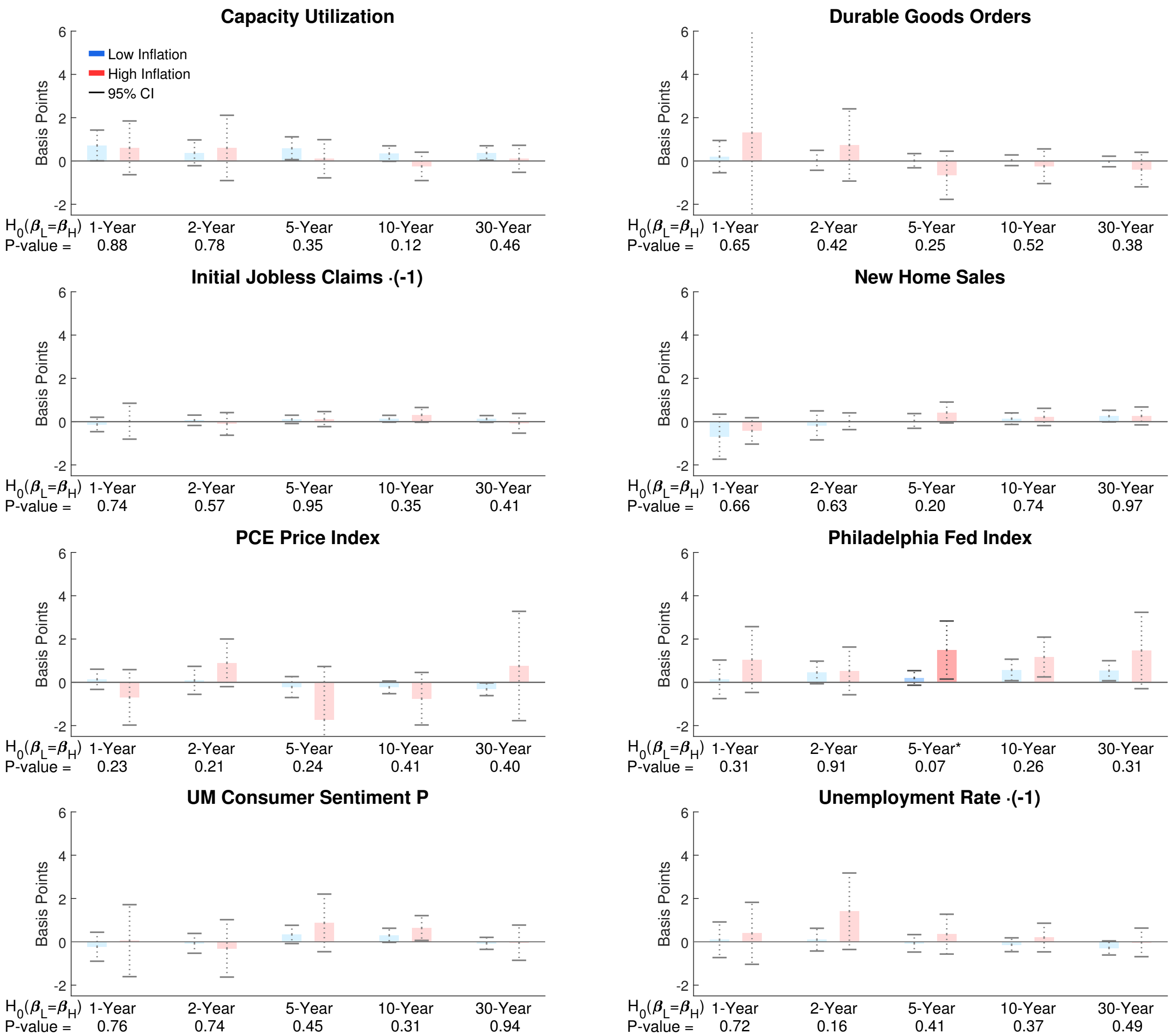
where x is the interest rate or inflation swap rate of interest, $x \in \{y, \pi\}$ and $h = -30, ..., 180$. Grey bands display 95 percent confidence bands. Heteroskedasticity-robust standard errors are used.

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



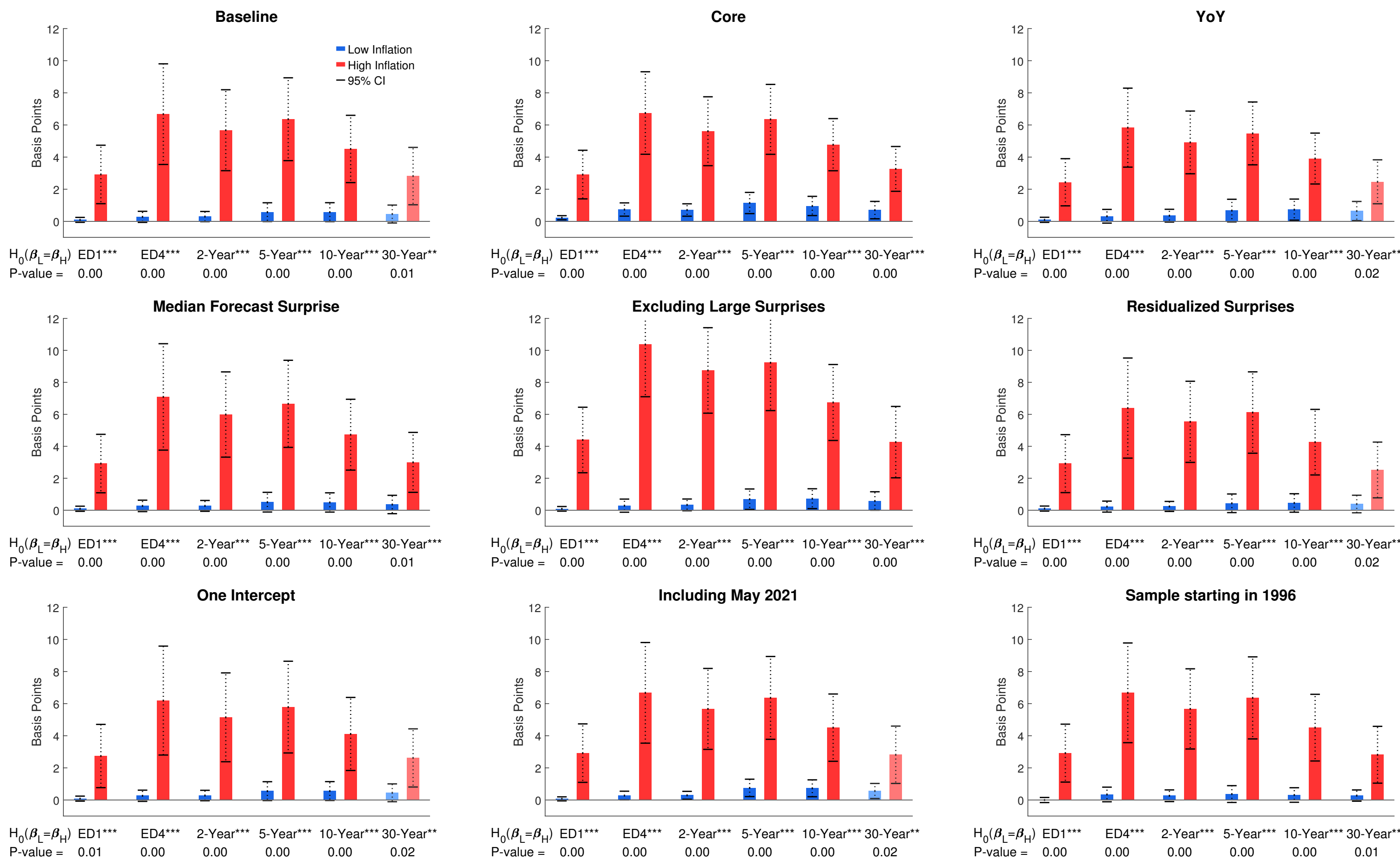
Notes: This figure shows the responses of interest rates to each of the 8 other macroeconomic announcements. Interest rate changes are expressed in basis points, and announcement surprises are normalized to standard deviations. Blue bars represent the effects during the low-inflation period (i.e., estimates of $\beta_L^{y|k}$ from equation (4)), while red bars represent the effects during the high-inflation period (i.e., estimates of $\beta_H^{y|k}$ from equation (4)). Black error bands show the 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level in rejecting the null hypothesis that $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are equal. The p-value for this hypothesis test is reported below each interest rate. Note that the sign of Initial Jobless Claims and Unemployment Rate surprises is flipped for ease of interpretation. A positive surprise thus corresponds to positive news about real economic activity, consistent with the other releases. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used throughout the analysis.

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



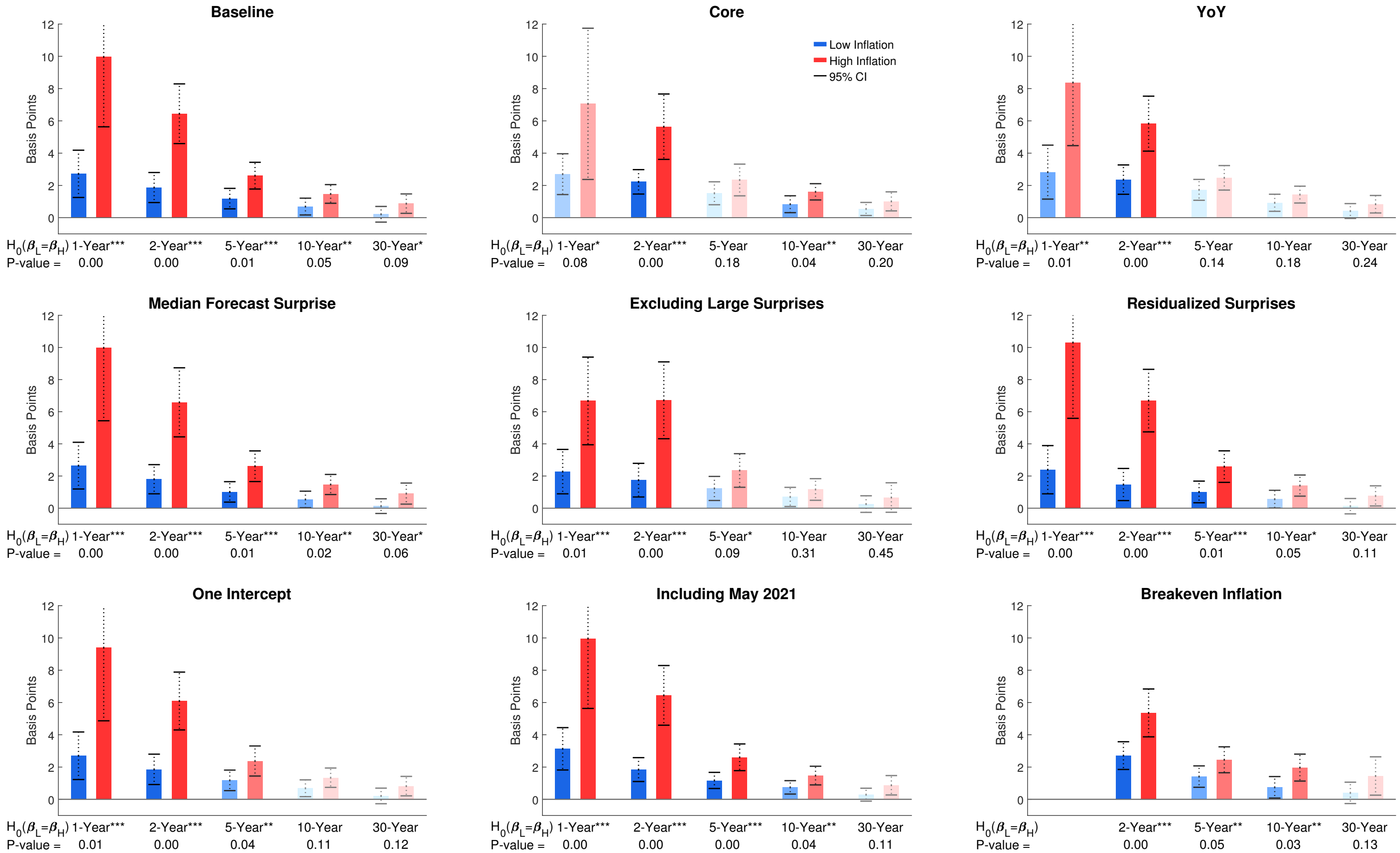
Notes: This figure shows the responses of inflation swap rates to each of the 8 other macroeconomic announcements. Inflation swap rate changes are expressed in basis points, and announcement surprises are normalized to standard deviations. Blue bars represent the effects during the low-inflation period (i.e., estimates of $\beta_L^{\pi|k}$ from equation (4)), while red bars represent the effects during the high-inflation period (i.e., estimates of $\beta_H^{\pi|k}$ from equation (4)). Black error bands show the 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level in rejecting the null hypothesis that $\beta_L^{\pi|k}$ and $\beta_H^{\pi|k}$ are equal. The p-value for this hypothesis test is reported below each inflation swap rate. Note that the sign of Initial Jobless Claims and Unemployment Rate surprises is flipped for ease of interpretation. A positive surprise thus corresponds to positive news about real economic activity, consistent with the other releases. ***, **, and * indicate significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are used throughout the analysis.

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



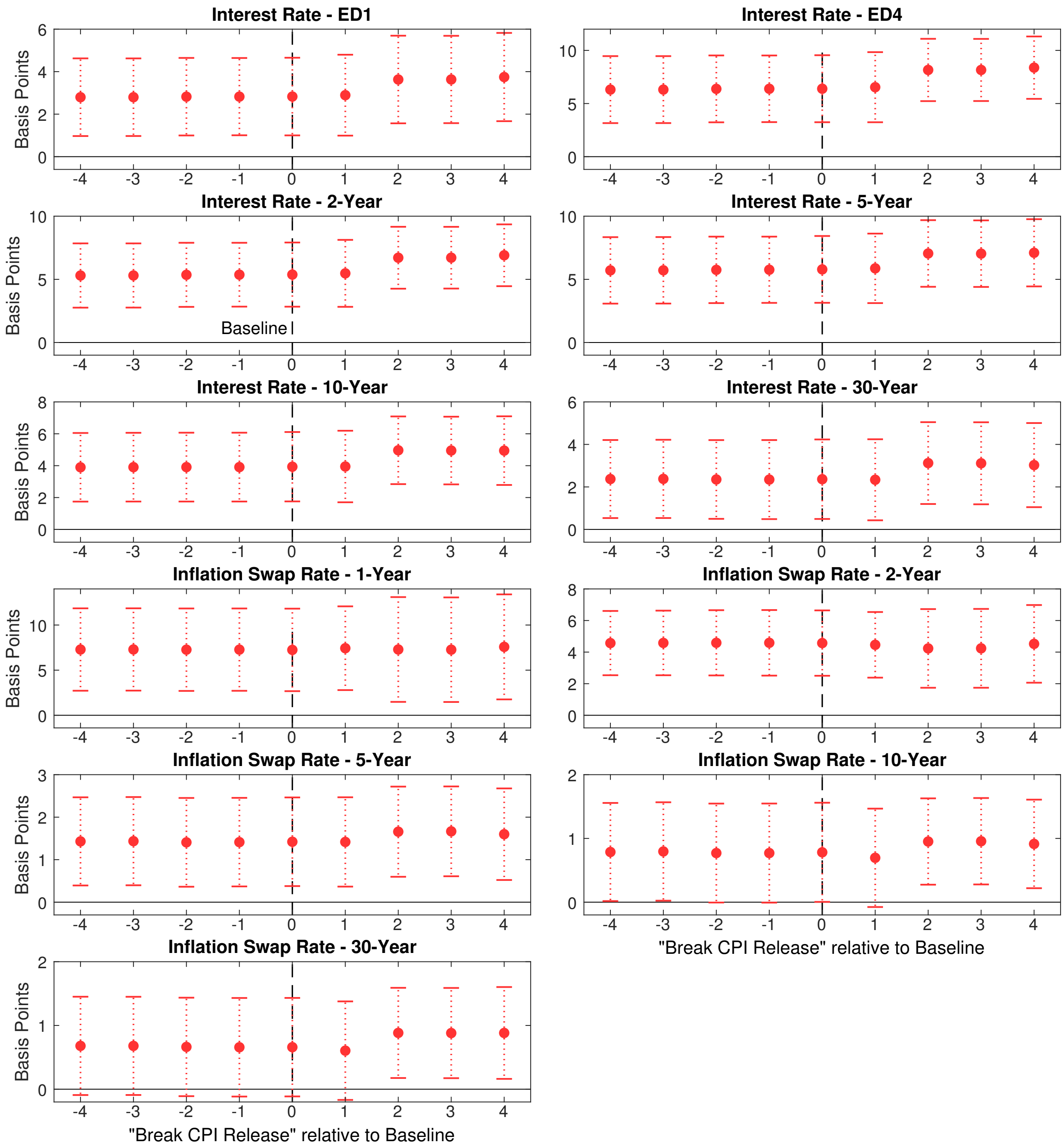
Notes: This figure shows the responses of interest rates to CPI news across alternative specifications of equation (4). Each panel corresponds to a distinct specification, with details provided in Section 4.4. Interest rate changes are expressed in basis points, and announcement surprises are normalized to standard deviations. Blue bars represent the effects during the low-inflation period (i.e., estimates of $\beta_L^{y|k}$ from equation (4)), while red bars represent the effects during the high-inflation period (i.e., estimates of $\beta_H^{y|k}$ from equation (4)). Black error bands show the 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level in rejecting the null hypothesis that $\beta_L^{y|k}$ and $\beta_H^{y|k}$ are equal. The p-value for 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 throughout the analysis.

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



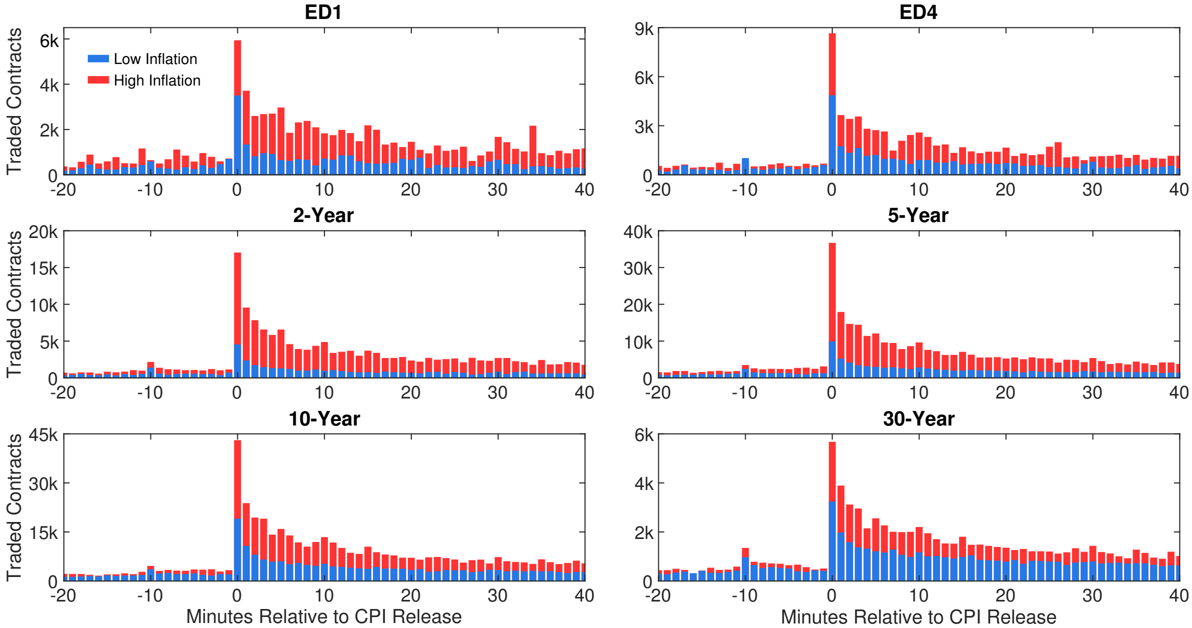
Notes: This figure shows the responses of inflation swap rates to CPI news across alternative specifications of equation (4). Each panel corresponds to a distinct specification, with details provided in Section 4.4. Inflation swap rate changes are expressed in basis points, and announcement surprises are normalized to standard deviations. Blue bars represent the effects during the low-inflation period (i.e., estimates of $\beta_L^{\pi|k}$ from equation (4)), while red bars represent the effects during the high-inflation period (i.e., estimates of $\beta_H^{\pi|k}$ from equation (4)). Black error bands show the 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level in rejecting the null hypothesis that $\beta_L^{\pi|k}$ and $\beta_H^{\pi|k}$ are equal. The p-value for 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 throughout the analysis.

Figure C7: Changes in Sensitivity to CPI releases under High Inflation—Robustness



Notes: The figure displays the changes in sensitivity to CPI news from the low-inflation period to the high-inflation period for alternative "break months". For a given asset price, each circle represents the estimate of $\delta_H^{x|k}$ from a specification of equation (5), where only the "break month" between the low-inflation period and the high-inflation period is altered relative to the baseline. Error bands show the 95 percent confidence intervals, where heteroskedasticity-robust standard errors are used.

Figure C8: Trading Volume of Interest Rate Futures around CPI Releases



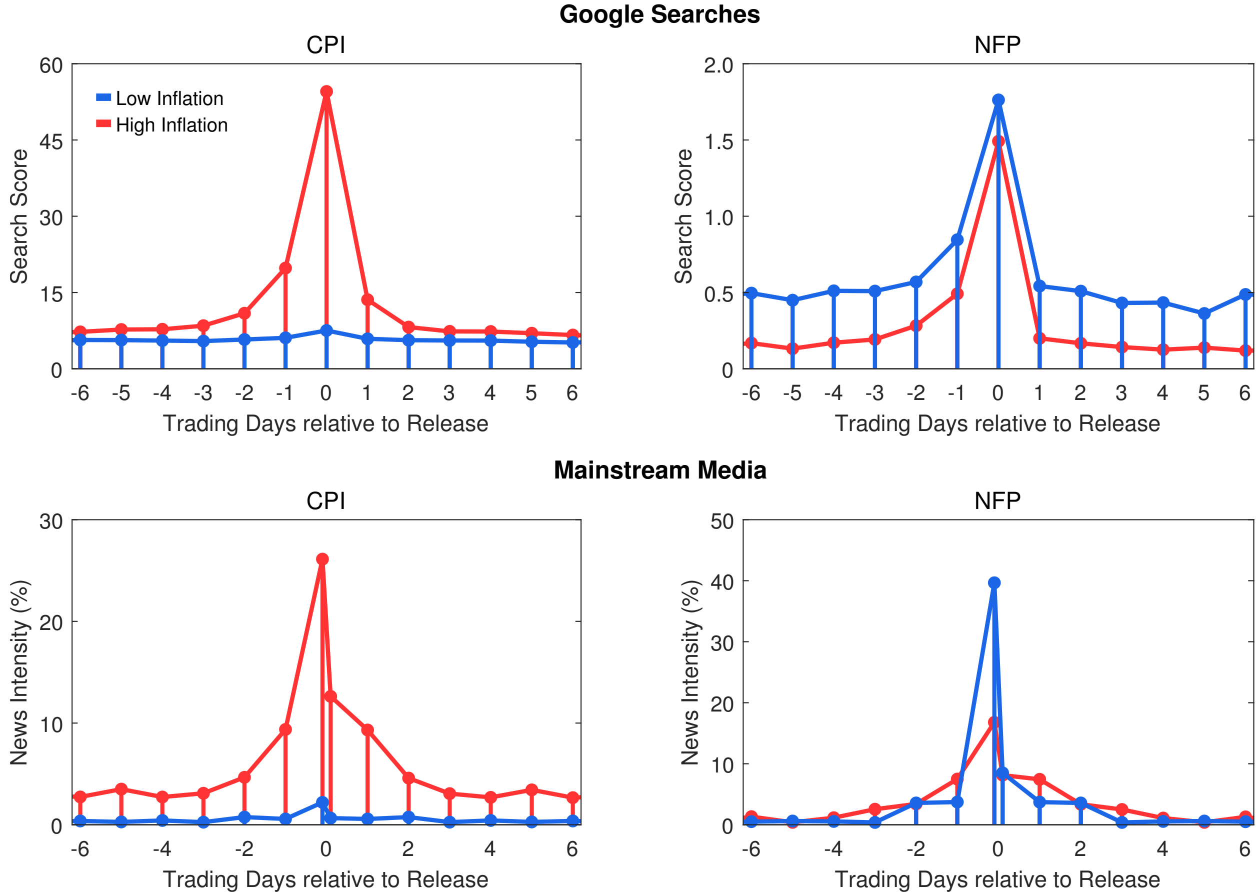
Notes: This figure displays the average trading volumes of interest rates futures around CPI releases during the low-inflation period (blue) and the high-inflation period (red). Each panel corresponds to the trading volume of a specific interest rate futures contract.

Table C1: Trading Volume around CPI Releases: Role of Investor Attention versus Disagreement

Trading Volume (thousands)	ED1	ED4	2-Year	5-Year	10-Year	30-Year
News	-0.76	4.59	5.81*	12.66**	16.72	2.47
	(2.19)	(2.85)	(3.02)	(6.12)	(10.47)	(2.00)
Investor Attention	17.02***	22.95***	34.21***	74.67***	88.33***	13.32***
	(3.11)	(4.59)	(3.65)	(6.69)	(11.48)	(2.20)
Inflation Volatility	-1.36	1.08	-5.92	0.09	9.57	-0.79
	(2.90)	(4.22)	(4.69)	(8.23)	(12.92)	(2.42)
Inflation Uncertainty	2.83	-7.57*	14.67***	26.06***	32.83**	5.47*
—Consumer Survey	(2.97)	(4.16)	(4.56)	(8.37)	(13.81)	(3.04)
Inflation Disagreement	5.54*	-2.44	1.08	-0.96	-3.81	0.03
—Bloomberg Survey	(3.19)	(3.48)	(4.36)	(7.29)	(11.33)	(2.62)
Monetary Policy	4.43	6.60*	11.76**	-2.40	-19.91	-2.94
Uncertainty	(2.71)	(3.75)	(4.52)	(7.81)	(12.72)	(2.55)
VIX	-0.89	-3.28	-0.87	-7.93	-16.86	-3.06
	(2.63)	(3.45)	(3.05)	(6.42)	(11.46)	(2.03)
Recession & ZLB Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.64	0.45	0.72	0.69	0.52	0.31
Observations	166	166	166	166	166	166

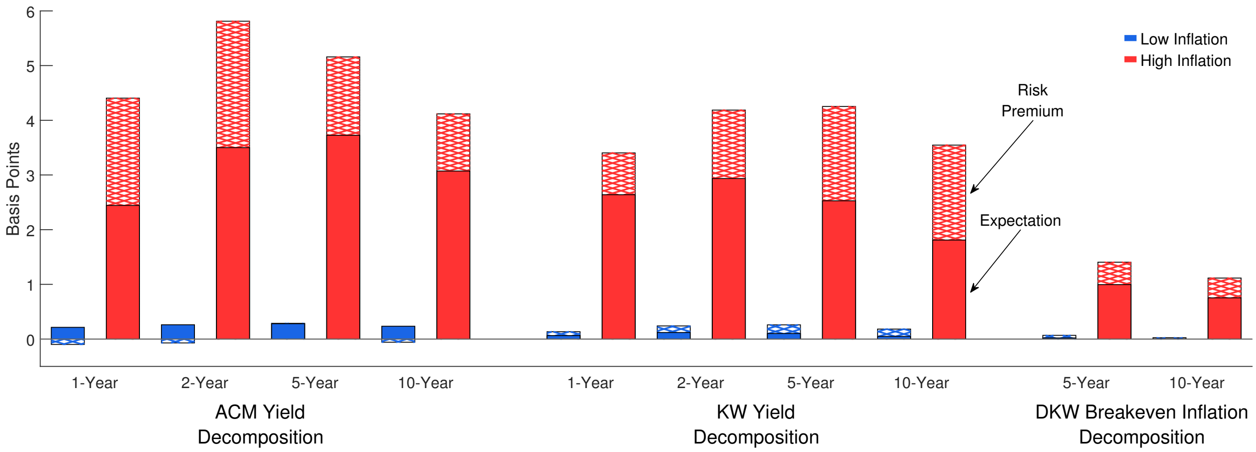
Notes: The table provides the estimates of the following specification: $tvol_t^{\mathrm{CPI}} = \alpha + \beta\, s_t^{\mathrm{CPI}} + \gamma\, \mathrm{IA}_t^{\mathrm{CPI}} + \Gamma\, Z_t + \varepsilon_t$, where $tvol_t^{\mathrm{CPI}}$ is the trading volume within the 60-minute window around CPI releases (measured in units of 1,000 traded contracts). $\mathrm{IA}_t^{\mathrm{CPI}}$ refers to the CPI investor attention, as defined in (7) and constructed from Bloomberg Terminal data. Z_t is a vector of uncertainty measures, detailed in Section 5.3. $\mathrm{IA}_t^{\mathrm{CPI}}$ and all variables in Z_t are demeaned and in units of standard deviations. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level. In unreported checks, I find that the results are very similar when using the investor attention measure based on Dow Jones Newswires data.

Figure C9: Public Attention around Macro Releases



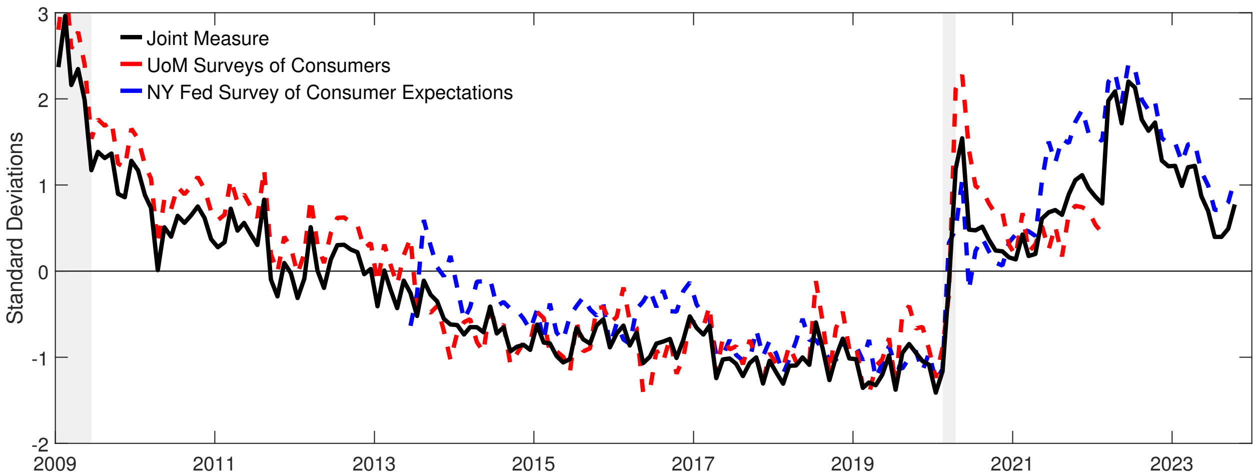
Notes: The figure plots the CPI and NFP public attention measures around the respective releases. Blue lines show the average values during the low-inflation period, while red lines show the average values during the high-inflation period. Measures in the top row are based on Google Searches, normalized such that 100 corresponds to the largest observation for the topic "Consumer Price Index" over the sample period. Measures in the bottom row represent the share of relevant articles in mainstream media on a given day, expressed as a percentage of economic- and business-related news articles. See Online Appendix B.3 for details on the construction of the measures.

Figure C10: Daily Effects of CPI news on Expectations and Risk Premia



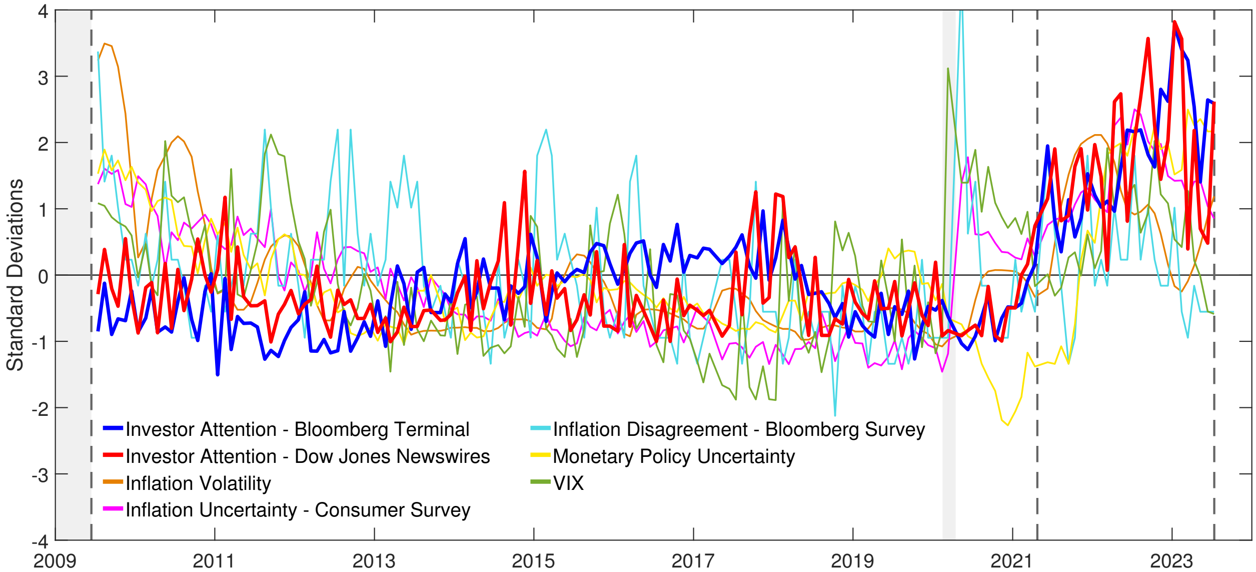
Notes: This figure shows the daily effects of CPI news on expectations and risk premia of yields and breakeven inflation rates under the low-inflation period and the high-inflation period. The figure presents estimates for three decompositions: the yield decompositions by Adrian, Crump, and Moench (2013) (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 solid red and the hatched red bar depict the effects on the expectation and the risk premium component during the high-inflation period, respectively (i.e., estimates of $\beta_H^{y|k}$ from equation (4), 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 during the low-inflation period.

Figure C11: Time Series of 1-Year-Ahead Inflation Uncertainty based on Consumer Surveys



Notes: The figure shows the time series of 1-year-ahead inflation uncertainty over the sample period. The red line depicts the measure based on the University of Michigan Survey of Consumers (MSC), while the blue line represents the measure based on the New York Fed's Survey of Consumer Expectations (SCE). The time series of the joint measure is shown in black. All series are demeaned and in units of standard deviations. The MSC measure comes from Binder (2017) who exploits the rounding behavior of reported inflation expectations of survey participants. See Binder (2017) for details on the construction. The SCE measure comes from the New York Fed and is based on the interquartile range of the survey participants' median density quartiles. See Armantier et al. (2017) for more details. The joint measure is the common factor of the MSC and SCE series and is estimated via a standard EM algorithm to account for missing observations (Stock and Watson, 2002).

Figure C12: CPI Pre-Announcement Investor Attention and Uncertainty



Notes: The figure plots the CPI pre-announcement investor attention (CPI-IA) series, as defined in (7). It also displays the uncertainty measures employed in Section 5.3. All series are demeaned and in units of standard deviations. See Section 5.3 for details on the measures.

Table C2: Effects of CPI News: Role of Investor Attention versus Uncertainty

Interest Rates (bp)	ED1		ED4		2-Year		5-Year		10-Year		30-Year	
News	0.74***	0.59***	1.80***	1.76***	1.55***	1.51***	1.94***	1.98***	1.52***	1.58***	1.08***	1.10***
	(0.20)	(0.15)	(0.34)	(0.29)	(0.28)	(0.24)	(0.34)	(0.33)	(0.30)	(0.29)	(0.27)	(0.28)
News × Investor Attention	0.98***	0.60**	1.99***	1.12***	1.70***	1.05***	1.80***	1.07***	1.18***	0.67**	0.62**	0.30
	(0.26)	(0.27)	(0.47)	(0.38)	(0.38)	(0.33)	(0.38)	(0.37)	(0.32)	(0.33)	(0.27)	(0.32)
News × Inflation Volatility		-0.56*		-0.45		-0.49		-0.17		-0.24		-0.35
		(0.32)		(0.58)		(0.50)		(0.65)		(0.56)		(0.52)
News × Inflation Uncertainty		0.55		1.10**		0.90**		0.98**		0.78*		0.67
—Consumer Survey		(0.38)		(0.46)		(0.39)		(0.47)		(0.41)		(0.41)
News × Inflation Disagreement		0.19		-0.63*		-0.50*		-0.67*		-0.53		-0.34
—Bloomberg Survey		(0.20)		(0.33)		(0.26)		(0.38)		(0.37)		(0.33)
News × Monetary Policy		0.76***		1.42***		1.02***		0.81*		0.66*		0.40
Uncertainty		(0.22)		(0.43)		(0.34)		(0.42)		(0.35)		(0.32)
News × VIX		0.07		0.02		0.21		0.18		0.17		0.27
		(0.17)		(0.31)		(0.27)		(0.35)		(0.31)		(0.28)
Recession & ZLB Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.55	0.67	0.59	0.68	0.60	0.69	0.52	0.59	0.44	0.52	0.30	0.40
Observations	166	166	166	166	166	166	166	166	166	166	166	166

Inflation Swap Rates (bp)	1-Year		2-Year		5-Year		10-Year		30-Year	
News	4.02***	4.20***	2.84***	2.83***	1.47***	1.82***	0.91***	1.04***	0.43**	0.48**
	(0.72)	(0.73)	(0.48)	(0.43)	(0.29)	(0.28)	(0.22)	(0.24)	(0.19)	(0.19)
News × Investor Attention	2.80***	2.26**	1.60***	0.87*	0.51**	0.01	0.21	-0.15	0.06	-0.13
	(1.03)	(0.87)	(0.33)	(0.50)	(0.24)	(0.34)	(0.16)	(0.22)	(0.14)	(0.19)
News × Inflation Volatility		1.49		0.56		0.99**		0.45		0.02
		(2.34)		(0.68)		(0.46)		(0.36)		(0.34)
News × Inflation Uncertainty		1.13		1.02		0.45		0.59		0.40
—Consumer Survey		(1.16)		(0.73)		(0.53)		(0.36)		(0.30)
News × Inflation Disagreement		-2.29***		-0.64		-0.67**		-0.23		0.09
—Bloomberg Survey		(0.74)		(0.49)		(0.29)		(0.26)		(0.25)
News × Monetary Policy		-1.44		-0.25		0.19		-0.01		0.16
Uncertainty		(1.04)		(0.59)		(0.35)		(0.28)		(0.26)
News × VIX		0.07		0.21		-0.60		-0.51*		-0.46**
		(0.75)		(0.39)		(0.38)		(0.28)		(0.22)
Recession & ZLB Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.45	0.53	0.44	0.52	0.21	0.36	0.17	0.28	0.12	0.18
Observations	166	166	166	166	166	166	166	166	166	166

Notes: The table presents estimates of β^x, γ^x, and Γ^x from equation (8), where investor attention denotes the CPI-IA series as defined in (7) and constructed from Dow Jones Newswires data. The top panel reports estimates for changes in interest rates as the dependent variables, while the bottom panel reports estimates for inflation swap rates. Changes in both interest rates and inflation swap rates are expressed in basis points. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level.

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Supplementary Appendix

for

How Markets Process Macro News: The Importance of Investor Attention*

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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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S1 Model Derivations

S1.1 Diagnostic Updating following CPI Release

Upon observing the CPI release,

$$s^{\text{CPI}} = \Delta\bar{\pi} + \eta, \quad \text{with } \eta \sim N\left(0, \sigma_\eta^2\right),$$

attentive investors, $i \in [0, \mu^k]$, update their expectation using the distorted posterior

$$f\left(\Delta\bar{\pi}|s^{\text{CPI}}\right) = f^{RE}\left(\Delta\bar{\pi}|s^{\text{CPI}}\right) H\left(\Delta\bar{\pi}\right)^{\kappa} \frac{1}{\Upsilon},$$

where $H\left(\Delta\bar{\pi}\right) = \frac{f^{RE}\left(\Delta\bar{\pi}|s^{\text{CPI}}\right)}{f^{RE}\left(\Delta\bar{\pi}|E_1^i[\Delta\bar{\pi}]\right)}$. Note that the Kalman filter under rational expectations is given by:

$$E_2^{i,RE}\left[\Delta\bar{\pi}|s^{\text{CPI}}\right] = E_1^{i,RE}\left[\Delta\bar{\pi}\right] + \frac{Var_1^{i,RE}\left[\Delta\bar{\pi}\right]}{Var_1^{i,RE}\left[\Delta\bar{\pi}\right] + \sigma_\eta^2}\left(s^{\text{CPI}} - E_1^{i,RE}\left[\Delta\bar{\pi}\right]\right).$$

Plugging in $E_1^{i,RE}\left[\Delta\bar{\pi}\right] = \Delta\bar{\pi}_{-1}$ and $Var_1^{i,RE}\left[\Delta\bar{\pi}\right] = Var_1^{i,RE}\left[\Delta\bar{\pi}_{-1} + \varepsilon_\pi\right] = \sigma_\pi^2$ yields

$$E_2^{i,RE}\left[\Delta\bar{\pi}|s^{\text{CPI}}\right] = \Delta\bar{\pi}_{-1} + \frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_\eta^2}\left(s^{\text{CPI}} - \Delta\bar{\pi}_{-1}\right).$$

As shown in Bordalo et al. (2020), among others, the diagnostic expectation can be written in terms of the rational expectation:

$$\begin{aligned}
E_2^i\left[\Delta\bar{\pi}|s^{\text{CPI}}\right] &= E_2^{i,RE}\left[\Delta\bar{\pi}|s^{\text{CPI}}\right] + \kappa\left(E_2^{i,RE}\left[\Delta\bar{\pi}|s^{\text{CPI}}\right] - E_1^{i,RE}\left[\Delta\bar{\pi}\right]\right) \\
&= (1+\kappa)\left(\Delta\bar{\pi}_{-1} + \frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_\eta^2}\left(s^{\text{CPI}} - \Delta\bar{\pi}_{-1}\right)\right) - \Delta\bar{\pi}_{-1} \\
&= \Delta\bar{\pi}_{-1} + (1+\kappa)\frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_\eta^2}\left(s^{\text{CPI}} - \Delta\bar{\pi}_{-1}\right).
\end{aligned}$$

Applying $\Delta\bar{\pi}_{-1} = 0$ leads to

$$E_2^i\left[\Delta\bar{\pi}|s^{\text{CPI}}\right] = (1+\kappa)\frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_\eta^2}s^{\text{CPI}}.$$

Using $\xi^{\text{CPI}} = \frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_\eta^2}$, the attentive investors' expectations of V_π and V_b are given by:

$$E_2^i\left[V_\pi\right] = E_2^{\mu^{\text{CPI}}}\left[V_\pi\right] = (1+\kappa)\,\xi^{\text{CPI}}s^{\text{CPI}}$$

and

$$E_2^i\left[V_b\right]=E_2^{\mu^{\text{CPI}}}\left[V_b\right]=1-\phi\left(1+\kappa\right)\xi^{\text{CPI}}s^{\text{CPI}},$$

for $i\in[0,\mu^k]$. The conditional variance of V_π is then given by

$$\begin{aligned}
Var_2^i\left[V_\pi\right] &= Var_2^{\mu^{\text{CPI}}}\left[V_\pi\right]=E_2^{\mu^{\text{CPI}}}\left[\left(V_\pi-E_2^{\mu^{\text{CPI}}}\left[V_\pi\right]\right)^2\right]=E_2^{\mu^{\text{CPI}}}\left[\left(\Delta\bar{\pi}-\left(1+\kappa\right)\xi^{\text{CPI}}s^{\text{CPI}}\right)^2\right]\\
&= E_2^{\mu^{\text{CPI}}}\left[\left(\Delta\bar{\pi}-\left(1+\kappa\right)\xi^{\text{CPI}}s^{\text{CPI}}\right)^2\right]=E_2^{\mu^{\text{CPI}}}\left[\left(\Delta\bar{\pi}-\left(1+\kappa\right)\xi^{\text{CPI}}\Delta\bar{\pi}-\left(1+\kappa\right)\xi^{\text{CPI}}\eta\right)^2\right]\\
&= E_2^{\mu^{\text{CPI}}}\left[\left(\left(1-\left(1+\kappa\right)\xi^{\text{CPI}}\right)\Delta\bar{\pi}-\left(1+\kappa\right)\xi^{\text{CPI}}\eta\right)^2\right]\\
&= E_2^{\mu^{\text{CPI}}}\left[\left(1-\left(1+\kappa\right)\xi^{\text{CPI}}\right)^2\Delta\bar{\pi}^2-2\left(1-\left(1+\kappa\right)\xi^{\text{CPI}}\right)\Delta\bar{\pi}\left(1+\kappa\right)\xi^{\text{CPI}}\eta+\left(\left(1+\kappa\right)\xi^{\text{CPI}}\right)^2\eta^2\right]\\
&= \left(\left(1-\left(1+\kappa\right)\xi^{\text{CPI}}\right)^2E_2^{\mu^{\text{CPI}}}\left[\Delta\bar{\pi}^2\right]+\left(\left(1+\kappa\right)\xi^{\text{CPI}}\right)^2E_2^{\mu^{\text{CPI}}}\left[\eta^2\right]\right)\\
&= \left(\left(1-\left(1+\kappa\right)\xi^{\text{CPI}}\right)^2\sigma_\pi^2+\left(\left(1+\kappa\right)\xi^{\text{CPI}}\right)^2\sigma_\eta^2\right)\\
&= \left(\sigma_\pi^2-2\left(1+\kappa\right)\xi^{\text{CPI}}\sigma_\pi^2+\left(\left(1+\kappa\right)\xi^{\text{CPI}}\right)^2\sigma_\pi^2+\left(\left(1+\kappa\right)\xi^{\text{CPI}}\right)^2\sigma_\eta^2\right)\\
&= \left(\sigma_\pi^2-2\left(1+\kappa\right)\xi^{\text{CPI}}\sigma_\pi^2+\left(1+\kappa\right)^2\xi^{\text{CPI}}\sigma_\pi^2\right)\\
&= \left(\sigma_\pi^2+\left(1+\kappa\right)\xi^{\text{CPI}}\sigma_\pi^2\left(-1+\kappa\right)\right)\\
&= \left(1-\left(1+\kappa\right)\left(1-\kappa\right)\xi^{\text{CPI}}\right)\sigma_\pi^2\\
&= \left(1-\left(1-\kappa^2\right)\xi^{\text{CPI}}\right)\sigma_\pi^2,
\end{aligned}$$

where I used

$$\begin{aligned}
&\left(\left(1+\kappa\right)\xi^{\text{CPI}}\right)^2\sigma_\pi^2+\left(\left(1+\kappa\right)\xi^{\text{CPI}}\right)^2\sigma_\eta^2\\
=\ &\left(1+\kappa\right)^2\left(\frac{\sigma_\pi^2}{\sigma_\pi^2+\sigma_\eta^2}\right)^2\left(\sigma_\pi^2+\sigma_\eta^2\right)=\left(1+\kappa\right)^2\xi^{\text{CPI}}\sigma_\pi^2.
\end{aligned}$$

The conditional variance of V_b is

$$Var_2^i\left[V_b\right]=Var_2^{\mu^{\text{CPI}}}\left[V_b\right]=\phi^2Var_2^{\mu^{\text{CPI}}}\left[V_\pi\right]=\phi^2\left(1-\left(1-\kappa^2\right)\xi^{\text{CPI}}\right)\sigma_\pi^2.$$

S1.2 Diagnostic Updating following NFP Release

Upon observing the NFP release,

$$s^{\text{NFP}}=\Delta\bar{z}+\nu,\quad \text{with } \nu\sim N\left(0,\varrho^2\sigma_\nu^2\right),$$

attentive investors, $i\in[0,\mu^k]$, update their expectation using the distorted posterior

$$f\left(\Delta\bar{z}|s^{\text{NFP}}\right)=f^{RE}\left(\Delta\bar{z}|s^{\text{NFP}}\right)H\left(\Delta\bar{z}\right)^\kappa\frac{1}{\Upsilon},$$

with $H(\Delta\bar{z}) = \frac{f^{RE}\left(\Delta\bar{z}|s^{\mathrm{NFP}}\right)}{f^{RE}\left(\Delta\bar{z}|E_1^i[\Delta\bar{z}]\right)}$. Note that the Kalman filter under rational expectations is given by:

$$E_2^{i,RE}\left[\Delta\bar{z}|s^{\mathrm{NFP}}\right] = E_1^{i,RE}[\Delta\bar{z}] + \frac{Var_1^{i,RE}[\Delta\bar{z}]}{Var_1^{i,RE}[\Delta\bar{z}] + \varrho^2\sigma_\nu^2}\left(s^{\mathrm{NFP}} - E_1^{i,RE}[\Delta\bar{z}]\right).$$

Plugging in $E_1^{i,RE}[\Delta\bar{z}] = \varrho\Delta\bar{\pi}_{-1}$ and $Var_1^{i,RE}[\Delta\bar{z}] = Var_1^{i,RE}[\varrho(\Delta\bar{\pi}_{-1} + \varepsilon_\pi)] = \varrho^2\sigma_\pi^2$ yields:

$$E_2^{i,RE}\left[\Delta\bar{z}|s^{\mathrm{NFP}}\right] = \varrho\Delta\bar{\pi}_{-1} + \frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_\nu^2}\left(s^{\mathrm{NFP}} - \varrho\Delta\bar{\pi}_{-1}\right).$$

The diagnostic expectation is then given by:

$$\begin{aligned} E_2^{i}\left[\Delta\bar{z}|s^{\mathrm{NFP}}\right] &= E_2^{i,RE}\left[\Delta\bar{z}|s^{\mathrm{NFP}}\right] + \kappa\left(E_2^{i,RE}\left[\Delta\bar{z}|s^{\mathrm{NFP}}\right] - E_1^{i,RE}[\Delta\bar{z}]\right) \\ &= (1+\kappa)\left(\varrho\Delta\bar{\pi}_{-1} + \frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_\nu^2}\left(s^{\mathrm{NFP}} - \varrho\Delta\bar{\pi}_{-1}\right)\right) - \varrho\Delta\bar{\pi}_{-1} \\ &= \varrho\Delta\bar{\pi}_{-1} + (1+\kappa)\frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_\nu^2}\left(s^{\mathrm{NFP}} - \varrho\Delta\bar{\pi}_{-1}\right). \end{aligned}$$

Imposing $\Delta\bar{\pi}_{-1} = 0$ results in:

$$E_2^{i}\left[\Delta\bar{z}|s^{\mathrm{NFP}}\right] = (1+\kappa)\frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_\nu^2}s^{\mathrm{NFP}}.$$

Using $\xi^{\mathrm{NFP}} = \frac{\sigma_\pi^2}{\sigma_\pi^2 + \sigma_\nu^2}$ and $\Delta\bar{\pi} = \frac{1}{\varrho}\Delta\bar{z}$, one obtains the attentive investors' expectations of V_π and V_b:

$$E_2^{i}[V_\pi] = E_2^{\mu^{\mathrm{NFP}}}[V_\pi] = \frac{1}{\varrho}(1+\kappa)\,\xi^{\mathrm{NFP}}s^{\mathrm{NFP}}$$

and

$$E_2^{i}[V_\pi] = E_2^{\mu^{\mathrm{NFP}}}[V_\pi] = 1 - \frac{\phi}{\varrho}(1+\kappa)\,\xi^{\mathrm{NFP}}s^{\mathrm{NFP}},$$

for $i \in [0, \mu^k]$. The conditional variance of V_π is then given by

$$\begin{aligned}
Var_2^i[V_\pi] &= Var_2^{\mu^{\text{NFP}}}[V_\pi] = E_2^{\mu^{\text{NFP}}}\left[\left(V_\pi - E_2^{\mu^{\text{NFP}}}[V_\pi]\right)^2\right] = E_2^{\mu^{\text{NFP}}}\left[\left(\Delta\bar{\pi} - \frac{1}{\varrho}(1+\kappa)\,\xi^{\text{NFP}}s^{\text{NFP}}\right)^2\right] \\
&= E_2^{\mu^{\text{NFP}}}\left[\left(\Delta\bar{\pi} - \frac{1}{\varrho}(1+\kappa)\,\xi^{\text{NFP}}s^{\text{NFP}}\right)^2\right] = E_2^{\mu^{\text{NFP}}}\left[\left(\Delta\bar{\pi} - (1+\kappa)\,\xi^{\text{NFP}}\Delta\bar{\pi} - \frac{1}{\varrho}(1+\kappa)\,\xi^{\text{NFP}}\nu\right)^2\right] \\
&= E_2^{\mu^{\text{NFP}}}\left[\left(\left(1-(1+\kappa)\,\xi^{\text{NFP}}\right)\Delta\bar{\pi} - \frac{1}{\varrho}(1+\kappa)\,\xi^{\text{NFP}}\nu\right)^2\right] \\
&= E_2^{\mu^{\text{NFP}}}\left[\left(1-(1+\kappa)\,\xi^{\text{NFP}}\right)^2\Delta\bar{\pi}^2 - 2\left(1-(1+\kappa)\,\xi^{\text{NFP}}\right)\Delta\bar{\pi}\frac{1}{\varrho}(1+\kappa)\,\xi^{\text{NFP}}\nu + \left(\frac{1}{\varrho}(1+\kappa)\,\xi^{\text{NFP}}\right)^2\nu^2\right] \\
&= \left(\left(1-(1+\kappa)\,\xi^{\text{NFP}}\right)^2 E_2^{\mu^{\text{NFP}}}\left[\Delta\bar{\pi}^2\right] + \left(\frac{1}{\varrho}(1+\kappa)\,\xi^{\text{NFP}}\right)^2 E_2^{\mu^{\text{NFP}}}\left[\nu^2\right]\right) \\
&= \left(\left(1-(1+\kappa)\,\xi^{\text{NFP}}\right)^2\sigma_\pi^2 + \left(\frac{1}{\varrho}(1+\kappa)\,\xi^{\text{NFP}}\right)^2\varrho^2\sigma_\nu^2\right) \\
&= \left(\sigma_\pi^2 - 2(1+\kappa)\,\xi^{\text{NFP}}\sigma_\pi^2 + \left((1+\kappa)\,\xi^{\text{NFP}}\right)^2\sigma_\pi^2 + \left((1+\kappa)\,\xi^{\text{NFP}}\right)^2\sigma_\nu^2\right) \\
&= \left(\sigma_\pi^2 - 2(1+\kappa)\,\xi^{\text{NFP}}\sigma_\pi^2 + (1+\kappa)^2\,\xi^{\text{NFP}}\sigma_\pi^2\right) \\
&= \left(\sigma_\pi^2 + (1+\kappa)\,\xi^{\text{NFP}}\sigma_\pi^2(-1+\kappa)\right) \\
&= \left(1-(1+\kappa)(1-\kappa)\,\xi^{\text{NFP}}\right)\sigma_\pi^2 \\
&= \left(1-\left(1-\kappa^2\right)\xi^{\text{NFP}}\right)\sigma_\pi^2,
\end{aligned}$$

where I used

$$\begin{aligned}
&\left((1+\kappa)\,\xi^{\text{NFP}}\right)^2\sigma_\pi^2 + \left((1+\kappa)\,\xi^{\text{NFP}}\right)^2\sigma_\nu^2 \\
= \;& \frac{1}{\varrho^2}(1+\kappa)^2\left(\frac{\sigma_\pi^2}{\sigma_\pi^2+\sigma_\nu^2}\right)^2\left(\sigma_\pi^2+\sigma_\nu^2\right) = \frac{1}{\varrho^2}(1+\kappa)^2\,\xi^{\text{NFP}}\sigma_\pi^2.
\end{aligned}$$

The conditional variance of V_b is

$$Var_2^i[V_b] = Var_2^{\mu^{\text{NFP}}}[V_b] = \phi^2 Var_2^{\mu^{\text{NFP}}}[V_\pi] = \phi^2\left(1-\left(1-\kappa^2\right)\xi^{\text{NFP}}\right)\sigma_\pi^2.$$

S1.3 Equilibrium Prices at Date 2

For date 2, the market clearing condition for $\tilde{\omega}_2^i$ implies

$$\begin{aligned}
0 &= \int_0^1 \tilde{\omega}_2^i\, di \\
0 &= \int_0^1 \frac{E_2^i[V_\pi] - \pi_2}{\gamma Var_2^i[V_\pi]}\, di \\
0 &= \frac{\mu^k}{\gamma Var_2^{\mu^k}[V_\pi]} E_2^{\mu^k}[V_b] + \frac{1-\mu^k}{\gamma Var_2^{1-\mu^k}[V_\pi]} E_2^{1-\mu^k}[V_b] - \pi_2\left(\frac{\mu^k}{\gamma Var_2^{\mu^k}[V_\pi]} + \frac{1-\mu^k}{\gamma Var_2^{1-\mu^k}[V_\pi]}\right),
\end{aligned}$$

which, using $g^k_{2,V_\pi} = \left(\frac{\mu^k}{\gamma Var_2^{\mu^k}[V_\pi]} + \frac{1-\mu^k}{\gamma Var_2^{1-\mu^k}[V_\pi]}\right)^{-1}$, can be written as:

$$\begin{aligned} \frac{\mu^k g^k_{2,V_\pi}}{\gamma Var_2^{\mu^k}[V_\pi]} E_2^{\mu^k}[V] + \frac{\left(1-\mu^k\right) g^k_{2,V_\pi}}{\gamma Var_2^{1-\mu^k}[V_\pi]} E_2^{1-\mu^k}[V_\pi] &= \pi_2 \\ \frac{\mu^k g^k_{2,V_\pi}}{\gamma Var_2^{\mu^k}[V_\pi]} E_2^{\mu^k}[V] + \left(1 - \frac{\mu^k g^k_{2,V_\pi}}{\gamma Var_2^{\mu^k}[V_\pi]}\right) E_2^{1-\mu^k}[V_\pi] &= \pi_2, \end{aligned}$$

where I used

$$\frac{1-\mu^k}{\gamma Var_2^{1-\mu^k}[V_\pi]} = \frac{\mu^k}{\gamma Var_1^{\mu^k}[V_\pi]} + \frac{1-\mu^k}{\gamma Var_2^{1-\mu^k}[V_\pi]} - \frac{\mu^k}{\gamma Var_1^{\mu^k}[V_\pi]} = \frac{1}{g^k_{2,V_\pi}} - \frac{\mu^k}{\gamma Var_1^{\mu^k}[V_\pi]}.$$

Using $h^k_{2,V_\pi} = \frac{\mu^k g^k_{2,V_\pi}}{\gamma Var_2^{\mu^k}[V_\pi]}$ yields:

$$\begin{aligned} h^k_{2,V_\pi} E_2^{\mu^k}[V_\pi] + \left(1 - h^k_{2,V_\pi}\right) E_2^{1-\mu^k}[V_\pi] &= \pi_2 \\ E_2[V_\pi] &= \pi_2, \end{aligned}$$

where the weighted average expectation is defined as $E_\tau[\cdot] = h^k_{\tau,\cdot} E_\tau^{\mu^k}[\cdot] + \left(1 - h^k_{\tau,\cdot}\right) E_\tau^{1-\mu^k}[\cdot]$. Note that this definition of the expectation operator is internally consistent as

$$g^k_{1,V_\pi} = \left(\frac{\mu^k}{\gamma Var_1^{\mu^k}[V_\pi]} + \frac{1-\mu^k}{\gamma Var_1^{1-\mu^k}[V_\pi]}\right)^{-1} = \gamma Var_1^{\mu^k}[V_\pi] \quad \text{and} \quad h^k_{1,V_\pi} = \frac{\mu^k g_1}{\gamma Var_1^{\mu^k}[V_\pi]} = \mu^k,$$

and hence

$$\begin{aligned} E_1[\cdot] &= h^k_{1,\cdot} E_1^{\mu^k}[\cdot] + \left(1 - h^k_{1,\cdot}\right) E_1^{1-\mu^k}[\cdot] \\ &= \mu^k E_1^{\mu^k}[\cdot] + \left(1 - \mu^k\right) E_1^{1-\mu^k}[\cdot] \\ &= E_1^i[\cdot]. \end{aligned}$$

CPI Release Plugging the expressions for the conditional variances ((A9) and (A10)) into the expression for g_{2,V_π}^{CPI} yields:

$$
\begin{aligned}
g_{2,V_\pi}^{\text{CPI}} &= \left(\frac{\mu^{\text{CPI}}}{\gamma Var_2^{\mu^{\text{CPI}}}\left[V_\pi\right]} + \frac{1-\mu^{\text{CPI}}}{\gamma Var_2^{1-\mu^{\text{CPI}}}\left[V_\pi\right]}\right)^{-1} = \left(\frac{\mu^{\text{CPI}}}{\gamma\left(1-\left(1-\kappa^2\right)\xi^{\text{CPI}}\right)\sigma_\pi^2} + \frac{1-\mu^{\text{CPI}}}{\gamma\sigma_\pi^2}\right)^{-1} \\
&= \gamma\sigma_\pi^2\left(\frac{\mu^{\text{CPI}}}{1-\left(1-\kappa^2\right)\xi^{\text{CPI}}} + \frac{\left(1-\mu^{\text{CPI}}\right)\left(1-\left(1-\kappa^2\right)\xi^{\text{CPI}}\right)}{1-\left(1-\kappa^2\right)\xi^{\text{CPI}}}\right)^{-1} \\
&= \gamma\sigma_\pi^2\left(\frac{\mu^{\text{CPI}}+\left(1-\mu^{\text{CPI}}\right)\left(1-\left(1-\kappa^2\right)\xi^{\text{CPI}}\right)}{1-\left(1-\kappa^2\right)\xi^{\text{CPI}}}\right)^{-1} \\
&= \gamma\sigma_\pi^2\left(\frac{1-\left(1-\kappa^2\right)\xi^{\text{CPI}}}{1-\left(1-\mu^{\text{CPI}}\right)\left(1-\kappa^2\right)\xi^{\text{CPI}}}\right).
\end{aligned}
$$

Subsequently, expression h_{2,V_π}^{CPI} is

$$
h_{2,V_\pi}^{\text{CPI}} = \frac{\mu^{\text{CPI}} g_{2,V_\pi}^{\text{CPI}}}{\gamma Var_2^{\mu^{\text{CPI}}}\left[V_\pi\right]} = \frac{\mu^{\text{CPI}}\gamma\sigma_\pi^2\left(\frac{1-\left(1-\kappa^2\right)\xi^{\text{CPI}}}{1-\left(1-\mu^{\text{CPI}}\right)\left(1-\kappa^2\right)\xi^{\text{CPI}}}\right)}{\gamma\left(1-\left(1-\kappa^2\right)\xi^{\text{CPI}}\right)\sigma_\pi^2} = \frac{\mu^{\text{CPI}}}{1-\left(1-\mu^{\text{CPI}}\right)\left(1-\kappa^2\right)\xi^{\text{CPI}}},
$$

allowing me to write the inflation swap price in terms of the signal:

$$
\begin{aligned}
\pi_2 &= h_{2,V_\pi}^{\text{CPI}} E_2^{\mu^{\text{CPI}}}\left[V_\pi\right] + \left(1-h_{2,V_\pi}^{\text{CPI}}\right) E_2^{1-\mu^{\text{CPI}}}\left[V_\pi\right] \\
\pi_2 &= \frac{\mu^{\text{CPI}}}{1-\left(1-\mu^{\text{CPI}}\right)\left(1-\kappa^2\right)\xi^{\text{CPI}}}\left(1+\kappa\right)\xi^{\text{CPI}}s^{\text{CPI}} + \left(1-\frac{\mu^{\text{CPI}}}{1-\left(1-\mu^{\text{CPI}}\right)\left(1-\kappa^2\right)\xi^{\text{CPI}}}\right)0 \\
\pi_2 &= \frac{\mu^{\text{CPI}}\left(1+\kappa\right)\xi^{\text{CPI}}}{1-\left(1-\mu^{\text{CPI}}\right)\left(1-\kappa^2\right)\xi^{\text{CPI}}}s^{\text{CPI}}.
\end{aligned}
$$

Defining $\Theta(\mu^k,\xi^k) = \frac{\mu^k(1+\kappa)\xi^k}{1-\left(1-\mu^k\right)(1-\kappa^2)\xi^k}$, the equilibrium prices at date 2 are

$$
\pi_2 = \Theta(\mu^{\text{CPI}},\xi^{\text{CPI}})s^{\text{CPI}} \text{ and } b_2 = 1-\phi\Theta(\mu^{\text{CPI}},\xi^{\text{CPI}})s^{\text{CPI}}.
$$

NFP Release Plugging (A11) and (A12) into the expression for g^{NFP}_{2,V_π} yields:

$$\begin{aligned}
g^{\text{NFP}}_{2,V_\pi} &= \left(\frac{\mu^{\text{NFP}}}{\gamma Var_2^{\mu^{\text{NFP}}}\left[V_\pi\right]} + \frac{1-\mu^{\text{NFP}}}{\gamma Var_2^{1-\mu^{\text{NFP}}}\left[V_\pi\right]}\right)^{-1} = \left(\frac{\mu^{\text{NFP}}}{\gamma\left(1-\left(1-\kappa^2\right)\xi^{\text{NFP}}\right)\sigma_\pi^2} + \frac{1-\mu^{\text{NFP}}}{\gamma\sigma_\pi^2}\right)^{-1} \\
&= \gamma\sigma_\pi^2\left(\frac{\mu^{\text{NFP}}}{1-\left(1-\kappa^2\right)\xi^{\text{NFP}}} + \frac{\left(1-\mu^{\text{NFP}}\right)\left(1-\left(1-\kappa^2\right)\xi^{\text{NFP}}\right)}{1-\left(1-\kappa^2\right)\xi^{\text{NFP}}}\right)^{-1} \\
&= \gamma\sigma_\pi^2\left(\frac{\mu^{\text{NFP}} + \left(1-\mu^{\text{NFP}}\right)\left(1-\left(1-\kappa^2\right)\xi^{\text{NFP}}\right)}{1-\left(1-\kappa^2\right)\xi^{\text{NFP}}}\right)^{-1} \\
&= \gamma\sigma_\pi^2\left(\frac{1-\left(1-\kappa^2\right)\xi^{\text{NFP}}}{1-\left(1-\mu^{\text{NFP}}\right)\left(1-\kappa^2\right)\xi^{\text{NFP}}}\right).
\end{aligned}$$

Subsequently, expression h^{NFP}_{2,V_π} can be written as:

$$h^{\text{NFP}}_{2,V_\pi} = \frac{\mu^{\text{NFP}} g^{\text{NFP}}_{2,V_\pi}}{\gamma Var_2^{\mu^{\text{NFP}}}\left[V_\pi\right]} = \frac{\mu^{\text{NFP}}\gamma\sigma_\pi^2\left(\frac{1-\left(1-\kappa^2\right)\xi^{\text{NFP}}}{1-\left(1-\mu^{\text{NFP}}\right)\left(1-\kappa^2\right)\xi^{\text{NFP}}}\right)}{\gamma\left(1-\left(1-\kappa^2\right)\xi^{\text{NFP}}\right)\sigma_\pi^2} = \frac{\mu^{\text{NFP}}}{1-\left(1-\mu^{\text{NFP}}\right)\left(1-\kappa^2\right)\xi^{\text{NFP}}},$$

which allows one to write

$$\begin{aligned}
\pi_2 &= h^{\text{NFP}}_{2,V_\pi} E_2^{\mu^{\text{NFP}}}\left[V_\pi\right] + \left(1-h^{\text{NFP}}_{2,V_\pi}\right) E_2^{1-\mu^{\text{NFP}}}\left[V_\pi\right] \\
\pi_2 &= \frac{\mu^{\text{NFP}}}{1-\left(1-\mu^{\text{NFP}}\right)\left(1-\kappa^2\right)\xi^{\text{NFP}}}\frac{1}{\varrho}\left(1+\kappa\right)\xi^{\text{NFP}} s^{\text{NFP}} + \left(1 - \frac{\mu^{\text{NFP}}}{1-\left(1-\mu^{\text{NFP}}\right)\left(1-\kappa^2\right)\xi^{\text{NFP}}}\right)0 \\
\pi_2 &= \frac{1}{\varrho}\frac{\mu^{\text{NFP}}\left(1+\kappa\right)\xi^{\text{NFP}}}{1-\left(1-\mu^{\text{NFP}}\right)\left(1-\kappa^2\right)\xi^{\text{NFP}}} s^{\text{NFP}}.
\end{aligned}$$

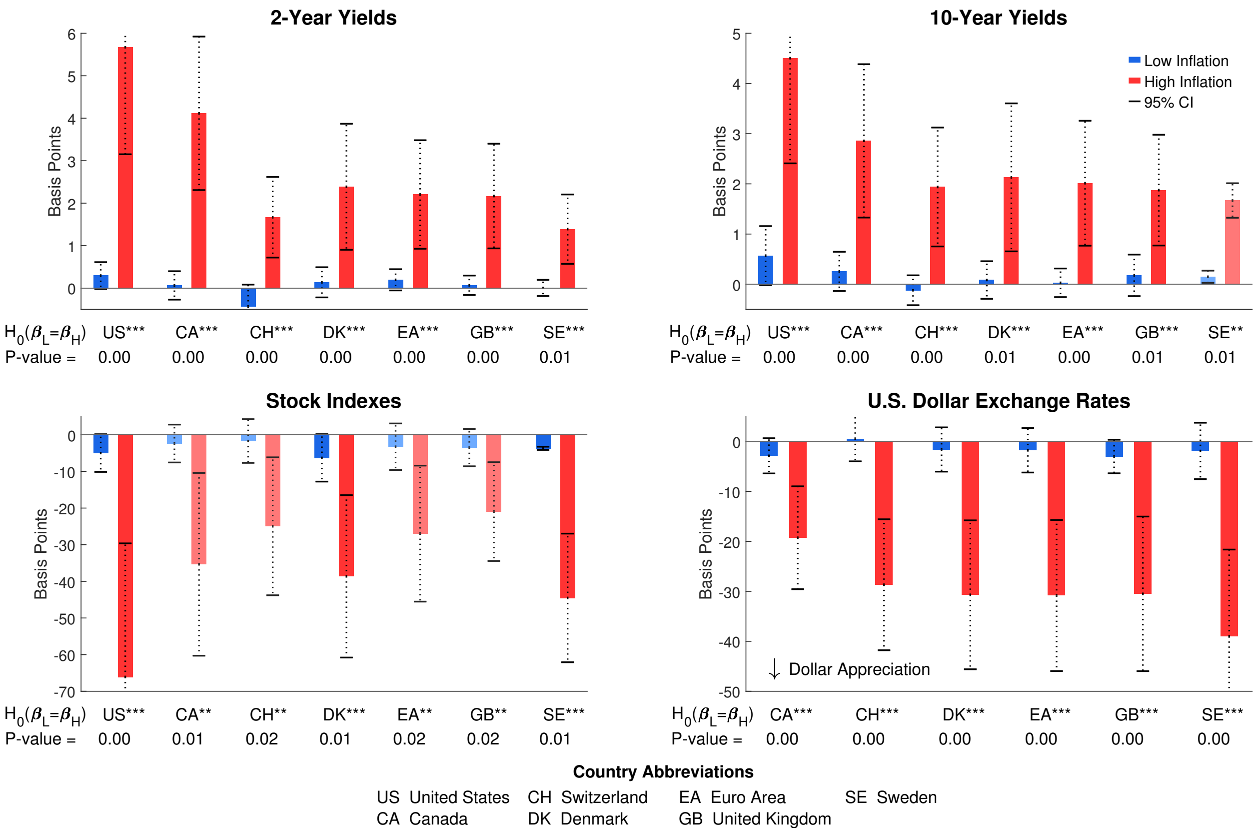
Then, the equilibrium prices at date 2 are

$$\pi_2 = \frac{1}{\varrho}\Theta(\mu^{\text{NFP}}, \xi^{\text{NFP}}) s^{\text{NFP}} \text{ and } b_2 = 1 - \frac{\phi}{\varrho}\Theta(\mu^{\text{NFP}}, \xi^{\text{NFP}}) s^{\text{NFP}}.$$

S2 International Spillovers

In this appendix, I examine whether the increased sensitivity to CPI news extends to the international transmission. To investigate this, I re-estimate equation (4) using a range of international asset prices as the dependent variable. Figure S2.1 presents the results, while Table S2.1 provides an overview of the asset prices used in the analysis.

Figure S2.1: Effects of CPI News on International Markets



Notes: This figure shows the effects of CPI news on international asset prices during the low-inflation period and the high-inflation period. The top-left and top-right panels display the results for various 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 estimates of $\beta_L^{x|k}$ and $\beta_H^{x|k}$ from equation (4) after replacing the left-hand side with the 60-minute change or (log-change) of the corresponding asset price. Blue bars represent the effects during the low-inflation period ($\beta_L^{x|k}$), while red bars represent the effects during the high-inflation period ($\beta_H^{x|k}$). Black error bands show the 95 percent confidence intervals. Darker shades of blue and red correspond to a higher confidence level in rejecting the null hypothesis that $\beta_L^{x|k}$ and $\beta_H^{x|k}$ are equal. The p-value for 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 throughout the analysis. Table S2.1 provides an overview of the employed asset prices.

The top-left and top-right panels of Figure S2.1 present estimates for 2-year and 10-year government yields across various countries, respectively. For reference, I also include the U.S. estimates from the main text. The results indicate a widespread increase in interest rate sensitivity to CPI news, which is both economically and statistically significant. While the effect sizes are generally smaller than in the U.S., they are fairly uniform across countries, except for Canada, where yields exhibit a somewhat stronger response. These findings align with the notion that market participants expect U.S. inflation to spill over internationally, leading central banks to raise policy rates in the near and medium term.

Moving on to stocks, the bottom-left panel of Figure S2.1 presents estimates for major stock

Table S2.1: 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	front-month E-mini S&P 500 futures	ESc1	2009–2023
Canada	front-month 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
U.S. Dollar Exchange Rates			
Canada	Canadian Dollar/U.S. Dollar	CAD=	2009–2023
Switzerland	Swiss Franc/U.S. Dollar	CHF=	2009–2023
Denmark	Danish Krone/U.S. Dollar	DKK=	2009–2023
Euro Area	Euro/U.S. Dollar	EUR=	2009–2023
United Kingdom	British Pound/U.S. Dollar	GBP=	2009–2023
Sweden	Swedish Krona/U.S. Dollar	SEK=	2009–2023

Notes: This table lists the asset prices from *LSEG Tick History* used to study the effects of CPI news on international markets. For all series, the sample period ends in July 2023. *Ticker* refers to the Reuters Instrument Code (RIC). Abbreviations: OIS—Overnight Index Swap.

indexes across countries.[1] Consistent with a dominant interest rate channel, stock prices decline in response to CPI news during both inflation periods. The increase in sensitivity during the high-inflation period is substantial and statistically significant. In terms of magnitude, the largest effect is observed for the U.S., which aligns qualitatively with the findings for interest rates.

Lastly, the bottom-right panel of Figure S2.1 presents results for the U.S. dollar against other major currencies. Consistent with the other findings, I observe a stark increase in sensitivity to CPI news during the high-inflation period. Moreover, in line with the larger rise in U.S. interest rates, the U.S. dollar appreciates during this period. The smaller appreciation against the Canadian dollar and the larger appreciation against the Swedish krona align with the relative interest rate responses. In summary, all four panels demonstrate that sensitivity to CPI releases of international

[1] To be precise, I use log-changes for stocks and exchange rates when they are the dependent variable.

asset prices increased significantly, both economically and statistically.

S3 Time-Varying Coefficient Approach

In this appendix, I investigate the high-frequency effects of CPI news over time. That is, instead of estimating the effects of CPI news across two inflation periods—as done in the main text—I now estimate the time-varying effects of CPI news. To do so, I employ the nonparametric estimation procedure based on Robinson (1989) and Cai (2007).[2] The approach allows estimating time-varying effects in a flexible way, i.e., without taking a stance on the underlying source of the sensitivity change. In particular, I estimate the following specification:

$$x_t = \alpha^{\mathrm{CPI}} + \beta_t^{x|\mathrm{CPI}} s_t^{\mathrm{CPI}} + \varepsilon_t^{\mathrm{CPI}}, \tag{S3.1}$$

where x_t is the 60-minute change in the asset price of interest.

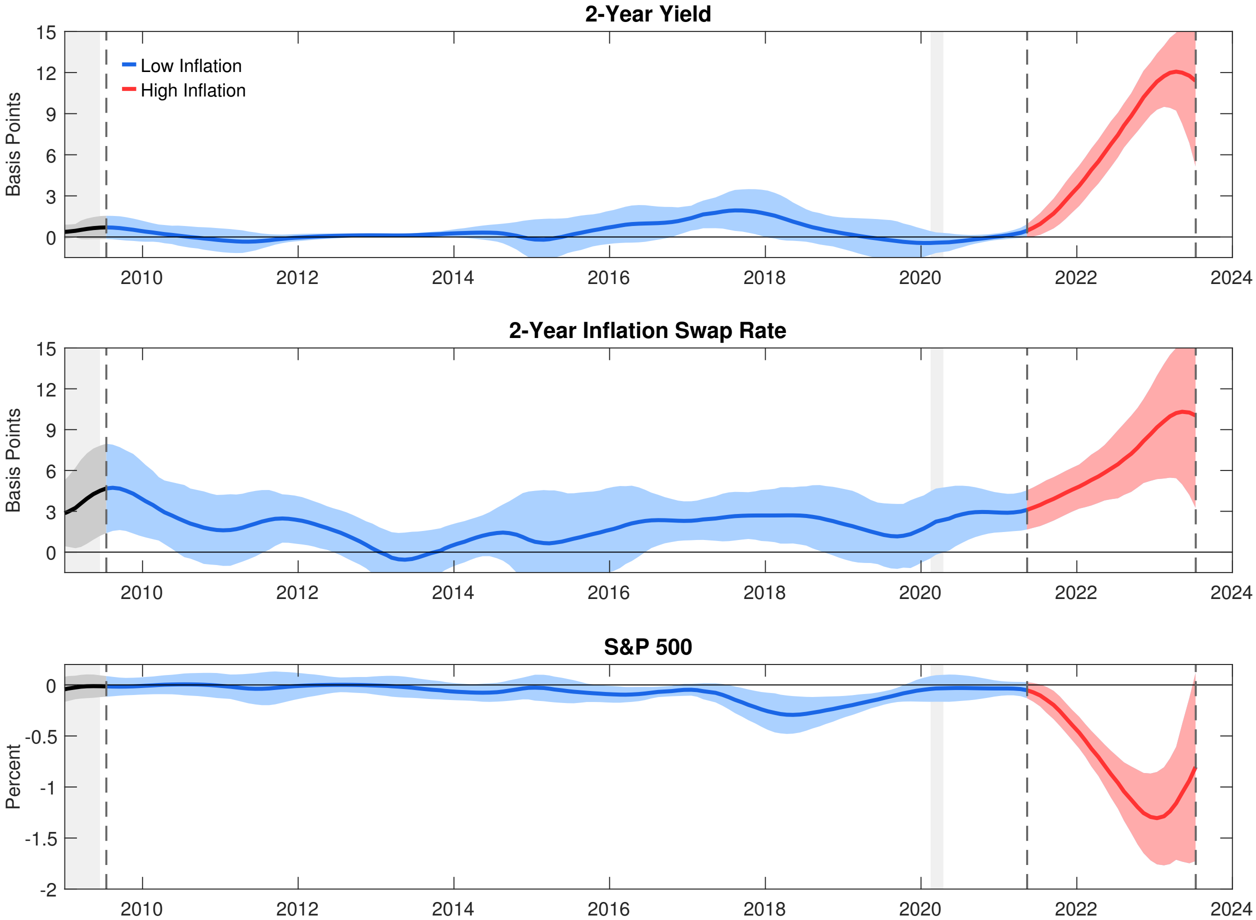
The idea of the estimation procedure is to treat the coefficient as a smooth function of time, i.e., $\beta_t^{x|\mathrm{CPI}} = \beta^{x|\mathrm{CPI}}\left(\frac{t}{T}\right)$, for $t = 1, 2, ..., T$. Hence, $\tau = \frac{t}{T}$ can be seen as the smoothing variable with $\tau \in [0, 1]$. I use the local constant method to estimate $\beta_t^{x|\mathrm{CPI}}$, employing a Gaussian kernel of bandwidth $b = \frac{12}{T}$. This means that the estimation performs a series of weighted least squares regressions around each point $\frac{t}{T}$, where the weights are based on a Gaussian density function with a standard deviation of 12 months (12 observations). Hence, points which are further away are less weighted. Confidence intervals are constructed following the bootstrap procedure by Fan and Zhang (2000) and Chen et al. (2018).[3]

For this analysis, I focus on the 2-year interest rate, the 2-year inflation swap rate, and the S&P 500. As done throughout the main text, the interest rate and the S&P 500 are measured through the corresponding futures contracts. Figure S3.1 shows the estimates for each of the three variables. Consistent with the evidence in the main text, the figure illustrates the increase in sensitivities to CPI news from 2021 onwards—when inflation started rising.

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

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

Figure S3.1: Time-Varying High-Frequency Effects of CPI News



Notes: This figure shows the time-varying high-frequency effects of CPI news on asset prices over the sample period. Estimates of $\beta_t^{x|\mathrm{CPI}}$ from equation (S3.1) are presented for three different dependent variables: the 2-year interest rate, 2-year inflation swap rate, and the S&P 500. 95 percent bootstrap confidence intervals are plotted around the coefficient estimates. Blue and red colors indicate whether the estimates correspond to the low-inflation period or the high-inflation period, respectively. Shaded areas indicate NBER recession periods, and vertical dotted lines mark the inflation periods, as defined in Section 3.1.

S4 Attention Measures based on Google Searches

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

1. For a given topic in Google Trends, I download daily data using a 90-day rolling window starting in January 1, 2009. 90 days is the maximum period 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 downloads. This process results in 91 subsamples, ending in October 2023.

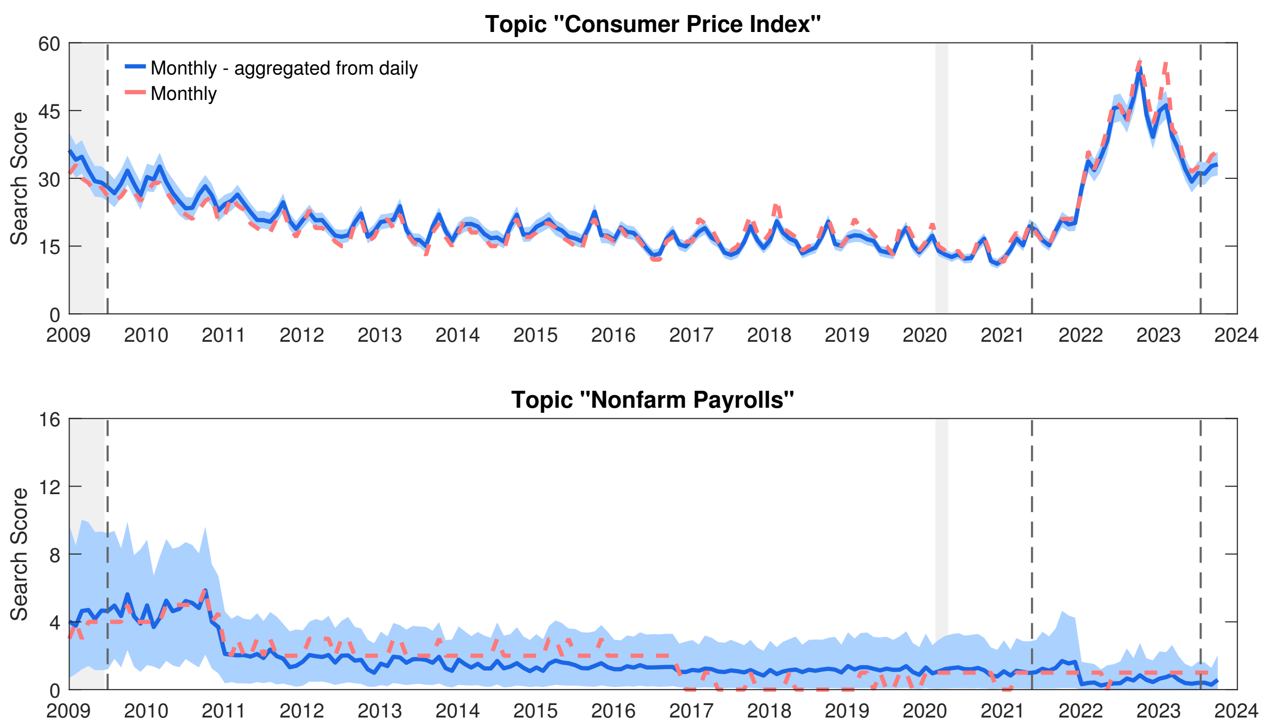
2. I merge the 91 subsamples into a continuous series by minimizing the Euclidean distance

between the overlapping period of two consecutive subsamples.

3. To reduce sampling noise, steps 1 and 2 are repeated 50 times. That is, for each topic I obtain 50 daily series of search scores. For my analysis, I use the median series, i.e., the median search score of a given day.

4. As Google Trends provides search scores in relative units, I need to make the daily series comparable across topics. To do so, I jointly download the search scores of all topics at the monthly frequency over the sample period. This enables rescaling all daily series to a common unit, minimizing the Euclidean distance between the monthly series and the daily series aggregated to the monthly level. Finally, I rescale all daily series such that 100 corresponds to the largest observation for topic "Consumer Price Index." As before, I repeat the joint monthly download 50 times and use the median of that series for the rescaling.

Figure S4.1: Comparison of Monthly Time Series of Google Search Scores



Notes: This figure shows the monthly time series of the search scores for the topics "Consumer Price Index" and "Nonfarm Payrolls" 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. Shaded areas indicate NBER recession periods, and vertical dotted lines mark the inflation periods, as defined in Section 3.1.

Figure S4.1 plots the monthly averages of the constructed daily Google search scores for topics "Consumer Price Index" and "Nonfarm Payrolls". It also shows the corresponding monthly series used for rescaling. As the figure illustrates, the series are close to each other for both topics.

This alignment confirms that the daily series preserve the monthly properties of the original data, validating the construction approach.

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