What Can Cross-Sectional Stocks Tell Us About Core Inflation Shocks?

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Abstract

We document an information channel for core inflation shocks in the relative pricing of cross-sectional stocks. We estimate stock-level core inflation exposures using an announcement-day approach, as, unlike the energy component, the release of the core component is concentrated on CPI announcement days. We find: 1) significant and persistent cross-sectional spread in core inflation exposure; 2) firms with positive inflation exposure later experience increased cash flow as inflation rises; and 3) the relative pricing of stocks with diverging core inflation exposures significantly predicts core inflation shocks and the economists' forecasting errors. The predictability is especially strong under heightened inflation risk, including the surges in 2021 and 1973, and when the Fed is behind the curve. Our overall results indicate active price discovery in cross-sectional stocks for core inflation shocks through the cash flow channel.

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1 Introduction

Understanding the relationship between stock returns and inflation has long been a topic of interest in financial economics. While prior research has predominantly focused on the aggregate stock market, the information content of cross-sectional stocks has been less studied.[1] In this paper, we study the extent to which the information contained in cross-sectional stocks can tell us about inflation shocks. Specifically, with respect to inflation exposure, how does the impact of inflation vary across firms and what drives this cross-sectional variation? With respect to inflation forecasting, can the relative pricing between stocks with high- and low-inflation exposure serve as an effective aggregator of investors' expectations of future inflation? If so, when is this information within the stock market most effective?

Our focus on inflation forecasting from cross-sectional stocks is motivated by the 2021 inflation surge, which was missed by the policymakers setting the U.S. monetary policy, and the economists contributing to the survey-based inflation forecasts.[2] As both policymakers and economists form their expectations by using the information available to them at the time, the 2021 experience highlights the need for alternative measures, potentially from financial markets, to enrich the existing forecasting tools. Relative to the Treasury bond market, whose yield curves have been widely used to forecast inflation, cross-sectional stocks can add value, especially when U.S. Treasury bond pricing is affected by non-inflationary factors like monetary policy expectations and flight-to-safety.[3] Relative to the commodity market, which contains rich information about energy prices, cross-sectional stocks can be more informative with respect to core inflation, both in terms of exposure and forecasting.

Relative to the aggregate stock market, our focus on the relative pricing between stocks with high and low inflation exposure allows us to shift away from the overall equity-market trends, which can also be influenced by expectations of monetary policy, and zero in on the inflation expectations contained in the cross-section. To the extent that stock-level inflation

[1] Fama and Schwert (1977) demonstrates that the aggregate stock market poorly hedges against inflation, and more recently, Fang et al. (2024) highlight the negative impact of core inflation on stock returns. Unlike Chen, Roll, and Ross (1986) and Boons et al. (2020), who study the inflation risk premium using cross-sectional stocks, we focus on the informational role of individual stocks in discovering inflation news.

[2] During the most consequential months of 2021, the Bloomberg economists' forecasts missed the rapid ascent of the core CPI, month-over-month, by 60 bps in April, 20 bps in May, and 50 bps in June.

[3] The illiquidity of the market for TIPS can also add noise to break-even inflation forecasts.

exposures are persistent over time and vary across firms, this cross-sectional approach allows us to harness the active price discovery that takes place in the equity market with respect to future inflation. This informational channel is akin to the seminal paper of Roll (1984), which examines the market's information processing ability by relating orange-juice futures price changes with subsequent errors in temperature forecasts issued by the National Weather Service.

To further illustrate this information channel, we build a simple stock valuation model with two important ingredients – 1) heterogeneous exposures b_i of firms' cash flows to inflation shocks; 2) a predictable component y in inflation shocks unique only to the stock market investors. As stock prices are the present values of future cash flows, such investors' estimates of the future cash flows are incorporated into the cross-sectional market prices. For a given positive shock in the predictable component y (e.g., the 2021 inflation surge), stocks with positive b_i would experience a positive price increase relative to those with negative b_i. Conversely, the difference in their market pricing contains information about the predictable component y, establishing the mechanism of inflation forecasting from cross-sectional stocks.[4] In contrast, fixed-income securities such as government bonds have fixed cash flows, and this channel of predictability is absent.

Cross-Sectional Inflation Exposure – One important implication of our illustrative model is that the cross-sectional variation in cash flow exposure b_i can be mapped into the cross-sectional variation in return exposure β_i. To empirically estimate the extent to which inflation expectations affect the pricing of individual stocks, we use two approaches. First, following the standard approach of Chen, Roll, and Ross (1986) and Boons et al. (2020), we estimate the full-month beta, β_i^{Full}, by regressing monthly stock returns on the contemporaneous-month inflation innovations. Second, we introduce an information-based announcement-day beta, β_i^{Ann}, estimated by regressing stock returns on the day of inflation announcements against inflation innovations.[5]

[4]Cross-sectional variation of cash flows to inflation exposure is suggested and studied by Fama (1981) and Boudoukh, Richardson, and Whitelaw (1994). These studies focus on the predictability of stock returns via expected inflation. We focus on the predictability of inflation via cross-sectional differences in realized stock returns, which arise from the heterogeneous exposure of firm-level cash flows to inflation shocks.

[5]Following Boons et al. (2020), we estimate inflation innovation using an ARMA(1,1) time series model, allowing us to trace the inflation exposure of securities back to the 1970s. Our estimation of inflation betas is robust to both survey-based and market-based measures of inflation surprises.

Both measures can effectively differentiate cross-sectional inflation exposure, though they vary in their informational content. Since components of the headline CPI, such as food and energy, are continuously and contemporaneously observable through commodity prices, the full-month inflation beta is most effective in capturing headline CPI exposure. Conversely, because core CPI components, such as goods and services, are not readily observable in real-time, it often leads to surprises on CPI announcement days. Consequently, the announcement-day beta is more effective in capturing core CPI exposure.[6] For this reason, we apply the full-month approach to headline CPI and the announcement-day approach to core CPI, referring to them as β^{Head} and β^{Core}, respectively.

We sort stocks into quintiles based on their pre-ranking beta, estimated using a 60-month rolling window, and form a monthly rebalanced top-minus-bottom quintile inflation portfolio (IP). The core-focused portfolio, IP^{Core}, is constructed using the announcement and core-focused β^{Core}, while the headline-focused inflation portfolio, IP^{Head}, is constructed using the full-month and headline-focused β^{Head}. Unlike the aggregate stock market, which typically exhibits a negative and unstable inflation exposure (Fama and Schwert (1977)), the long-short inflation portfolio can better capture cross-firm variations by isolating the aggregate component. Importantly, the post-ranking betas for the inflation portfolios are significantly positive – IP^{Core} responds significantly and positively to core-CPI shocks on announcement days. This indicates that not only is there substantial cross-sectional variation in firms' inflation exposure, but also that such variations are persistent over time.

The Cash Flow Mechanism – To demonstrate that the returns of the inflation portfolio, particularly IP^{Core}, are driven by the impact of inflation on firm cash flows – a central component of our illustrative model – we present the following evidence: First, we show that firms with higher β_i^{Core} also have a higher cash flow beta b_i, meaning their quarterly cash flows increase with positive inflation shocks. This indicates a significant alignment between the return-based inflation beta and the cash flow-based inflation beta.[7]

Second, we demonstrate that firms with more positive β^{Core} tend to experience better

[6]When estimating inflation betas for both Treasury bonds and commodity markets, we observe a similar pattern: inflation-sensitive securities tend to move with headline CPI during the contemporaneous month and respond to core CPI on announcement days.

[7]Consistent with existing literature, firms with higher β^{Core} tend to have shorter cash flow duration and more immediate cash flows (e.g., higher dividend payouts). In contrast, firms with lower β^{Core} are more likely to be growth firms.

sales growth and stronger cash flows over the subsequent quarter after observing a high IP^{Core}. Analysts also update their beliefs upward about these firms' long-term growth in response to increased inflation expectations. Specifically, a one standard deviation increase in inflation expectation, as captured by IP^{Core}, predicts a 3.2% standard deviation increase in cash flow over the next quarter for firms in the top β^{Core} quintile relative to those in the bottom quintile. This evidence highlights the channel through which inflation shocks can have a heterogeneous impact on firms' future cash flows, forming the basis for active price discovery of inflation news among cross-sectional stocks.

Finally, we do not find empirical support for the risk premium channel. In particular, IP^{Core} neither predicts firms' subsequent returns nor is driven by a time-varying inflation risk premium. Unlike the full-month headline-beta sorted IP^{Head}, which shows a significant negative risk premium in the pre-2002 period (Boons et al. (2020)), the returns of IP^{Core} are insignificant both before and after 2002. This suggests that the full-month headline beta is more effective at capturing the inflation risk premium, while for the purpose of identifying inflation shocks, the information-based announcement-day beta is more effective.

Inflation Forecasting with IP Portfolios – Using the inflation portfolio for inflation forecasting, we document significant and non-redundant information from IP^{Core} in predicting core-CPI shocks, consistent with the model's implications. Specifically, a one standard deviation increase in IP^{Core} observed at the end of month t predicts a 2.2 bps (t-stat=2.98) increase in core-CPI innovations and a 7.9 bps increase (t-stat=6.54) in headline-CPI innovations for month $t+1$. Given that the standard deviations of core- and headline-CPI innovations are 16 bps and 26 bps, respectively, such a magnitude of predictability is noteworthy. In contrast, while the risk-based and full-month constructed IP^{Head} can capture the time-varying inflation risk premium, it fails to predict core-CPI movements.

We further compare the information content of IP^{Core} against the two market-based forecasts known for reflecting inflation expectations – the commodity return of the Goldman Sachs Commodity Index (GSCI) and the break-even inflation return between real and nominal U.S. Treasury bonds (TIPS-UST)[8] – we find that although these forecasts can effectively predict headline inflation innovations, they are considerably less effective at forecasting core

[8]The break-even inflation return, TIPS-UST, is constructed by taking a long position in Treasury Inflation-Protected Securities (TIPS), which are neutral to inflation, and a short position in nominal U.S. Treasury bonds (UST), which are negatively impacted by inflation.

inflation. When used jointly to predict core CPI, IP^{Core} is the only forecaster that significantly predicts core-CPI movements. Given the outsized influence of core CPI on the Fed's monetary policy, forecasting core inflation is of enormous importance, and this is where the inflation expectations captured by our IP^{Core} can be most beneficial.

Additionally, using IP^{Core} to predict economists' forecasting errors, we find similar evidence. Between the observation of our inflation forecast at the end of month t and the announcement of the month-$t+1$ CPI around mid-month $t+2$, more than a month elapses. Despite being available over a month in advance, economists fail to sufficiently integrate the information from IP^{Core} into their forecasts, such that IP^{Core} can predict the announcement-day errors made by economists above and beyond other market-based predictors. In particular, a one standard deviation increase in IP^{Core} predicts a 2.3 bps (t-stat=3.10) and 3.8 bps (t-stat=4.22) increase in core and headline CPI surprises, respectively. As the respective CPI surprises have standard deviations of 11 bps and 13 bps, the information from cross-sectional stocks is non-trivial, suggesting that economists could enhance their forecasting accuracy by integrating information from IP^{Core}.[9]

When is Our IP Core More Informative? – To better understand the information channel driving the predictability of IP^{Core}, we explore its cross-sectional heterogeneity and time-varying informativeness. First, we show that IP^{Core} exhibits stronger predictive power when constructed from firms with better information environments, such as larger firms, those with greater analyst coverage, and higher institutional ownership. This is because when investors have limited capacity or face constraints on arbitrage, inflation expectations may not be quickly incorporated into individual stock prices. Consequently, we observe more pronounced price discovery in firms with superior information environments.

Second, in our analysis of time-varying predictability, we show that IP^{Core} becomes increasingly informative during periods when inflation poses a significant risk and when there is heightened disagreement about inflation. The inflation surges of 2021 and 1973 serve as prime examples: During the early stages of the 2021 inflation surge, which are largely overlooked by economists and policy makers,[10] IP^{Core} effectively issued a series of alerts.

[9]The predictability of IP^{Core} remains robust when applied to forecasting quarterly inflation growth and movements in inflation swap rates.

[10]Throughout 2021 and into March 2022, the Fed maintained a zero interest-rate policy, pivoting only in March 2022 and tightening aggressively since June 2022.

Over the 24 months from October 2020 to the peak of core CPI in September 2022, the predictability of IP^{Core} increases with an R-squared of 17.7%. When using the market-based predictors, including IP^{Core}, TIPS-UST, and GSCI, to jointly forecast core CPI during this period, IP^{Core} emerges as the sole significant predictor, dominating others in both economic and statistical significance.

The 1973 inflation surge offers a compelling parallel to the 2021 experience. Tracking IP^{Core}'s performance during the 24 months leading up to the core-CPI peak from May 1973 to April 1975, we observe a similar pattern: IP^{Core} significantly predicts core-CPI innovations with a substantially improved R-squared of 28.4% and an economic magnitude of 19.5 bps (t-stat=3.43). Similar to the 2021-22 case, this enhanced predictability is captured exclusively by our core-focused inflation portfolio, rather than by the Treasury or commodity markets. These instances suggest that the effectiveness of inflation forecasting varies over time. Our IP^{Core} provides the most timely and valuable information during the initial stages of inflation surges, making it particularly useful for policymakers and economists trying to forecast core inflation shocks.

Further exploring the time-varying predictability, we show that the informativeness of IP^{Core} is stronger when the Fed is "behind the curve", as measured by the gap between the Fed funds rate and the rate recommended by the Taylor rule. Specifically, the predictability of IP^{Core} during periods when the Fed is behind the curve is twice as strong compared to other times. This suggests that a higher-than-usual signal from cross-sectional stocks does not automatically translate into sustained increases in core inflation, as seen in the inflationary episodes of 2021 and 1973. When the Fed is ahead of the curve, actively adjusting monetary policy fighting against price pressures, inflation can be effectively contained, resulting in much muted predictability from IP^{Core}. Conversely, when the Fed falls behind the curve, allowing inflation to escalate unchecked, the predictability of IP^{Core} strengthens.

Lastly, we demonstrate that the predictability of IP^{Core} on inflation shocks remains robust out-of-sample. When benchmarked against the ARMA (1,1) time-series model, IP^{Core} enhances the forecasting accuracy of core-CPI growth by approximately 4-6%, outperforming all other predictors we tested, including signals from commodity and treasury markets, household and economist surveys, and macroeconomic variables.[11] Moreover, the out-of-

[11] For predicting headline CPI out-of-sample, the RMSE improvement ranges from 7-11%.

sample predictive power is particularly strong during the 2021 inflation episode, periods of above-median inflation uncertainty, and when the Fed lags behind the curve.

Related Literature: We contribute first and foremost to the literature on inflation forecasting. Studies by Ang, Bekaert, and Wei (2007) and Faust and Wright (2013) show that the economists' surveys are the most accurate predictors of future inflation, outperforming all market-based measures they examined. Through the construction of inflation portfolio, we show that the information embedded in cross-sectional stock returns can significantly predict both inflation shocks and economists' forecasting errors, for both core and headline CPI. This is especially relevant during the early stages of inflation surges when forecasters are slow to respond.[12]

Titman and Warga (1989) and Downing, Longstaff, and Rierson (2012) explore the forecasting ability of aggregate stock market and industry portfolios on inflation. We extend this line of research by demonstrating that our cross-sectional approach can minimize the influence of the aggregate market, which is often shaped by expectations of monetary policy. For the purpose of capturing inflation exposure and forecasting inflation, dynamically sorting individual stocks based on their inflation sensitivities into an inflation portfolio proves to be a more effective strategy. This is particularly important as new technologies alter the inflation exposure of certain industries, making a dynamic and stock-specific approach more adaptable to changing economic environments.

Our paper also contributes to the literature on measuring inflation exposure by introducing the announcement-day approach to capture core inflation shocks. Traditionally, inflation exposure is estimated by examining the sensitivity of monthly stock returns to headline inflation innovations, as in Chen, Roll, and Ross (1986), Boons et al. (2020), and Chaudhary and Marrow (2024). Additionally, Bekaert and Wang (2010), Ang, Brière, and Signori (2012), and Boudoukh, Richardson, and Whitelaw (1994) have shown that inflation betas, estimated using the traditional approach, vary significantly across industries and over time.[13] Methodologically, we contribute by proposing two distinct approaches for estimating headline and

[12]TIPS and inflation swaps are only available for recent periods. This limitation is particularly pronounced in emerging markets, where tools like surveys and inflation-linked assets are often unavailable or underdeveloped. In these contexts, our cross-sectional stock-based approach becomes especially valuable.

[13]Gil de Rubio Cruz et al. (2023) also examine announcement-day inflation exposure, though their focus is on its relationship with firm characteristics.

core inflation exposures. We demonstrate that, for identifying firms' core inflation exposure, the information-based announcement-day beta is more effective.

The differential pricing impact of core versus headline inflation has been explored recently in Ajello, Benzoni, and Chyruk (2020), who focus on the Treasury yield curve, and in Fang, Liu, and Roussanov (2024), who examine aggregate asset classes. Consistent with Fang, Liu, and Roussanov (2024), we find that negative inflation exposure is generally more pronounced for core CPI than for headline CPI. Unlike their focus on the aggregate stock market, we show that to differentiate stocks by their relative inflation exposure, the full-month β^{Full} is more effective for headline CPI, while the announcement-day β^{Ann} is more effective for core CPI.

Finally, our paper contributes to the emerging literature inspired by the post-pandemic inflation surge.[14] Focusing on belief formation, Bianchi, Ludvigson, and Ma (2024) and Weber, Gorodnichenko, and Coibion (2023) use machine learning techniques and household data to examine inflation expectations. On the supply and demand dynamics of inflation, Feng et al. (2024) assess the predictability of supply-chain inflation on stock returns, while Cieslak, Li, and Pflueger (2024) explore its connection to the Treasury convenience yield. Regarding monetary policy, Andrei and Hasler (2023) examine the Fed's ability to control inflation, emphasizing the learning effect in shaping financial market expectation. In terms of firm-level impacts, Bhamra et al. (2023) and Bonelli, Palazzo, and Yamarthy (2024) study how inflation affects firm default risk and credit spreads. Our contribution lies in documenting the impact of inflation on firm cash flows and highlighting the forward-looking nature of financial assets in detecting inflation shocks during the 2021 surge.

The rest of our paper is organized as follows. Section 2 and 3 describes the data and methodology for inflation beta estimation. Section 4 introduces the model and the cash flow mechanism related to predictability. Section 5 examines the ability of inflation portfolios to predict inflation shocks and economists' forecasting errors. Section 6 discusses robustness checks and additional tests, and Section 7 concludes.

[14]Cieslak and Pflueger (2023) provide a review of the time-varying impact of inflation on the economy.

2 Data

We obtain monthly inflation data, including Headline, Core, and Energy CPI from the U.S. Bureau of Labor Statistics (BLS).[15] The CPI announcement dates are also collected from the BLS. Following Chen, Roll, and Ross (1986), Ang, Bekaert, and Wei (2007), Bekaert and Wang (2010), CPI growth is defined as the difference in the natural logarithm of monthly CPI: $\pi_t = \ln(P_t) - \ln(P_{t-1})$, where P_t is the level of CPI for month t. For each type of CPI series, CPI innovation is constructed using the ARMA(1,1) time series model, following Fama and Gibbons (1984), Ang, Bekaert, and Wei (2007), and Boons et al. (2020). The ARMA(1,1) model is estimated by maximum likelihood with the following specification:

$$\pi_t = \mu + \phi\pi_{t-1} + \varphi\varepsilon_{t-1} + \varepsilon_t. \tag{1}$$

To avoid look-ahead bias, following Ang, Bekaert, and Wei (2007), we estimate the ARMA(1,1) model using all the historical observations up to and including month t. We then use the estimated coefficients to forecast the month $t+1$ inflation growth, denoted by $\widehat{\pi_{t+1}}$, and the CPI innovation for month $t+1$ is calculated as the actual inflation growth minus the forecasted growth:

$$\text{CPI-Innov}_{t+1} = \pi_{t+1} - \widehat{\pi_{t+1}}\,, \tag{2}$$

where we require at least ten years of observations to estimate $\widehat{\pi_{t+1}}$. Since data on core CPI starts after 1957, the sample on CPI innovations starts from 1967.

Appendix Table IA1 reports the summary statistics for CPI innovations. Headline-CPI innovation has a mean of -0.01 bps with a standard deviation (STD) of 26 bps, and core-CPI innovation has a mean of -0.07 bps with a STD of 16 bps. The close-to-zero average value of CPI innovations suggests that the ARMA(1,1) model does a good job of capturing the overall inflation pattern. Consistent with the intuition that core CPI, which excludes food and energy components, is generally more persistent than its non-core counterparts, the standard deviation of core CPI is smaller than that of headline CPI. We also use economists' forecasting errors, constructed as the actual monthly CPI growth value minus the median

[15] The BLS CPI data series include: Headline (CPIAUCSL), Core (CPILFESL), and Energy (CPIENGSL).

forecast by Bloomberg economists, to capture surprises in CPI announcements. The headline forecasting error on average is 0.1 bps with a STD of 13 bps, and the core forecasting error is on average -0.23 bps with a STD of 10.9 bps.

Data on cross-sectional stocks are obtained from the Center for Research in Security Prices (CRSP), and accounting information is from Compustat. We include all common stocks traded on the NYSE, Amex, and NASDAQ. Stock returns are adjusted for delisting (Shumway (1997)), setting a -30% return if performance-related delisting data is missing. The CRSP value-weighted market return (VWRETD) serves as the aggregate stock market return, with the one-month T-bill return as the risk-free rate, sourced from Kenneth French's website. To capture bond market dynamics, we use 2-year and 10-year U.S. Treasury yields from the Federal Reserve Bank of St. Louis. As Treasury Inflation-Protected Securities (TIPS) provide a natural hedge against headline inflation, we use the return difference between the Bloomberg U.S. Treasury Inflation Notes Total Return Index (TIPS, average maturity of 7.8 years) and the Bloomberg U.S. Treasury Total Return Index (UST, average maturity of 7.2 years) to capture the real-nominal bond return difference. Since data on daily TIPS returns are only available after May 1998, our sample starts from 1998 when TIPS are included as a control variable. To capture commodity market performance, we use the Goldman Sachs Commodity Index return (GSCI).[16]

3 Measuring Inflation Exposure

In this section, we explain how we estimate the inflation beta for stocks and assets, highlighting the differences between the announcement-day and full-month approaches.

3.1 Methodology: Announcement Day vs. Full Month

Financial markets incorporate inflation-related news not only throughout the month as inflation data is realized but also on the CPI announcement day, when unexpected inflation figures can have a significant impact on the market. Traditionally, studies such as Chen, Roll, and Ross (1986), Boons et al. (2020), and Fang, Liu, and Roussanov (2024) measure

[16] Goldman Sachs launched GSCI in April 1991. Information prior to the launch date is hypothetically back-tested by Goldman Sachs based on the index methodology at the launch date.

inflation beta by assessing the sensitivity of security returns to contemporaneous-month CPI innovations. Given that announcement days contain rich information about unexpected inflation shocks, using a narrow window to identify a security's inflation exposure could shed additional light on how inflation influences asset prices.

We therefore use two approaches to estimate securities' inflation exposure. The announcement-day inflation beta is constructed by regressing securities' announcement-day excess returns on the announcement-day CPI innovations. To capture the varying sensitivity of core and non-core components of CPI on asset prices, we estimate the inflation betas using core, headline, and energy CPI innovations with the following regression model:

$$R_{i,A_t} = \alpha_i + \beta_i^{\text{Ann}}\,\text{CPI-Innov}_{A_t} + \varepsilon_{i,A_t}, \tag{3}$$

where A_t denotes the CPI announcement day, R_{i,A_t} is the excess return of security i on the announcement day A_t, and CPI-Innov_{A_t}, as defined in Equation (2), captures the CPI innovation released on the announcement day A_t. The announcement-day inflation beta, β_i^{Ann}, captures the sensitivity of security i to inflation shocks on the CPI announcement days.

The full-month inflation beta is constructed by regressing securities' monthly excess returns on contemporaneous-month CPI innovations, following the methodology in Chen, Roll, and Ross (1986), Boons et al. (2020), and Fang, Liu, and Roussanov (2024):

$$R_{i,t} = \alpha_i + \beta_i^{\text{Full}}\,\text{CPI-Innov}_t + \varepsilon_{i,t}, \tag{4}$$

where t denotes the calendar month, and $R_{i,t}$ denotes security i's excess return in month t.[17]

3.2 Inflation Exposures in Cross-Sectional Stocks

Following equations (3) and (4), we begin by constructing pre-ranking inflation betas for individual stocks using a rolling five-year window for estimation. The timeline for this beta estimation process is detailed in Section I of the Internet Appendix. After each CPI

[17] We follow Boons et al. (2020) and Ang, Bekaert, and Wei (2007) by using an ARMA(1,1) time series model to measure inflation innovation, which enables us to track the inflation exposure of securities back to the 1970s. Our estimates of inflation betas and the results remain robust when using survey-based and market-based inflation surprise measures from the 1990s, as discussed in detail in Section 6.4.

announcement, denoted as A_t, we estimate the announcement-day inflation beta for firm i using data from announcement A_{t-59} to announcement A_t, requiring at least 24 months of data out of the last 60 months available. Similarly, we estimate the full-month beta, β^{Full}, using monthly stock returns and inflation innovations from month M_{t-59} to month M_t. Since CPI innovation data is available starting from 1967, and given the five-year estimation periods, the individual stocks' CPI beta estimates begin in 1972.[18]

For each individual stock and on each announcement day A_t, we estimate the announcement-day and full-month (pre-ranking) inflation betas using different components of inflation innovations (core, headline, energy). We then form 2×5 equal-weighted portfolios by two-way sorting all stocks into five inflation beta quintiles within each of the two size groups. The two size groups are defined by the 50th percentile of NYSE market capitalization at the end of the previous month, following Fama and French (1993). These portfolios are held until the next CPI announcement day A_{t+1}, at which point the new CPI value is released, allowing us to update the estimates of inflation exposure.

Table 1 presents the post-ranking inflation betas for stock portfolios sorted according to their pre-ranking inflation betas, with the two size groups combined.[19] Consistent with Fang, Liu, and Roussanov (2024), the core-inflation betas of individual stocks are significantly more negative than their headline betas. Additionally, we observe significant and persistent cross-sectional variations in firms' core-CPI betas on CPI announcement days, but not for headline-CPI and energy-CPI betas. A one standard deviation increase in core-CPI innovation negatively affects the bottom quintile of core beta-sorted stocks by -14.7 bps (t-stat=3.23) on the CPI announcement days. Conversely, similar increases in headline- and energy-CPI innovations result in a positive and negligible effect on stocks' announcement-day returns.

As our focus is on the cross-sectional dispersion in individual stocks' inflation exposure, Panel B of Table 1 provides the beta estimates while controlling for the aggregate stock market return, i.e., controlling for announcement-day market return and full-month market

[18] Appendix Figure IA1 shows that the estimation of individual stocks' inflation beta is highly persistent. For a stock in the top (bottom) quintile sorted based on month-t inflation beta, the probability of it remaining in the same quintile is 76% and 74% after 6 months.

[19] For each inflation beta, the reported post-ranking betas correspond specifically to the type of beta used for sorting the portfolios.

return in the estimation of β^{Ann} and β^{Full}, respectively. By removing the negative inflation exposure at the market level, the inflation estimates become generally less negative. Still, we observe significant dispersion in cross-sectional stocks' post-ranking announcement-based core-inflation beta. The row labeled "Quintile 5-1" refers to an inflation portfolio constructed with a long position in the top quintile (most positive inflation beta stocks) and a short position in the bottom quintile (most negative inflation beta stocks). A one standard deviation increase in announcement-day core innovation leads to a 4.6 bps (t-stat=2.49) return increase in the core beta-sorted portfolio, while such dispersion is absent for headline and energy beta-sorted portfolios on CPI announcement days. This suggests significant cross-sectional variations in firms' core-inflation exposure: firms that exhibit strong sensitivity to core-CPI shocks on past announcement days continue to respond significantly to core shocks in future announcements.

The full-month inflation betas, in contrast, show significant and persistent sensitivity to headline inflation, primarily driven by the energy component, but not to the core component. For instance, focusing on the inflation beta estimated while controlling for the market returns, the post-ranking headline beta increases monotonically from -1.5 bps for the quintile stocks with the most negative pre-ranking headline beta to 40.8 bps for those with the most positive pre-ranking headline beta. The full-month inflation exposure for the top-minus-bottom quintile portfolios, sorted based on their respective pre-ranking inflation betas, is 3.9 bps (t-stat=0.35) for core inflation, 42.3 bps (t-stat=2.96) for headline inflation, and 37 bps (t-stat=2.23) for energy inflation.[20]

Overall, the cross-sectional analysis of stocks' inflation exposure indicates persistent variations in inflation exposure across firms. The information-based announcement-day approach is most effective in capturing core-inflation exposure, while the contemporaneous-month approach excels in capturing headline exposure. This contrast aligns with the intuition that non-core inflation components, such as energy and food, are easily observable and can be hedged with commodity instruments as investors encounter inflation throughout the month. Conversely, core components, like goods and services, are not readily observable and tend to result in larger surprises on CPI announcement days. Therefore, we refer to the

[20]The β^{Full} is inherently larger in magnitude because it is estimated using monthly returns, whereas β^{Ann} is estimated using the daily returns of announcement days.

announcement-day estimated core beta as β^{Core} and the full-month estimated headline beta as β^{Head} for short in our subsequent analyses.

3.3 Inflation Exposures Across Asset Classes

When estimating the inflation exposure for a variety of inflation-sensitive assets, we consistently observe a contrast between inflation betas constructed on announcement days and those constructed over full months. In particular, we estimate equations (3) and (4) for each asset using observations from the entire sample. To ensure comparability across asset classes, all variables – both dependent and independent – are standardized to have a mean of zero and a standard deviation of one during the beta estimations.

Focusing first on announcement days, Table 2 shows that core-inflation shocks have a significantly positive impact on inflation-sensitive instruments, including nominal yields, the spread between real and nominal bond returns, and commodities. In contrast, the effects of headline and energy shocks on asset prices are minimal on these days. Specifically, nominal yields rise significantly in response to announcement-day core inflation shocks. The TIPS-UST return spread, which reflects the return associated with break-even inflation by isolating the real component, responds even more strongly to core innovations announced on CPI days. A one standard deviation increase in core innovations leads to a 22% (t-stat = 4.09) standard deviation increase in TIPS-UST.

On the other hand, consistent with the pattern observed in cross-sectional stocks, asset returns during the contemporaneous month are more sensitive to headline-CPI innovations, primarily driven by the energy component, and less sensitive to core-CPI innovations. For instance, a one standard deviation increase in headline innovation leads to a 31% (t-stat = 2.87) standard deviation increase in the TIPS-UST during the CPI month. In contrast, the same increase in core-CPI innovation leads to only a 5% (t-stat = 0.70) standard deviation increase.

The last two rows of Table 2 present the beta estimates for the aggregate stock market, along with the inflation betas estimated for the long-short portfolio formed from the cross-section of stocks (IP portfolio).[21] Comparing the two, it is evident that the IP portfolio

[21] The inflation beta magnitude for the IP portfolio differs from that in Panel B of Table 1 because the portfolio returns are standardized for cross-asset comparison.

behaves more like inflation-sensitive assets, in contrast to the aggregate stock market. This is due to the significant cross-sectional variations in firms' inflation exposure; some firms exhibit positive inflation exposure, while others exhibit negative exposure. The aggregate market sensitivity reflects the average of all firms. Thus, even if the market-wide inflation exposure may show an unstable and negative relation to inflation shocks (Fama and Schwert (1977), Bekaert and Wang (2010)), the relative cross-firm variation in inflation exposure remains stable and positive.[22]

3.4 Determinants of Inflation Beta

To better understand the variations in inflation exposure across different firms, we next examine the relation between firms' underlying characteristics and their inflation exposure. Specifically, is there a link between a firm's inflation exposure and its cash flows? Do firms with positive inflation betas experience increased cash flows during positive inflation shocks?

To answer these questions, we begin by estimating each firm's cash flow inflation beta, b^{Core} and b^{Head}, using a method similar to that for estimating return-based inflation betas. The cash flow beta is estimated using a rolling five-year window, by regressing quarter-t changes in cash flow on quarter-t core-CPI innovations and headline-CPI innovations, respectively. Columns (1) to (6) of Table 3 present the relationship between return-based and cash flow-based core betas, while columns (7) to (12) focus on the headline betas. We find a generally positive and significant relationship between return-based and their corresponding cash flow-based inflation betas. A one standard deviation increase in CF beta (b^{Core}) is associated with roughly a 3% standard deviation increase in β^{Core}, and this relationship remains consistent when controlling for firm characteristics and Fama-French 48 industry fixed effects. As for headline betas, a similar pattern is observed, although the coefficient becomes insignificant when industry fixed effects are included. This suggests that return-based and cash flow-based betas align well with each other.

Further examining the role of other firm characteristics, we include firm market-to-book

[22]This announcement-day approach could also be applied to identify other macro exposures, provided that the macro announcements create significant cross-firm variations in returns, where some firms benefit while others are adversely affected. Announcements such as those from the FOMC and CPI might be suitable, whereas those like NFP and GDP, which tend to affect all firms in the same direction, may be less effective.

ratio, cash flow, dividend payout ratio, and the cash flow duration from Weber (2018).[23] The findings, presented in Table 3, indicate that firms with more positive core inflation betas generally exhibit lower growth potential, higher dividend payouts, and higher cash flows. This suggests a concentration of immediate cash flows realized in the near term but lower long-term cash flows, resulting in a shorter cash flow duration. This is supported by the significantly negative coefficient on cash flow duration. In contrast, firms with more negative core betas exhibit longer cash flow duration and are typically growth firms.

Despite the significant relationship between β^{Core} and firm cash flow characteristics, the explanatory power is weak, with an R^2 of 2%. This suggests that, beyond the static linear relationship with cash flow characteristics, other factors might be contributing to variations in core beta. Notably, when industry fixed effects are included, the R^2 increases only slightly to 3.4%, implying that inflation beta is more of a firm-specific property rather than an industry-specific one. In line with this observation, Appendix Table IA3 demonstrates that the price discovery of inflation news occurs more at the firm level than at the industry level.

Finally, columns (7) to (12) report the determinants regression for β^{Head}, where a similar but weaker pattern emerges. Firms with more negative headline betas also exhibit longer cash flow durations, but show weaker relationships with dividend payout, growth potential, and cash flows. The weaker relationship with cash flows may be attributed to the energy component in headline inflation, which experiences stronger temporal fluctuations and has a less persistent impact on firm cash flows compared to the core component.

4 An Illustrative Model and the Mechanism

In this section, we present a model illustrating how inflation affects firm valuations differently through its impact on cash flows. We show that investors' inflation expectations can be derived from cross-firm variations in returns and used to forecast inflation shocks. Additionally, we provide empirical evidence supporting this cash flow mechanism.

[23]Detailed descriptions of variables are provided in Appendix A.

4.1 An Illustrative Model

We use a simple model to illustrate the interaction channel between inflation innovations and stock returns. The inflation innovation for time $t+1$ includes a component from time t that predicts the firm cash flow (dividend) growth at time $t+1$. Consequently, a high stock price at time t can be driven by these predictable inflation shocks, alongside other components of dividend shocks. This mechanism explains how stock return shocks can forecast inflation innovations, akin to the orange juice example by Roll (1984). The variation in predictability across firms is due to differing levels of inflation exposure in their cash flows. In contrast, this channel does not exist for government bonds, as their cash flows are fixed.

Let P_t be the time-t price level, and $\pi_{t+1} = \ln(P_{t+1}) - \ln(P_t)$ be the inflation growth, with the following dynamics,

$$\pi_{t+1} = \mu_t^\pi + \sigma_\pi \epsilon_{t+1}^\pi,$$

where μ_t^π is the inflation forecast made by the econometrician, accounting for lagged inflation terms. Mapping it to our empirical specification in Section 2, $\mu_t^\pi = \widehat{\pi_{t+1}}$, where $\widehat{\pi_{t+1}}$ is the time-t fitted value of the ARMA(1,1) model for the purpose of forecasting the time-$t+1$ inflation growth. We further model the unanticipated inflation shock in the econometrician's information set via ϵ_{t+1}^π, and use the constant parameter σ_π to model the conditional volatility of the inflation shock.

For market participants, however,

$$\epsilon_{t+1}^\pi = y_t + \epsilon_{t+1},$$

where y_t represents the market participants' superior information regarding the inflation shock. We use ϵ_{t+1}, which is standard normal and independent over time, to denote the inflation surprises within their information set. The market participants' signal y_t is assumed as,

$$y_t = \sigma_y \epsilon_t^y,$$

where ϵ_t^y is standard normal and independent over t. Additionally, ϵ_t and ϵ_t^y are assumed to be independent.

The short rate r_t is modeled as:

$$r_t = \mu_r + \alpha y_t + \sigma_r \epsilon_t^r,$$

where we allow the market participants' expectations, y_t, to influence the short rate r_t via the constant coefficient α. We use ϵ_t^r, which is standard normal, to model additional shocks to the short rate. Finally, all three shocks, ϵ, ϵ^y, and ϵ^r, are mutually independent.

The time-t dividend D_t^i for stock i is given by

$$D_t^i = D_{t-1}^i \exp\left(\mu_i + b_i \sigma_\pi \epsilon_t^\pi - \frac{1}{2}\sigma_i^2 + \sigma_i \epsilon_t^i\right),$$

where the parameter b_i captures stock i's cash flow (dividend) exposure to inflation shocks $\sigma_\pi\, \epsilon_t^\pi$. The heterogeneous exposures of firms' cash flows to inflation shocks are supported empirically. Specifically, our empirical findings in Sections 4.2 and 4.3 indicate that y_t is a significant predictor of cross-firm variations in cash flows at time $t+1$, but it does not have a significant impact on the risk premium. For this reason, we build the time-varying inflation impact (i.e., y_t) into the firm valuation through the cash flow channel, but not the risk premium channel. We further use ϵ_t^i, standard normal, for the shock in firm-i's dividend growth, and assume it to be independent of ϵ, ϵ^y, and ϵ^r.

Under this framework, the time-t stock price for firm i with parameter θ_i can be calculated as

$$S_t^i = \mathrm{E}_t\left[\sum_{v=1}^{\infty} \exp\left(-\sum_{u=0}^{v-1} r_{t+u}\right) D_{t+v}^i\right] = D_t^i\, f(y_t, \theta_i),$$

where, excluding the risk premium channel from the valuation problem, we take the expectation under the physical measure.[24] The price-dividend ratio can be further calculated as

$$f(y_t, \theta_i) = \frac{S_t^i}{D_t^i} = \frac{\exp\left(\mu_i - \mu_r + (b_i\sigma_\pi - \alpha) y_t - \sigma_r \epsilon_t^r + \frac{1}{2} b_i^2 \sigma_\pi^2\right)}{1 - \exp\left(\mu_i - \mu_r + \frac{1}{2}(\sigma_r^2 + b_i^2\sigma_\pi^2 + (b_i\sigma_\pi - \alpha)^2 \sigma_y^2)\right)}, \tag{5}$$

where it is important to note that the time-t stock price contains the superior information possessed by the market participants, namely y_t. Moreover, the price dependence varies

[24]As the risk premium under our setting does not depend on y_t, the market price of risk is a constant. One way to take account of this constant risk premium is to interpret r_t as the discount rate, with the constant μ_r incorporating the risk premium. Regardless, the constant risk premium will not alter our main results on beta estimation and inflation forecasting.

across firms via $b_i\sigma_\pi - \alpha$, where b_i enters via the cash-flow channel and differs cross-sectionally, while α enters via the risk-free rate channel and is the same for all firms.[25]

For the infinite sum of the price-dividend ratio $f(y_t, \theta_i)$ to converge, we need the transversality condition:

$$\mu_r - \mu_i - \frac{1}{2}\left(\sigma_r^2 + b_i^2\sigma_\pi^2 + (b_i\sigma_\pi - \alpha)^2\sigma_y^2\right) > 0.$$

The bond price of a consol is a special case of $D_t^i = 1$ with $b_i = 0$ and $\sigma_i = 0$. The details of the derivation, as well as the propositions below, are provided in Section I of the Internet Appendix.

Proposition 1. *For the cross-sectional inflation portfolio (IP) that takes a long position of \$1 in stock i and a short position of \$1 in stock j, the inflation exposure is given by* $\beta_{ij} = \frac{b_i - b_j}{\sigma_y^2 + 1}$.

By regressing the log-returns of stock i on inflation innovations, we can derive the return beta for stock i:

$$\ln S_{it+1}/S_{it} = \alpha_i + \beta_i\sigma_\pi\epsilon_{t+1}^\pi + u_{it+1}\,,$$

where the population estimate of the return beta for stock i is

$$\beta_i = \frac{\mathrm{E}[\ln S_{it+1}/S_{it}\sigma_\pi\epsilon_{t+1}^\pi]}{\mathrm{var}[\sigma_\pi\epsilon_{t+1}^\pi]} = \frac{\sigma_\pi\mathrm{E}[(\alpha y_t + b_i\sigma_\pi\epsilon_{t+1})(y_t + \epsilon_{t+1})]}{\mathrm{var}[\sigma_\pi\epsilon_{t+1}^\pi]} = \frac{\sigma_\pi(\alpha\sigma_y^2 + b_i\sigma_\pi)}{\sigma_\pi^2(\sigma_y^2 + 1)}.$$

For the IP portfolio that takes a long position of \$1 in stock i and a short position of \$1 in stock j, its return beta is:

$$\beta_{ij} = \frac{\mathrm{E}[(\ln S_{it+1}/S_{it} - \ln S_{ij+1}/S_{jt})\sigma_\pi\epsilon_{t+1}^\pi]}{\mathrm{var}[\sigma_\pi\epsilon_{t+1}^\pi]} = \frac{b_i - b_j}{\sigma_y^2 + 1}.$$

Note that the term involving α, which accounts for the effect of y_t on the short rate, is eliminated in the IP portfolio return or excess return. As a result, the IP portfolio return beta is directly proportional to the cash flow beta, $b_i - b_j$. We further utilize the IP portfolio to predict inflation.

[25]Note that $e^{-r_t+\mu_i+b_i\sigma_\pi y_t+\frac{1}{2}b_i^2\sigma_\pi^2}$ is the one-period conditional discount rate net of the dividend growth rate, and $e^{-\mu_i+\mu_r-\frac{1}{2}(\sigma_r^2+b_i^2\sigma_\pi^2+(b_i\sigma_\pi-\alpha)^2\sigma_y^2)}$ is the unconditional discount rate net of dividend growth.

Proposition 2. *Consider the predictive regression of inflation innovation on the IP portfolio:*

$$\sigma\epsilon^{\pi}_{t+1} = \gamma_{ij0} + \gamma_{ij}\Big(\ln S_{it}/S_{it-1} - \ln S_{jt}/S_{jt-1}\Big) + u_{ijt+1}.$$

The population estimate of γ_{ij} *is*

$$\gamma_{ij} = \frac{(b_i - b_j)\sigma_\pi^2}{(b_i - b_j)^2\sigma_\pi^2(1 + 1/\sigma_y^2) + (\sigma_i^2 + \sigma_j^2 - 2\rho_{ij}\sigma_i\sigma_j)/\sigma_y^2},$$

where ρ_{ij} *is the correlation coefficient between* ϵ^i_{t+1} *and* ϵ^j_{t+1}.

The time-t price-dividend ratio, as described in equation (5), and consequently the time-t realized stock return (as shown in Section I of Internet Appendix, equations (8) and (9)), depend monotonically on y_t. This dependence is the source of the predictability of realized stock returns on inflation innovations. The heterogeneity of this dependence, characterized by b_i, is the key reason for using the long-short IP portfolios. Since the cash flows of government bonds are fixed, the cash flow predictability channel stemming from this heterogeneity is absent in bond returns.

4.2 The Cash Flow Channel

Our model builds on the heterogeneous effect of inflation on firm cash flows. As shown in Equation (5), this cash flow channel leads to a link between stock returns and the market participants' superior information, namely y_t. To empirically test the cash flow channel of our model, we utilize the IP portfolio return to capture the time-series variations in y_t and examine whether an increase in IP^{Core} disproportionately affects the cash flows of firms with negative β^{Core} compared to those with more positive β^{Core}. We focus on the β^{Core} constructed portfolio because the announcement-day-based β^{Core} better captures core information shocks, and our later analysis indicates that IP^{Core} is most effective in capturing variations in y_t.

Table 4 reports the relationship between y_t and firm cash flows in quarter $t+1$. The dependent variables include quarterly sales growth, cash flow, and IBES long-term growth forecast. The variable of interest is the interaction between the quintile rank of inflation beta $\beta^{\text{Core}}_{\text{Rank}}$ and IP^{Core}, as it captures the additional effect of heightened inflation expectations, i.e., an increase in IP^{Core}, on firm fundamentals for the more positive β^{Core} quintile firms compared to the more negative ones. We control for other firm characteristics, including size, lagged values of the dependent variables, asset growth, market-to-book, and dividend payout as indicated. Firm and time fixed effects are included in all specifications.

Across all specifications, inflation has a significantly more positive effect on sales growth, cash flow, and the IBES long-term growth forecast for firms with higher β^{Core}. Specifically, focusing on sales growth and cash flow, a 10% increase in IP$^{\text{Core}}$ translates to a 7.8% standard deviation increase in sales growth and a 7.1% standard deviation increase in cash flow as the quintile ranks of β^{Core} move from the lowest to the highest quintile. Analysts seem to either be well-informed about the impact of inflation on firm cash flows or adjust their expectations for earnings growth quickly in response to observing a high y_t. Consequently, a 10% increase in IP$^{\text{Core}}$ predicts a 4.4% standard deviation increase in the long-term growth forecast of firm EPS.

Figure 1 offers a more intuitive graphical illustration. At the end of each quarter $t-1$, we sort all stocks into quintile groups based on their core beta ($\beta^{\text{Core}}_{t-1}$) and compute the equal-weighted average quarter-t cash flow for stocks in each quintile group. The upper graph plots the cash flow difference between the top and bottom quintiles, alongside the IP$^{\text{Core}}$ return in quarter t. We observe a comovement between the return and cash flow of IP$^{\text{Core}}$, indicating that firms with higher β^{Core} (those less negatively impacted by inflation) tend to have relatively better cash flows during periods of rising inflation expectations. The lower graph zooms in on the cash flow distribution during the recent inflation run-up episode from 2019 Q1 to 2023 Q4. Accompanied by the warning signal sent by our IP$^{\text{Core}}$ in the first quarter of 2021, firms with more positive β^{Core} experienced relatively more positive cash flows from 2021 Q2 to 2022 Q4. As inflation started to decline after 2022, the cash flow difference between high and low-β^{Core} firms returned to normal levels. Overall, these analyses highlight the significant impact of inflation expectations on firm cash flows.

4.3 Inflation Risk Premium

We further test whether or not the cross-firm variations in returns, particularly IP$^{\text{Core}}$, are driven by the inflation risk premium. If the variations in IP$^{\text{Core}}$ are driven by the time-varying inflation risk premium, we would expect firms with higher β^{Core} to have lower required rates of return when inflation expectations rise, assuming that inflation is negatively priced. However, our findings do not support this risk premium channel. Following the same regression framework, the last two columns of Table 4 report the impact of IP^{Core} on firm returns. The coefficients of the interaction term are insignificant, indicating a lack of return dispersion between stocks with high and low β^{Core}.

Furthermore, Table 5 reports the inflation risk premium for the β^{Core} sorted quintile portfolios over the period from January 1972 to December 2023, as well as for subsamples split around December 2002.[26] As shown in Panel A, over the full sample, there is no clear monotonic pattern in returns for β^{Core} sorted quintile portfolios. The return difference between the top and bottom quintiles, i.e., IP^{Core}, is a positive and insignificant 1.2% (t-stat=1.06). The subsample analysis yields similar results: both in the pre-2002 and post-2002 subsamples, the return of IP^{Core} remains insignificant and positive. However, for the β^{Head} sorted quintile portfolios, as reported in Panel B, we observe a different pattern. Annualized excess returns for β^{Head} sorted portfolios decrease from 9.8% for the bottom quintile to 7.6% for the top quintile, resulting in a top-minus-bottom return difference, i.e., IP^{Head}, of -2.2% (t=-1.67) for excess return and -2.7% (t=-1.98) for CAPM alpha. In sum, β^{Head} and β^{Core} contain uniquely different information, with β^{Head} better capturing the risk premium and β^{Core} better capturing the information shocks.

To further explore whether the variations in IP portfolio returns are driven by the time-varying risk premium of inflation, we analyze the inflation risk premium conditional on the nominal-real covariance (NRC) following Boons et al. (2020). We regress excess returns of the inflation beta-sorted portfolios, holding from month $t+1$ to $t+K$ (K has a value of one, three, and twelve) on month-t NRC using the following regression specification:

$$R_{t+1:t+K} = \alpha + \beta^{\text{NRC}}\text{NRC}_t + \varepsilon_{t+1:t+K}, \tag{6}$$

The intercept measures the unconditional inflation risk premium, and β^{NRC} measures the increase in annualized portfolio return resulting from a one standard deviation increase in NRC. Focusing on the β^{Head} sorted portfolios in Panel B of Appendix Table IA2, we find consistent evidence, as in Boons et al. (2020), that IP^{Head} strongly co-moves with the

[26]Prior literature shows that the time-varying relation between inflation and consumption growth changed sign from negative to positive around 2002 (e.g., Boons et al. (2020), Bekaert and Wang (2010), Campbell, Sunderam, and Viceira (2017)).

nominal-real covariance, reflecting a compensation for inflation risk. In contrast, as shown in Panel A, for β^{Core} sorted portfolios, the effect of NRC is insignificant, and the sign is even negative. This indicates that variations in IP^{Core}, and hence the predictability of IP^{Core} on inflation shocks, are not driven by the time-varying inflation risk premium.

5 Inflation Forecasting

In this section, we show that the inflation portfolio, in particular IP^{Core}, contains unique and non-redundant information about future core inflation shocks.

5.1 Predicting Inflation Innovations

We use the top-minus-bottom quintile inflation beta-sorted portfolio, as discussed in Section 3 and 4, to predict inflation shocks. The core-focused inflation portfolio, IP^{Core}, is constructed using the announcement-day core beta β^{Core}, while the headline-focused inflation portfolio, IP^{Head}, is constructed using the full-month headline beta β^{Head}. As outlined in Proposition 2, a positive inflation shock more negatively impacts the cash flows of firms with a more negative β^{Core}. Anticipating this, investors tend to underprice stocks in the bottom quintile more aggressively than those in the top quintile, resulting in a positive IP return. In other words, a higher-than-usual IP return could serve as an early warning from the equity market about an upcoming surge in inflation.

5.1.1 Event Study around Extreme CPI Months

We start by analyzing the performance of inflation portfolios around extreme CPI events to better understand the timing of price discovery. As noted by Lo and MacKinlay (1990), large stocks tend to have better liquidity and often incorporate market-wide information faster than small stocks. For this reason, we focus on inflation portfolios constructed using large-cap stocks.[27] To identify months with extreme CPI values, we divide all CPI events into quintiles based on headline- and core-CPI innovations. The top quintile represents months with very positive CPI surprises, while the bottom quintile captures months with

[27] We compare the forecastability of large stocks versus small stocks in Section 6.1.

very negative surprises. We then plot the cumulative performance of the inflation portfolios, $\mathrm{IP}^{\mathrm{Core}}$ and $\mathrm{IP}^{\mathrm{Head}}$, over a window from $t = -50$ trading days before the start of the CPI month to $t = 50$ days afterward, as shown in Figure 2, with $t = 0$ marks the start of the CPI month.

In the upper graph, we observe that during the month of extreme CPI events, the performance of inflation portfolios remain flat, irrespective of whether the headline-CPI innovations are extremely high or low. Interestingly, about 30 days before the onset of months with higher-than-expected headline-CPI innovations, the IP performance starts to drift upwards. The red line is positioned above the yellow line, suggesting that the announcement-based, core-focused $\mathrm{IP}^{\mathrm{Core}}$ identifies heightened inflation information more quickly than the full-month-based, headline-focused $\mathrm{IP}^{\mathrm{Head}}$. The lower graph, which shows IP performance around extreme core-CPI events, reveals a similar pattern.

To determine when the equity market begins to incorporate next-month inflation expectations, Table 6 presents the predictability of inflation portfolio returns, with returns calculated over 10-day intervals. For instance, the interval [-10,-1] denotes returns from 10 trading days before the CPI month to the last trading day before the CPI month. To provide a comparison with information discovery in other asset markets, we also include TIPS-UST returns to reflect Treasury market dynamics and GSCI returns for the commodity market. All regressors are standardized with means of zero and standard deviations of one to facilitate interpretation.

The IP portfolios exhibit strong predictive power for both core and headline CPI, beginning approximately 30 days before the CPI month. Taking the [-30,-20] day window return as an example, a one standard deviation increase in the 10-day return of $\mathrm{IP}^{\mathrm{Core}}$ predicts a 1.8 bps (t-stat=2.37) increase in core-CPI innovations and a 4.6 bps (t-stat=2.73) increase in headline-CPI innovations. While returns are inherently noisy, the coefficient estimates remain consistently positive throughout this 30-day period but become insignificant, and even reverse sign, during the earlier [-40, -30] window. This pattern holds true not only for the inflation portfolios but also for TIPS-UST and GSCI, indicating active price discovery of inflation news across various asset classes, around 30 days before the CPI month begins. These findings are consistent with Downing, Longstaff, and Rierson (2012), highlighting the forward-looking nature of asset prices in incorporating market participants' inflation expectations.

5.1.2 Predictability of Core-Focused Inflation Portfolio

Building on the event window analysis from Section 5.1.1, we evaluate the effectiveness of the 30-day return of IP^{Core} in predicting inflation shocks. We analyze the incremental forecasting ability of IP^{Core} by comparing it with the headline-inflation portfolio and market-based signals from Treasury bond and commodity markets. The forecasting timeline is detailed in Section I of the Internet Appendix. At the end of each month t, we use the 30-day returns observed by the end of month t to forecast CPI innovations for month $t+1$ using the following regression specification:

$$\text{Core-Innov}_{t+1} = \alpha + \gamma^{\text{IP}}\text{IP}_t^{\text{Core}} + \gamma^X X_t + \varepsilon_{i,t+1}, \tag{7}$$

where Core-Innov_{t+1} denotes month-$t+1$ core-CPI innovations, and X_t includes the 30-day return of TIPS-UST and GSCI observed at the end of month t. To predict headline-CPI innovations, we replace the dependent variable with Head-Innov_{t+1}. For ease of comparison, the independent variables are standardized with means of zero and standard deviations of one.

Table 7 shows the predictive power of IP^{Core} on inflation innovations. Specifically, a one standard deviation increase in the 30-day return of IP^{Core}, observed at the end of month t, predicts a 2.2 bps (t-stat=2.98) increase in core-CPI innovations and a 7.9 bps (t-stat=6.54) increase in headline-CPI innovations for month t+1. Given the sample standard deviations of core- and headline-CPI innovations are 16 bps and 26 bps, respectively, the economic significance of IP^{Core} is non-trivial. This evidence confirms our finding in Section 5.1.1, suggesting that a significant portion of inflation shock is anticipated by market participants and is already reflected in the cross-section of stock prices well before the actual CPI month begins.

The predictability of IP^{Core} remains strong when controlling for market indicators from the Treasury and commodity markets. Given that TIPS are directly linked to headline inflation and commodities are key inputs for it (Gorton and Rouwenhorst (2006) and Downing, Longstaff, and Rierson (2012)), it is unsurprising that TIPS-UST and GSCI are strong predictors of headline-CPI innovations.[28] Including GSCI with IP^{Core} boosts the predictability on headline inflation from an R^2 of 9.1% to 24%, while adding TIPS-UST enhances the R^2 to 20.3%. In both cases, the coefficient estimate on IP^{Core} remains robust both economically and statistically.

While TIPS-UST and GSCI can predict headline-CPI innovations, their ability to forecast core-CPI innovations is much limited. According to the estimates in column (4), a one standard deviation increase in IP^{Core} predicts a 2.4 bps increase in core-CPI innovations (t-stat=2.47), whereas TIPS-UST and GSCI predict increases of 0.7 bps (t-stat=0.71) and 1.0 bps (t-stat=1.3), respectively. These findings suggest that while price discovery for headline CPI, particularly its energy component, is more active in the commodity and Treasury markets, the information embedded in cross-sectional stocks provides significant additional value, particularly in forecasting core-CPI shocks.

Finally, columns (5)-(6) and (11)-(12) analyze the effectiveness of headline-focused IP^{Head} in predicting inflation innovations. While the headline beta sorted portfolio provides valuable information about headline shocks, it has limited effectiveness for core inflation. Specifically, a one standard deviation increase in IP^{Head} predicts a 7.4 bps (t-stat=5.78) increase in headline-CPI innovations, which is quite similar to the 7.9 bps (t-stat=6.54) increase predicted by IP^{Core}. However, when forecasting core-CPI innovations, the coefficient for IP^{Head} is an insignificant 0.9 bps (t-stat=1.47) when GSCI and TIPS-UST are included. Thus, compared to IP^{Head}, the core-focused IP^{Core} excels in forecasting both headline- and core-inflation innovations. Core inflation is particularly important because, via the exclusion of food and energy, it reflects price changes that are less affected by temporary shocks. Given the Fed's reliance on core CPI for policy decisions, the unique information derived from cross-sectional stock portfolios is crucial.[29]

5.2 Do Economists Update Beliefs about Inflation?

Our IP^{Core} is constructed at the end of month t, while the inflation data for month-$t+1$ is typically announced in the second or third week of month $t+2$. This creates a lag of over one

[28]In 2023, the GSCI index was composed of 61% energy, 24% food, and 15% metals.

[29]While the predictive power of IP^{Core} is moderate in the full sample, it increases to an R^2 of around 20% during periods when inflation poses a major risk to the economy, as discussed in Section 5.3.

month between the formation of the signal and the CPI announcement. This timing raises an interesting question: Do economists update their inflation expectations based on market-based information, particularly that embedded in cross-sectional stock data? If economists do not fully incorporate the information from IP^{Core}, to what extent can the inflation portfolio predict the announcement-day forecasting errors made by economists?

To capture economists' expectations for month-$t+1$ inflation, we use the headline- and core-CPI month-over-month growth forecast from Bloomberg economists' survey. These surveys provide the most up-to-date consensus view of inflation just prior to the official announcement. We define the change in forecasts as the difference between economists' forecast of inflation growth for month-$t+1$ and the benchmark value predicted by the ARMA (1,1) time-series model. The announcement-day forecasting error is defined as the actual inflation growth for month $t+1$ minus the forecast of Bloomberg economists' survey.

Table 8 shows that while economists are generally responsive to market-based inflation signals, particularly the one from the commodity market, they do not sufficiently incorporate the information embedded in IP^{Core}. Consequently, IP^{Core} can significantly predict announcement-day forecasting errors with notable magnitude. Focusing first on the economists' belief updates (left panels), a one standard deviation increase in the GSCI return predicts an upward adjustment of 1.3 bps (t-stat=2.73) and 10.5 bps (t-stat=5.02) in the economists' forecast of core and headline inflation, respectively. When controlling for GSCI return, the coefficient on IP^{Core} is only marginally significant, suggesting that economists do not fully maximize the use of IP^{Core}.

The right panel of Table 8 highlights the significant predictive power of IP^{Core} in forecasting announcement-day errors, also known as survey-based announcement surprises. A one standard deviation increase in IP^{Core} predicts a 2.3 bps (t-stat=3.1) increase in core-CPI surprise and a 3.8 bps (t-stat=4.22) increase in headline-CPI surprise, beyond what other market-based predictors can achieve. Given that the standard deviations of core- and headline-CPI forecasting errors are 11 bps and 13 bps, respectively, the information from cross-sectional stocks is significant and can enhance economists' forecasting accuracy. Yet, this information, available over a month in advance, does not seem to be fully incorporated into the economists' forecasts.

5.3 Time-Varying Predictability

The impact of inflation on the economy and its influence on asset prices can vary significantly over time, as noted by Cieslak and Pflueger (2023) and Bauer, Pflueger, and Sunderam (2024). In periods of low inflation, its effect on firms' fundamentals is minimal, which can limit the predictive power of our inflation portfolio. Conversely, when inflation emerges as a major risk factor in the capital market, the process of price discovery for inflation-related news among assets becomes more pronounced. This section explores the changing informativeness of core-focused inflation portfolios, with a particular focus on key inflation episodes and their interaction with monetary policy.

The Episode of 2021 – In 2021, the global economy saw a significant surge in inflation, driven by post-pandemic disruptions of supply chain, increased demand from fiscal and monetary stimulus, and rising energy prices. Core CPI exceeded the Fed's 2% inflation target in April 2021 and hit a 40-year high of 6% in September 2022. Despite this, the Fed maintained its zero interest-rate policy throughout 2021, only beginning to tighten in mid-2022. Economists also underestimated the severity of inflation. The upper graph of Figure 3 shows core-CPI (MoM) growth against Bloomberg economists' forecasts from October 2020 to September 2022. During critical months in 2021, the median forecasts missed the rapid ascent of core CPI by 10 bps in March, 60 bps in April, 20 bps in May, and 50 bps in June. The April 2021 forecast error was particularly notable, being a 5.5-sigma event given that the standard deviation of forecasting error is 10.9 bps in the whole sample.[30]

Analyzing the performance of inflation portfolios during this period, we find that IP^{Core} effectively captured the inflation surge in 2021. The lower graph of Figure 3 plots the 30-day IP^{Core} return (red line), observed by the end of month $t-1$, together with the month-t core CPI (blue bars). Notably, IP^{Core} rose significantly just before the core CPI surge in April 2021: The magnitude of IP^{Core} observed at the end of March 2021 is 3.7 times its sample standard deviation. It closely mirrored the core CPI's movements, accurately identifying the local low in July 2021 and the peaks in April 2021 and June 2022. Additionally, the upper left graph of Figure 4 provides a scatter plot that further highlights the predictability of IP^{Core}. Specifically, a 10% increase in IP^{Core}, observed at the end of month t, predicts a

[30]Relating the policy rate with economists' forecasts, Bauer, Pflueger, and Sunderam (2024) show that economists do not expect the Fed to react to inflation changes until after the liftoff in March 2022.

26.3 bps (t-stat=2.31) increase in core-CPI innovations for month $t+1$, with an R-squared of 17.7%.

Looking at other market-based predictors, their performance in forecasting this inflation surge is quite disappointing. The upper right graph in Figure 4 shows that signals from the bond market, specifically TIPS-UST, not only fail to predict core-CPI innovations but also show a negative correlation. Panel A of Table 9 further reports regression estimates using various market-based predictors to forecast core-CPI innovations and economists' forecasting errors. Among these, IP^{Core} stands out as the only significant predictor, demonstrating both economic and statistical significance that far exceeds other predictors.[31] Notably, the coefficient estimates of IP^{Core} regarding core-CPI innovation and survey-based forecasting error are more than three times larger than the full-sample estimates. This underscores the critical role of the core-focused inflation portfolio in discovering inflation-related news during the 2021 episode.

The Episode of 1973 – Drawing parallels to the inflationary surge of 2021, the 1973 experience is frequently revisited to provide insights into recent inflation dynamics. The buildup to the Great Inflation began in the early 1970s, and by the end of 1973, inflation had escalated to 8.6%, significantly exceeding the average inflation rate of 2.5% observed between 1947 and 1972. Like the situation in 2021, this surge was fueled by stimulative fiscal policies, excessive government spending for the Vietnam War, and the Arab oil shock. In both periods, highly accommodative monetary policies preceded the inflationary episodes.

Similar to the case of 2021, economists and policymakers in the early 1970s also severely underestimated the rate of inflation growth. However, the core-focused inflation portfolio demonstrated exceptional power in forecasting inflation during the 1973 episode. We form the 1973 episode by including 24 months after May 1973 to capture the run-up period of the Great inflation. May 1973 is the first time when the year-over-year core-CPI growth crossed above 3% and stayed there afterward for a prolonged decade. The lower left graph of Figure 4 shows that a 10% increase in IP^{Core}, observed at the end of month t, can predict an increase of 76.2 bps (t-stat=3.43) in month-$t+1$ core-CPI innovations, with a much improved R-squared of 28.4%. This enhanced predictability on core-CPI innovations is uniquely captured

[31] The coefficient estimates in Figure 4 and Table 9 differ because the independent variables are in units of return in Figure 4 and are standardized in Table 9.

by our IP^{Core}, mirroring the results observed in the 2021 episode. Columns (5) and (6) of Table 9 further report the predictability of bond and commodity-based forecasters together with IP^{Core}.[32] Among all these forecasters, IP^{Core} is again the only significant variable that predicts core-CPI innovations during the Great Inflation episode.

Inflation Uncertainty and Monetary Policy – To further explore the time-varying nature of inflation predictability, we estimate the forecastability of IP^{Core}, conditional on inflation uncertainty and inflation disagreement. We hypothesize that our stock-based inflation portfolio will add the most value when the market is most uncertain about the future course of inflation. Conversely, when consensus is reached and market participants pay little attention to inflation news, the potential for improvement from our inflation portfolios is limited.

We use two proxies to capture the time-varying nature of inflation uncertainty: (a) |CPI Innovation|, the absolute value of CPI innovation in the last month; (b) CPI disagreement, the difference between the 75th percentile and 25th percentile of quarterly CPI forecasts from the Survey of Professional Forecasters (SPF) database.[33] Panel B of Table 9 reports the predictability of IP^{Core} on core-CPI innovations and the forecasting errors (survey-based surprises) for subsamples defined using the median cutoffs of the two proxies.

The forecasting power of IP^{Core} is much stronger when the last-month |CPI Innovation| and the CPI disagreement are above the median cutoff. For example, a one standard deviation increase in IP^{Core} predicts a 3.9 bps (t-stat=3.34) and 2.9 bps (t-stat=2.39) increase in core innovations and core forecasting errors during periods with above-median inflation risk. In contrast, during periods of low inflation risk, the predictive power is only 0.4 bps and 1.8 bps, respectively.[34] Overall, the evidence suggests that IP^{Core} can provide valuable information about future inflation expectations when the market most needs it.

We further explore how monetary policies impact the time-varying informativeness of IP^{Core}. The Taylor rule provides a useful framework for describing activist monetary policy (Taylor (1993)). When prices deviate from the 2-3% inflation target, the central bank can implement monetary policy to restore the target. When the Fed aggressively combats

[32] Given that inflation-linked TIPS securities were unavailable in the 1970s, we use month-t change in 10-Year US Treasury yield as a proxy.

[33] Unlike the monthly Bloomberg Economists' Survey Forecasts that start in 1997, SPF offers quarterly forecasts but has the advantage of being traceable back to the third quarter of 1981.

[34] We focus on predicting core CPI due to its crucial role in the Fed's decision-making process. The results for headline-CPI predictions are qualitatively similar.

inflation preemptively, inflation can be effectively contained, reducing the predictability of market-based forecasters. For instance, during the 1989-1991 inflation period, driven by the first Gulf War and rising oil prices, annual CPI rose to 5% in May 1989 but was controlled to below 3% by October 1991. The effective federal funds rate was maintained around 9%, successfully preventing runaway inflation. Hence, the Fed's timely intervention may limit the ability of market-based forecasters to predict inflation spikes. Conversely, when the Fed reacts sluggishly, as in 2021 and 1973, inflation becomes uncontrollable, and with the lack of Fed intervention, market-based forecasters could become more effective in predicting inflation.

To test the predictability of inflation indicators conditional on Fed monetary policy, we measure the extent to which the Fed is behind-the-curve by the distance between the Fed funds rate recommended by the Taylor rule and the actual federal funds rate. The recommended Fed funds rate is calculated as 2.5%+1.5*(Core-CPI YoY Growth-2%)+0.5*OutPut Gap, where the output gap is estimated by the percentage deviation of real output from the long-run trend (Taylor (1993)). We use response coefficients of 1.5 for inflation deviations and 0.5 for output gap, following Piazzesi (2022).[35] Panel B of Table 9 reports the subsample regression estimates, where "Behind" refers to the periods when the difference between the rate implied by the Taylor rule and the actual Fed funds rate is above the 67% percentile cutoff. A one standard deviation increase in IP^{Core} predicts a 3.7 bps (t-stat=2.8) increase in core-CPI innovations with an R-squared of 5.6%, when the Fed is behind the curve. For the rest of the periods, the predictability of IP^{Core} is 1.3 bps (t-stat=1.83) with an R-squared of 0.4%.

As a graphical illustration, Figure 5 plots the time-series predictive power of IP^{Core}. For each time t, we estimate equation (7) using a rolling five-year window from $t-59$ to t and plot the coefficient estimate γ^{IP} on the left axis.[36] On the right axis, the upper and lower graphs plot the volatility of inflation shocks and the extent to which the Fed is behind the curve, respectively. We observe a strong co-movment between the γ^{IP} estimate and the importance of inflation risk at the time. γ^{IP} peaks during significant core inflationary episodes in 1973–82 and 2021–2022. Zooming into these periods, the predictive power is

[35]The target core-inflation rate is set at 2%, following Clarida (2021).

[36]Appendix Figure IA2 plots the regression R-squared.

consistently stronger at the beginning of the inflation run-up when the Fed is behind the curve in combating inflation. Conversely, when the Fed aggressively fights inflation, such as during the early 1980s under Paul Volcker and in late 2022 with aggressive rate hikes, the γ^{IP} estimate decreases dramatically.

5.4 Out-of-Sample Forecastability

Section 5.1 to 5.3 presents in-sample evidence that the core-focused inflation portfolio has strong predictive power for future inflation shocks, particularly the core component. To better reflect real-time information available to market participants, we follow the methodologies of Ang, Bekaert, and Wei (2007) and Faust and Wright (2013), examining the out-of-sample forecasting power of $\mathrm{IP}^{\mathrm{Core}}$ alongside other leading inflation indicators. Out-of-sample tests provide a more realistic performance assessment using public data available at the time and help alleviate concerns of overfitting.

To forecast inflation growth for month $t+1$, we estimate the forecasting model $\pi_t = a + \sum_{k=1}^{N} b_k\, X_{t-1}^k + \epsilon_t$ using only publicly available information up to and including month t. Here, X_{t-1}^k represents the forecasting signal k observed at the end of month $t-1$, and π_t denotes the inflation growth for month t. We then use the estimated coefficients to forecast inflation growth for month $t+1$. The forecasting error for month $t+1$ is calculated as the actual inflation growth minus the forecasted growth. Out-of-sample accuracy is measured by relative RMSE, which is the ratio of the root-mean-square forecasting error (RMSE) for a particular model relative to that of the benchmark model. We use an ARMA(1,1) time-series model as our benchmark. Additional forecasting signals such as $\mathrm{IP}^{\mathrm{Core}}$, commodity-based GSCI returns, and TIPS-UST returns are added to evaluate their incremental forecasting power. A relative RMSE below 1 indicates that the indicator improves the benchmark model's performance. To ensure sufficient historical data for training the forecasting model, the out-of-sample period begins in May 2003, five years after the introduction of TIPS data in May 1998.

Table 10 shows the relative RMSE for various forecasting models. $\mathrm{IP}^{\mathrm{Core}}$ improves the forecasting accuracy of month-$t+1$ core and headline CPI by 3.6% (p-value=0.05) and 7.3% (p-value=0.00), respectively, relative to the ARMA(1,1) model. Among all forecasters from the Treasury, equity, and commodity markets, $\mathrm{IP}^{\mathrm{Core}}$ has the highest incremental forecasting power for core CPI and ranks the second for headline CPI, after GSCI. Consistent with the in-sample evidence, GSCI has the highest forecasting power for headline CPI, with an RMSE improvement of 14.2%. Interestingly, while TIPS-UST, designed to track inflation expectations, only improves forecasting accuracy by 6.9%. Besides, we find limited out-of-sample evidence that aggregate stock market and nominal bond yields can forecast upcoming inflation growth.

In addition to these market-based indicators, we include economists' and households' inflation forecasts from the Survey of Professional Forecasters (SPF) database and the Surveys of Consumers by the University of Michigan. Ang, Bekaert, and Wei (2007) and Faust and Wright (2013) show that subjective survey forecasts outperform those from Phillips curve or term structure models. The importance of household subjective expectations is also emphasized by Weber, Gorodnichenko, and Coibion (2023) and D'Acunto and Weber (2024). Since we are predicting month-$t+1$ inflation growth at the end of month t, we use the latest survey forecast available at that time.[37] Table 10 indicates that economists' preliminary forecasts at month t can improve the time-series model by only 1.7%. Motivated by the Phillips curve economic model (e.g., Stock and Watson (1999)), we also include real GDP growth, output gap, unemployment rate, labor income share, and CFNAI as proxies for economic activity in the forecasting model. Consistent with Ang, Bekaert, and Wei (2007), real activity measures do not add value.

Finally, Panel B of Table 10 reports the out-of-sample performance of IP^{Core} for subsamples when inflation is particularly significant to the economy. Consistent with Section 5.3, the forecasting power of IP^{Core} is stronger during periods when inflation plays a critical role. The out-of-sample predictability for core and headline CPI improves by 6.4% and 11.2%, respectively, during the 2021 inflation episode. For periods when inflation risk is above the median or when there is significant noise from the Treasury market, improvements are 3.8% for core CPI and 8.3% for headline CPI. Overall, IP^{Core} provides unique information about inflation both in-sample and out-of-sample, particularly during heightened inflation periods.

[37] We do not use Bloomberg Economist Forecasts here because we are forecasting month-$t+1$ inflation at the end of month t, and the Bloomberg forecasts are updated until the last minute before the announcement.

6 Other Discussions and Robustness Tests

6.1 Firm Information Environment

Our hypothesis assumes that sophisticated market participants can understand the effects of inflation on firm cash flows and integrate these effects into stock pricing. However, not all firms are the same. If investors have limited capacity, expectations about inflation may not be promptly reflected in stock prices. In such cases, the predictability of IP^{Core} should be stronger among firms with a more opaque information environment, which we capture through analyst coverage. Additionally, pricing efficiency relies on sophisticated investors, such as arbitrageurs, to incorporate information in a timely manner and bring stock prices to their intrinsic value. Therefore, we expect that the predictability of inflation portfolios will be more pronounced among firms subject to fewer limits to arbitrage, as proxied by firm size and institutional ownership.

Specifically, at the end of month t, we first divide firms into halves based on the median of the information environment proxy X (X $\in$ size, residual institutional ownership, residual analyst coverage).[38] We then sort stocks within each category by their β^{Core} into quintiles. Table 11 reports the informativeness of the top-minus-bottom quintile IP^{Core} portfolios constructed within each group. While IP^{Core} (X$\leq$Median), constructed based on the stocks with below-median information environments, is sometimes significant in predicting the core-CPI shocks, its predictive power is fully absorbed by IP^{Core} (X>Median) when included together in columns (3), (6), and (9). This evidence is consistent with our hypothesis and indicates a stronger active price discovery among larger firms with higher institutional ownership and analyst coverage.

6.2 Predicting Inflation-Linked Asset Returns

Given that IP^{Core} effectively predicts both inflation innovations and economists' forecasting errors, it is worthwhile to examine whether IP^{Core} can also predict interest rate changes, especially the inflation component. This potential predictability builds on the assumption

[38] Since analyst coverage and institutional ownership are strongly correlated with firm size, we further orthogonalize these variables with respect to firm size and use the residual values for sorting (Hong, Lim, and Stein (2000)). The two size groups are defined by the median cutoff of NYSE market capitalization. Stocks with size > Median are the large stocks that we focus on in the baseline results.

that the information embedded in the cross-sectional stocks may not yet be fully incorporated by other assets. We focus on changes in inflation swap rates and nominal yields, as they are directly influenced by inflation expectations. An inflation swap allows one party to exchange a fixed payment for one linked to an inflation index, directly reflecting changes in inflation expectations. If IP^{Core} can predict the inflation component, it may also predict nominal yield changes, provided the real component does not perfectly offset the inflation change. This predictability of inflation-linked assets could help investors hedge against or speculate on inflation risk.

Table 12 reports the predictability of IP^{Core}, observed at the end of month t, on the change in inflation swap rates (Panel A) and the change in nominal yields (Panel B) from the end of month t to the announcement day when the actual inflation of month $t+1$ is publicly released. For ease of interpretation, IP^{Core} is standardized with a mean of zero and a standard deviation of one. A one standard deviation increase in IP^{Core} predicts a 19.4 bps (t-stat=2.93) increase in the one-year inflation swap rate, with the magnitude declining monotonically with maturity. This indicates that the information from the cross-section of stocks is mostly concentrated in the short run. Similarly, a one standard deviation increase in IP^{Core} also predicts an increase in nominal yields, with the magnitude decreasing from the highest of 11.7 bps for the one-year yield to the lowest of 4.5 bps for the 30-year yield. These yield changes align roughly with the monthly predictability of around 2.2 bps in forecasting CPI innovations. Overall, it suggests that IP^{Core} can capture information not yet incorporated by inflation-linked assets.

6.3 Industry vs. Stock-Specific Information

To determine whether the predictability of inflation portfolios is influenced more by industry or firm-specific factors, we calculate inflation betas for the Fama and French 48 Industries, using a method similar to that for individual stocks. This allows us to analyze the distribution of betas across industries and compare price discovery at the industry level with that at the firm level.

Panel A of Table IA3 presents the top 10 and bottom 10 industries that are most and least sensitive to announcement-day core-CPI innovations and full-month headline-CPI innovations, respectively. Consistent with previous studies by Boudoukh, Richardson, and

Whitelaw (1994) and Ang, Brière, and Signori (2012), there exist significant variability in inflation exposure across industries. Notably, industries such as oil, mining, and metals serve as effective inflation hedges, with positive full-month headline betas. In contrast, cyclical industries like soda, restaurants, hotels, and insurance are more negatively impacted by unexpected headline inflation shocks.

The announcement-day core-based inflation betas, on the other hand, exhibit a different pattern. For instance, the industry of shipping containers appears in the top 10 for β^{Core} with a positive core beta of 0.03 per announcement day but falls into the bottom 10 for β^{Head} with a negative headline beta of -0.14 per month. This contradictory behavior makes intuitive sense: although rising energy prices increase input costs for companies operating shipping containers, the rise in prices for goods and services could potentially benefit those providing shipping services.

Given these significant cross-industry variations in inflation exposure, we further investigate whether the predictive power of our stock-based inflation portfolios is subsumed when we control for industry-based inflation portfolios. Panel B of Table IA3 examines the forecastability of industry-constructed inflation portfolios. The 30-day cumulative returns for these portfolios, denoted as $\text{IP}^{\text{Core}}_{\text{Ind}}$ and $\text{IP}^{\text{Head}}_{\text{Ind}}$, are constructed by taking long positions in top-quintile inflation beta industries and short positions in the bottom-quintile. $\text{IP}^{\text{Core}}_{\text{Ind}}$ exhibits weak predictability for core-CPI innovations, with an R-squared of just 0.3%. When we use both $\text{IP}^{\text{Core}}_{\text{Ind}}$ and IP^{Core} to predict core-CPI innovations, the information content of industry portfolios is fully absorbed by stock-based portfolios. In summary, our evidence suggests that the inflation exposure of stocks is not merely a byproduct of their industry affiliation, but rather that there exists active price discovery of inflation news among cross-sectional stocks.

6.4 Alternative Measures of IP and Robustness Tests

Forecasting CPI Growth – In our baseline analyses, we focus on predicting one-month ahead CPI shocks. Our findings remain robust when using IP^{Core} to predict CPI growth and when extending to longer horizons. Appendix Table IA4 demonstrates the predictability of IP^{Core}, observed at the end of month t, for month-$t+1$ CPI growth and for quarterly CPI growth. To account for serial correlation in CPI growth, we control for the lagged dependent variable, akin to controlling for an AR(1) series of CPI. Consistent with our baseline estimates in Table 7, a one standard deviation increase in IP^{Core} predicts a 2.0 bps increase (t-stat=2.93) in next-month core-CPI growth and a 6.5 bps increase (t-stat=5.72) in headline-CPI growth. For quarterly (three-month) CPI growth, a one standard deviation increase in IP^{Core} predicts a 7.3 bps increase (t-stat=4.03) in core-CPI growth and a 15.6 bps increase (t-stat=4.69) in headline-CPI growth over the next three months.

Ann-Day Surprise Estimated Beta – In our baseline specification, we use ARMA(1,1) computed inflation innovations to estimate stocks' inflation exposure, a method also adopted by Boons et al. (2020) and Ang et al. (2007), among others. However, some of the information in these CPI innovations may already be incorporated into asset prices well before the official announcement. Ideally, the surprise measure should be based on real market forecasts made prior to the announcement. The challenge is that surprise data based on economists' forecasts, such as money market service data and Bloomberg surveys, is only available from 1991 onward (Swanson and Williams (2014)). Therefore, we rely on the time-series model to measure inflation innovations, which allows us to track inflation movements back to the 1970s in our main analysis.

To ensure robustness, we use alternative measures of inflation surprises, including economists' forecasting errors of core CPI, announcement-day changes in 2-year and 5-year Inflation Swap Rates, and changes in 2-year and 5-year UST yields.[39] Appendix Table IA5 presents the baseline results on inflation exposure and forecasting using these five alternative measures of announcement-day surprises. The post-ranking announcement-day inflation betas are significantly positive for the top-minus-bottom portfolio constructed based on the corresponding pre-ranking betas. For inflation forecasting, we construct long-short IP portfolios using surprise-based inflation betas. Panel B shows that, consistent with our baseline results, all five inflation portfolios significantly predict core-CPI innovations.

Beta Estimated By All Historical Observations – In our baseline specification, we estimate individual stocks' inflation betas using a five-year rolling window (Fama and French (1993)). Appendix Table IA6 further presents results based on inflation betas constructed following the methodology in Boons et al. (2020), using a weighted least squares (WLS) regression

[39]Using market-based instruments (e.g., inflation swaps) to capture inflation beta has the additional drawback that the beta might also reflect comovements in the risk premium.

with exponential weights over an expanding window that includes all historical observations. In line with Table 1, there is a significant post-ranking beta difference between the top and bottom quintiles for core CPI on the announcement day and for headline CPI (mainly the energy component) during the full month. The announcement-day core-CPI exposure of the inflation portfolio (Quintile 5-1) is 4.7 bps (t-stat=2.38), and the full-month headline-CPI exposure of the inflation portfolio is 43.4 bps (t-stat=2.89). Using the rolling all-year window estimated β^{Core} to form inflation portfolios and to predict inflation shocks yields similar results, both in terms of predicting CPI innovations and economists' forecasting errors.

Risk Factors and Portfolio Alpha – Panel A of Appendix Table IA7 presents the beta loadings of the inflation portfolios on the Fama-French five factors. Consistent with the results in Table 3, IP^{Core} has a positive loading on HML, although the t-stat is only marginally significant. Panel B further details the predictive power of the Fama-French five-factor adjusted alphas for the IP portfolios in forecasting inflation shocks. The findings are robust and demonstrate similar economic magnitudes.

7 Conclusions

In this paper, we examine how inflation news is incorporated into the prices of cross-sectional stocks and how the relative pricing of these stocks can be utilized to forecast inflation. To understand the variation in firms' exposure to inflation, we compare the full-month constructed headline beta with the announcement-day constructed core beta. Our analysis shows that the risk-based, headline-focused inflation beta effectively captures time-varying inflation risk premiums, while the information-based, core-focused inflation beta successfully identifies core inflation shocks. Both theoretically and empirically, we show that inflation affects firm valuations primarily through the cash flow channel. It is through this channel that our IP portfolio can predict future inflation shocks that are unexpected by both econometricians and economists.

Given the weak contemporaneous correlation between the aggregate stock market and inflation documented by Fama and Schwert (1977), the common belief is that the stock market is not an active place for price discovery with respect to inflation. Our findings suggest that information from cross-sectional stocks can add significant value, particularly for core inflation components. Specifically, our inflation portfolio predicts inflation shocks with R-squared values of 17.7% during the inflation surge of 2021 and 28.4% during the inflationary period of 1973. Key to our predictability is the cross-sectional approach, in which the relative pricing between stocks with high and low inflation exposure allows us to shift away from the overall equity market trends and focus on inflation expectations. Compared to Treasury and commodity markets, which are typically used for forecasting headline inflation, this cross-sectional approach offers more value in predicting core inflation shocks and when the Fed is slow to respond to rising inflation.

Regarding economists' forecasting errors, we find that economists do not fully incorporate the information from the inflation portfolio, with considerable room for improvement, particularly during the 2021 episode. As both policymakers and economists form their forecasts by incorporating all of the information available to them, their initial miss of the 2021 inflation surge reflects the limitations of existing inflation forecast measures and suggests a need for more diverse sources of information. By leveraging the inflation expectations embedded in cross-sectional stocks, our paper offers a novel approach to improving inflation forecasts. Going forward, the methodology we developed can be applied to other macroeconomic shocks to better understand market perceptions of macroeconomic states, provided these shocks have diverse impacts across different stocks.

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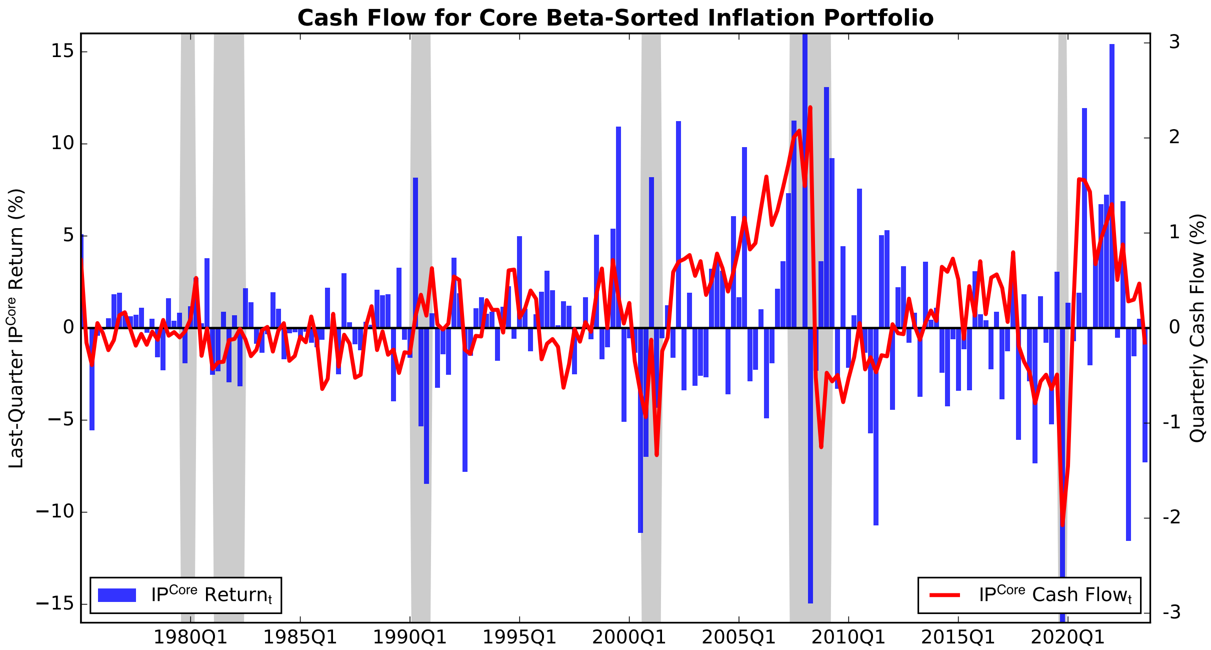
Figure 1. Core Beta and Firm Future Cash Flows

This figure reports the quarterly cash flow for inflation beta sorted portfolios. At the end of each quarter $t-1$, we sort all the stocks into quintile groups based on their core beta ($\beta_{t-1}^{\text{Core}}$), and compute the average quarter-t cash flow for stocks in each quintile group. The upper graph plots the cash flow difference between the top (most positive) and bottom (most negative) quintiles, along with the IP^{Core} return in quarter t. The grey areas denote the NBER recession periods. The lower graph plots the average cash flow for the top and bottom quintile groups from 2019 Q1 to 2023 Q4, along with the IP^{Core} return in quarter t. The shaded areas indicate the 95% confidence interval.



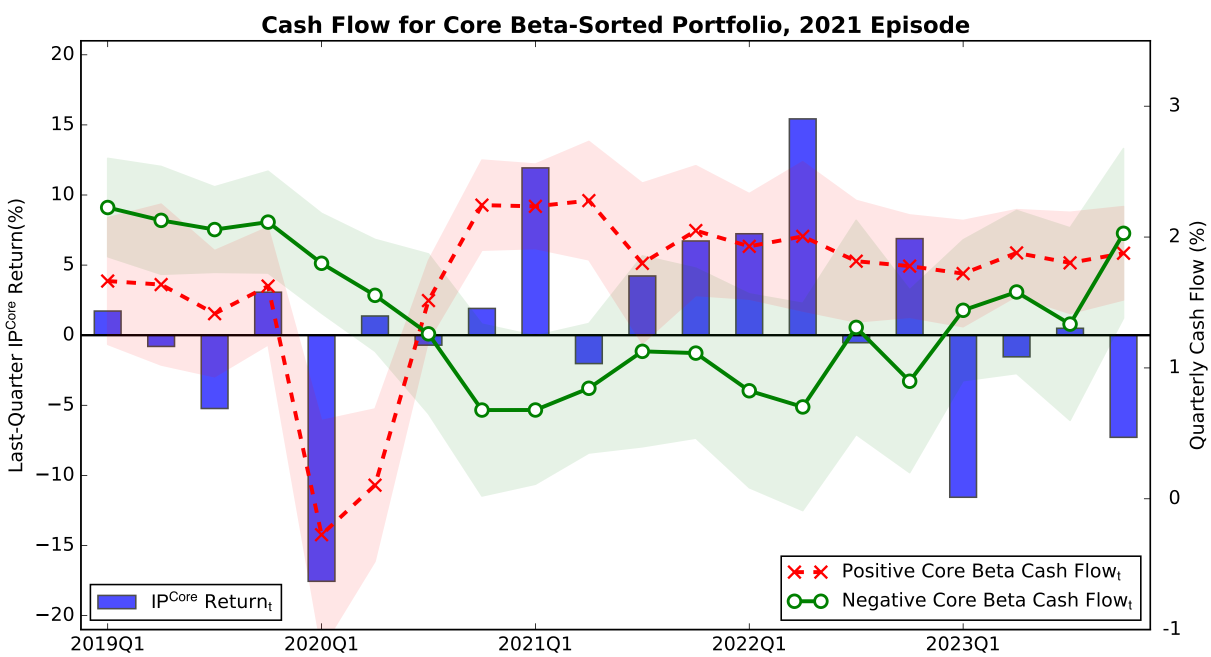
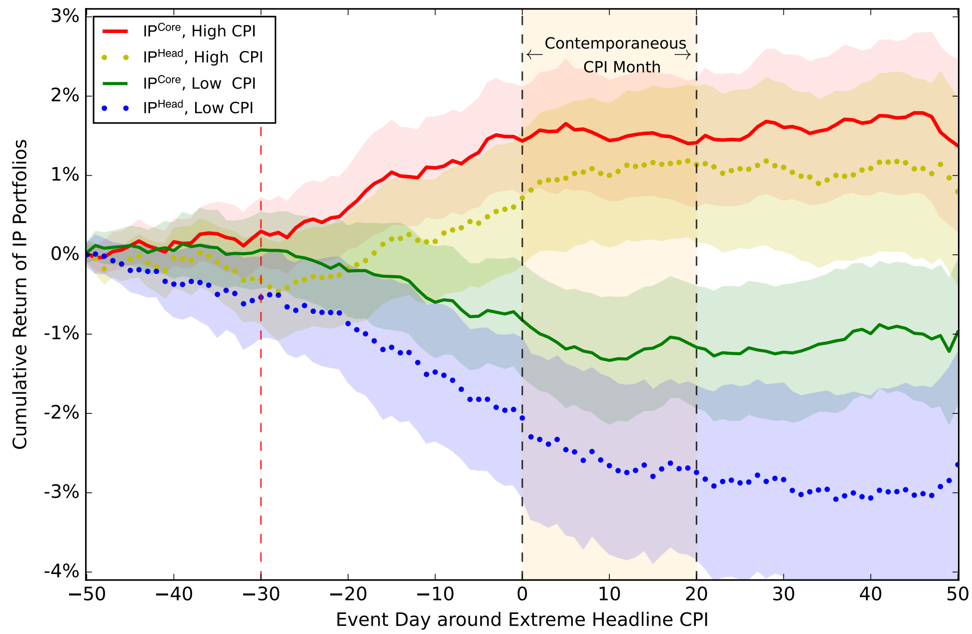


Figure 2. Performance of Inflation Portfolios around Extreme CPI Months

The upper graph shows the performance of IP^{Core} and IP^{Head} during the [-50, +50] trading day period surrounding extreme headline-CPI events, where t=0 denotes the beginning of the CPI data month. We sort all the CPI values into quintiles to define extreme CPI events. High (low) CPI events are those in the top (bottom) quintile ranks. The lower graph reports the corresponding performance of inflation portfolios when extreme CPI events are defined based on core-CPI innovations.



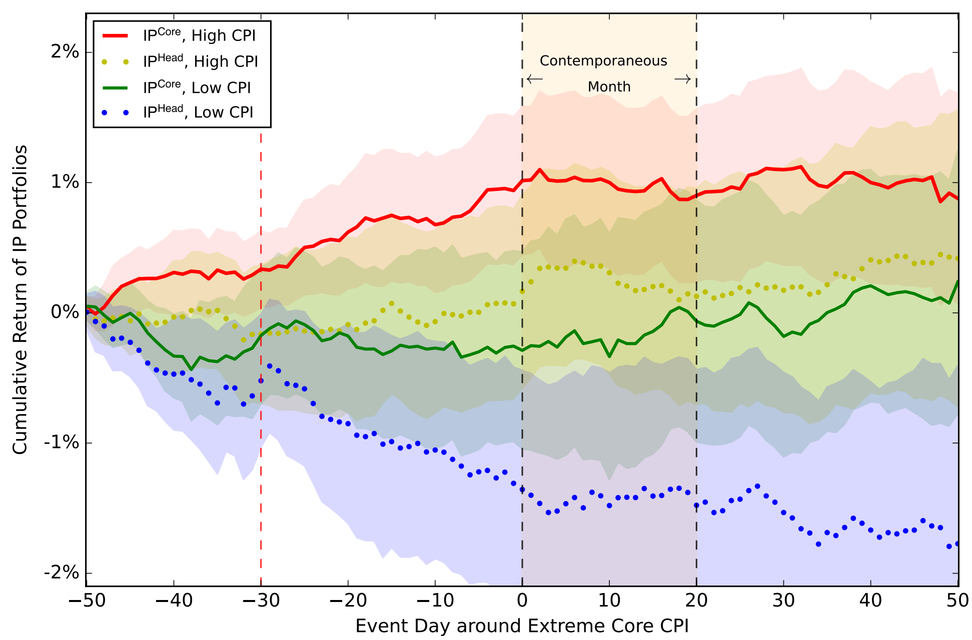


Figure 3. Economists' Forecasts and $\mathrm{IP}^{\mathrm{Core}}$ in the 2021 Episode

The upper graph plots the month-over-month core-CPI growth for the period from October 2020 to September 2022. The solid red line denotes the median forecast value of core-CPI (MoM) as made by Bloomberg economists. The dotted lines represent the highest and lowest values of Bloomberg forecasts. The lower graph plots the monthly values of $\mathrm{IP}^{\mathrm{Core}}$ and TIPS-UST during the same period.

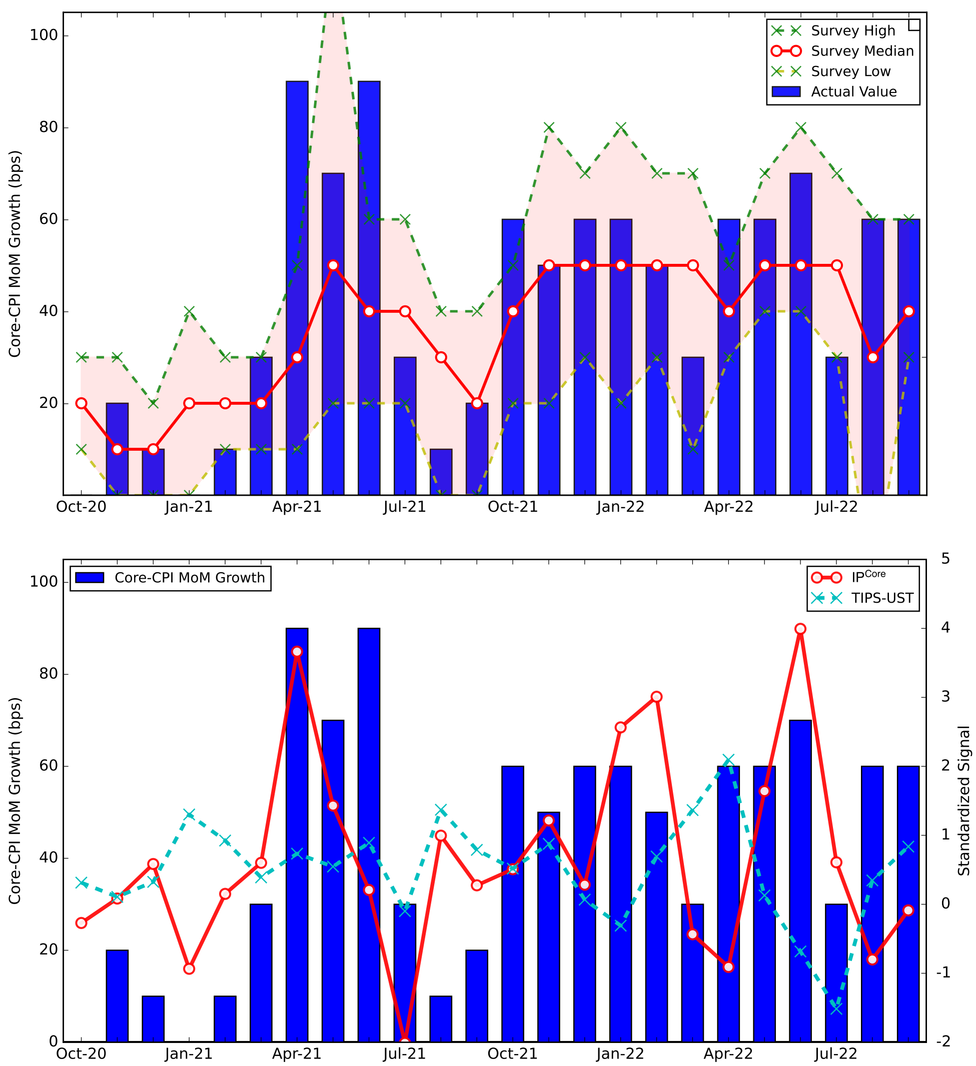


Figure 4. Predictability During Heightened Inflation Periods

The upper graphs plot the ability of IP^{Core} and TIPS-UST to predict core-CPI innovations during the 24-month window around the 2021 inflation run-up, i.e., from October 2020 to September 2022. The lower graphs plot the corresponding relationships for the 24-month window around the 1973 inflation run-up, from May 1973 to April 1975. Since TIPS were unavailable in the 1970s, we use the change in the 10-Year U.S. Treasury yield as a substitute.

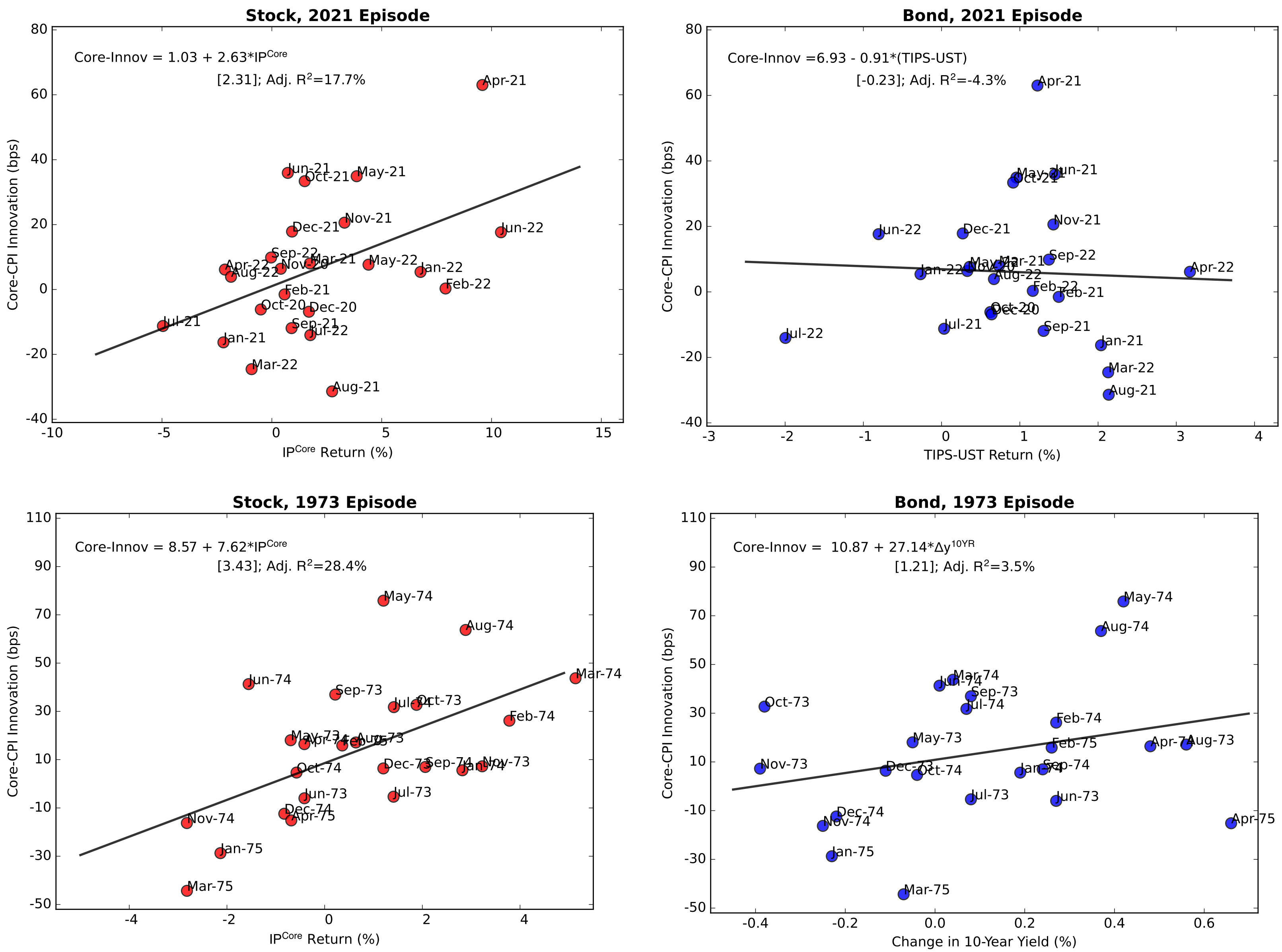
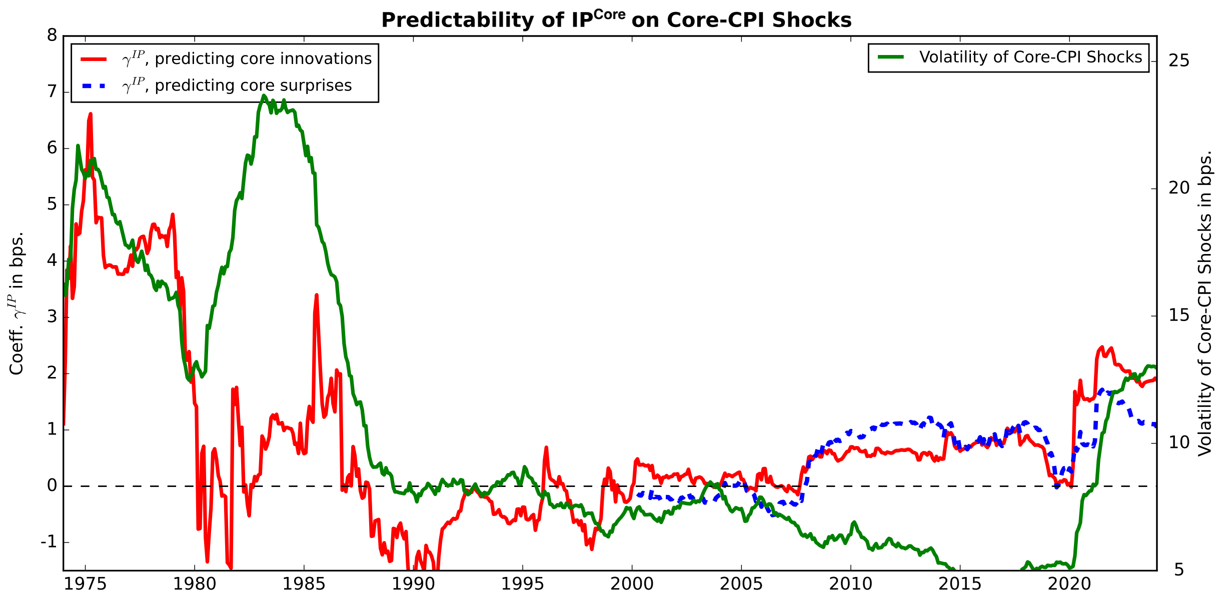


Figure 5. Predicting CPI Shocks using $\mathrm{IP}^{\mathrm{Core}}$

The graphs display the predictive coefficients, γ^{IP}, estimated using a rolling five-year window for core-CPI shocks. For each time t, we estimate the model: CPI $\mathrm{Shock}_{t+1} = \alpha + \gamma^{\mathrm{IP}} \times \mathrm{IP}_t^{\mathrm{Core}} + \varepsilon_{t+1}$, using observations from $t-59$ to t. We require at least 24 months of data for estimation. The sample period spans from December 1973 to December 2023. The red solid line shows the γ^{IP} with shocks measured by CPI innovations, while the blue dotted line represents CPI shocks measured by Bloomberg economists' forecasting errors. In the upper graph, the right axis plots the volatility of core shocks, measured by the average absolute value of core-CPI innovations in the corresponding rolling five-year window. In the lower graph, the right axis plots the extent to which the Fed is behind the curve, calculated as the Fed funds rate implied by the Taylor rule minus the actual Fed funds rate.



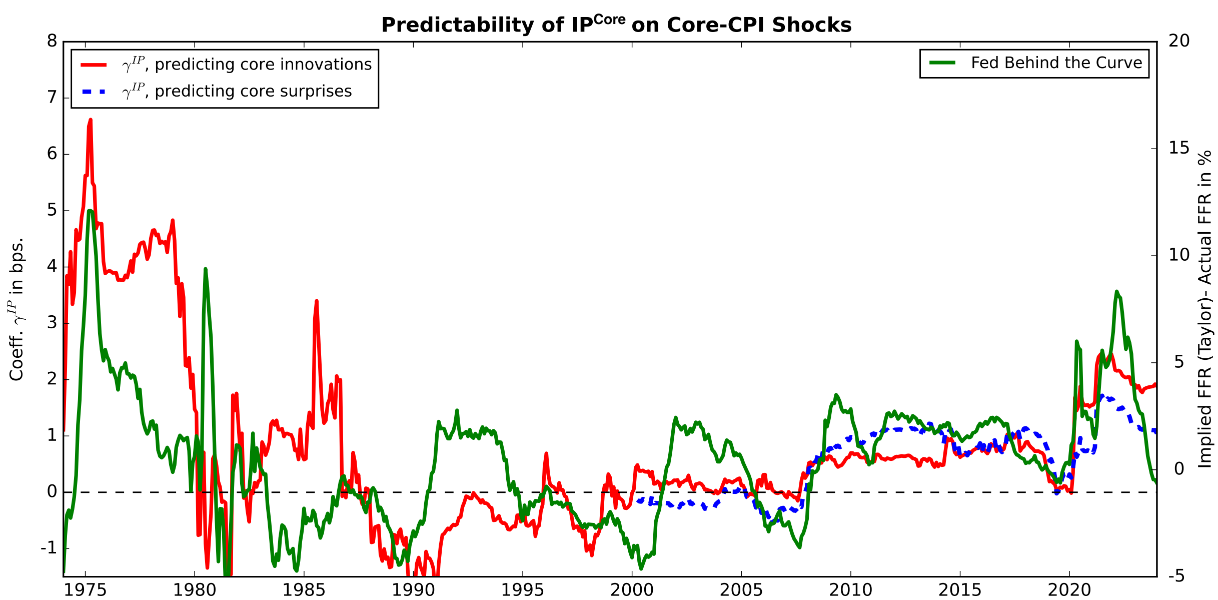


Table 1. Inflation Beta in Cross-Sectional Stocks: Ann-Day vs. Full-Month

For each stock on every CPI announcement day, we estimate the pre-ranking announcement-day betas by regressing the announcement-day firm excess returns on the inflation innovations released on the announcement days. Pre-ranking full-month betas are computed by regressing firm monthly excess returns on the contemporaneous-month inflation innovations. The "Raw Model" and "CAPM Model" present the estimates when inflation betas are estimated without and with market return (VWRETD) as controls, respectively. Stocks are then sorted into quintile groups based on their pre-ranking inflation betas within the NYSE size median cutoff groups, and we subsequently form equal-weighted 2×5 size and CPI beta sorted portfolios. These portfolios are rebalanced at each CPI announcement day when CPI information becomes available. The upper and lower panels report the post-ranking core, headline, and energy betas for portfolios sorted based on the corresponding pre-ranking betas, under the "Raw Model" and "CAPM Model", respectively. The portfolio returns are in bps. For ease of comparison, the inflation innovations are standardized with means of zero and standard deviations of one. The sample spans from January 1972 to December 2023. Standard errors are adjusted for heteroskedasticity, and the t-stats are presented in parentheses.

Panel A. Post-Ranking Inflation Beta, Raw Model

	Announcement-Day (β^{Ann})			Full-Month (β^{Full})		
	Core	*Headline*	*Energy*	*Core*	*Headline*	*Energy*
Q1 (Low)	−14.68	1.56	4.50	−68.02	−32.87	25.21
	(−3.23)	(0.19)	(0.57)	(−2.48)	(−0.87)	(0.72)
Q2	−9.75	2.32	6.27	−58.14	−28.24	23.02
	(−2.37)	(0.27)	(0.75)	(−2.47)	(−0.88)	(0.78)
Q3	−8.85	2.10	5.53	−57.99	−27.11	27.63
	(−2.18)	(0.23)	(0.57)	(−2.58)	(−0.94)	(1.00)
Q4	−8.63	1.71	4.39	−66.58	−22.35	29.24
	(−2.00)	(0.17)	(0.43)	(−2.84)	(−0.78)	(1.03)
Q5 (High)	−9.48	0.18	2.87	−68.09	2.58	58.31
	(−1.94)	(0.02)	(0.25)	(−2.46)	(0.07)	(1.50)
Q5 − Q1	5.21	−1.38	−1.63	−0.06	35.46	33.10
	(2.48)	(−0.31)	(−0.33)	(−0.00)	(1.77)	(1.36)

Panel B. Post-Ranking Inflation Beta, CAPM Model

	Announcement-Day (β^{Ann})			Full-Month (β^{Full})		
	Core	*Headline*	*Energy*	*Core*	*Headline*	*Energy*
Q1 (Low)	−2.19	−1.10	−1.29	−9.50	−1.51	−4.69
	(−1.14)	(−0.52)	(−0.64)	(−0.70)	(−0.12)	(−0.35)
Q2	0.75	1.27	0.10	−9.23	−4.64	−3.72
	(0.44)	(0.62)	(0.06)	(−1.04)	(−0.55)	(−0.38)
Q3	1.75	1.20	1.02	−16.29	−4.85	1.71
	(0.92)	(0.59)	(0.45)	(−2.09)	(−0.63)	(0.21)
Q4	2.10	2.55	0.96	−13.74	3.89	8.53
	(1.01)	(1.11)	(0.44)	(−1.56)	(0.44)	(0.90)
Q5 (High)	2.37	1.43	−2.09	−5.57	40.75	32.33
	(1.01)	(0.50)	(−1.05)	(−0.47)	(2.73)	(1.91)
Q5 − Q1	4.56	2.53	−0.80	3.93	42.25	37.02
	(2.49)	(0.98)	(−0.39)	(0.35)	(2.96)	(2.23)

Table 2. Inflation Beta Across Asset Classes: Ann-Day vs. Full-Month

This table presents the announcement-day and full-month inflation betas across various asset classes. Announcement-day core, headline, and energy betas are derived by regressing announcement-day asset excess returns on announcement-day core-, headline-, and energy-CPI innovations, respectively. Full-month core, headline, and energy betas are estimated by regressing monthly asset excess returns on contemporaneous-month inflation innovations. We assess the inflation exposure for different assets, including the change in the 2-Year U.S. Treasury yield ($\Delta y^{2\mathrm{YR}}$), the change in 10-Year U.S. Treasury yield ($\Delta y^{10\mathrm{YR}}$), the negative value of the Bloomberg U.S. Treasury Index return (-UST), the difference between the Bloomberg U.S. Treasury Inflation Notes Index return and the Bloomberg U.S. Treasury Index return (TIPS-UST), the Goldman Sachs Commodity Index return (GSCI), the aggregate stock market return (VWRETD), and the cross-sectional IP return. To facilitate comparison, all variables (both dependent and independent) are standardized with means of zero and standard deviations of one. The sample period spans from the earliest available date for each data series to the end of 2023, as shown in the last column. Standard errors are adjusted for heteroskedasticity, and the t-stats are presented in parentheses.

	Announcement-Day (β^{Ann})			Full-Month (β^{Full})			Sample Period
	Core	*Headline*	*Energy*	*Core*	*Headline*	*Energy*	
$\Delta y^{2\mathrm{YR}}$	0.120	0.037	0.019	0.120	0.140	0.068	1976-2023
	(2.14)	(0.83)	(0.51)	(1.67)	(3.44)	(2.11)	
$\Delta y^{10\mathrm{YR}}$	0.122	0.061	0.041	0.104	0.195	0.146	1972-2023
	(2.40)	(1.09)	(0.90)	(1.72)	(4.08)	(3.58)	
-UST	0.156	0.091	0.080	0.034	0.238	0.221	1998-2023
	(2.97)	(1.18)	(1.23)	(0.61)	(3.50)	(3.20)	
TIPS-UST	0.224	0.250	0.122	0.052	0.306	0.263	1998-2023
	(4.09)	(2.58)	(1.57)	(0.70)	(2.87)	(2.73)	
GSCI	0.060	−0.010	−0.045	0.035	0.218	0.284	1972-2023
	(1.84)	(−0.20)	(−0.89)	(0.74)	(4.12)	(6.05)	
Stock Market	−0.115	0.005	0.051	−0.105	−0.056	0.051	1972-2023
	(−2.82)	(0.06)	(0.60)	(−2.43)	(−0.94)	(0.95)	
Cross-Section IP	0.107	0.068	−0.025	0.019	0.173	0.137	1972-2023
	(2.49)	(0.98)	(−0.39)	(0.35)	(2.96)	(2.23)	

Table 3. Determinants of Inflation Beta

This table examines the determinants of cross-sectional stocks' inflation beta. The dependent variables are core beta (β^{Core}) and headline beta (β^{Head}). Cash flow betas (b^{Core} and b^{Head}) are estimated using a rolling five-year window, by regressing changes in quarterly cash flow on quarterly core- and headline-CPI innovations, respectively. We control for firm size (Log(Size)), market-to-book ratio (ME/BE), cash flow, dividend payout, and the cash flow duration from Weber (2018). All variables (both dependent and independent) are standardized with means of zero and standard deviations of one for ease of interpretation. Time and industry fixed effects are included as indicated. The sample spans from January 1972 to December 2023. Standard errors are double clustered at the quarter and firm levels, and the t-stats are presented in parentheses. See Appendix A for variable definitions.

	Core Beta (β^{Core})						Headline Beta (β^{Head})					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Size)	0.025	0.027	0.024	0.019	0.021	0.011	0.009	0.009	0.010	0.020	0.024	0.012
	(1.95)	(2.16)	(1.90)	(1.50)	(1.58)	(0.83)	(0.64)	(0.64)	(0.68)	(1.45)	(1.66)	(0.89)
CF Beta, $b^{\text{Core (Head)}}$	0.032	0.031	0.031	0.031	0.033	0.031	0.025	0.026	0.027	0.024	0.026	0.016
	(3.16)	(3.09)	(3.08)	(3.01)	(3.20)	(3.04)	(2.23)	(2.34)	(2.36)	(1.88)	(1.98)	(1.25)
ME/BE		−0.029	−0.037	−0.027	−0.015	−0.002		−0.018	−0.017	−0.038	−0.021	0.000
		(−2.08)	(−2.55)	(−2.22)	(−1.25)	(−0.21)		(−1.70)	(−1.60)	(−3.63)	(−1.88)	(−0.01)
Cash Flow			0.032	0.040	0.047	0.032			−0.003	0.020	0.026	0.003
			(2.95)	(3.51)	(4.13)	(3.18)			(−0.32)	(1.43)	(2.32)	(0.30)
Dividend Payout				0.019	0.018	0.012				−0.007	−0.007	−0.021
				(2.68)	(2.55)	(1.84)				(−0.77)	(−0.78)	(−2.51)
CF Duration					−0.029	−0.037					−0.049	−0.052
					(−2.11)	(−2.68)					(−2.94)	(−3.30)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	N	Y	N	N	N	N	N	Y
Observations	159,622	155,456	155,354	143,124	141,201	139,501	159,622	155,456	155,354	143,124	141,201	139,501
Adj. R^2	1.3%	1.4%	1.5%	1.9%	2.0%	3.4%	2.0%	2.1%	2.1%	2.3%	2.4%	5.6%

Table 4. Core Beta and Firm Future Cash Flows

This table presents the predictive regressions of quarter-$t+1$ firm fundamentals conditional on quarter-t core betas and inflation expectations. The dependent variables are quarter-$t+1$ firm sales growth, cash flow, change of IBES long-term growth forecast of EPS (IBES LTG), and quarterly return. The independent variables include the interaction of the quintile rank of β^{Core} ($\beta^{\text{Core}}_{\text{Rank}}$) with IP^{Core}, $\beta^{\text{Core}}_{\text{Rank}}$, Log(Size), asset growth, ME/BE, and dividend payout, all observed at the end of quarter t. To control for the persistence in firm fundamentals, we also include the quarter-t value of the dependent variable as controls (Y_t). All variables (except $\beta^{\text{Core}}_{\text{Rank}}$ and IP^{Core}) are standardized with means of zero and standard deviations of one for ease of interpretation. Time and firm fixed effects are included. The sample spans from January 1972 to December 2023. Standard errors are double clustered by quarter and firm, and the t-stats are presented in parentheses.

	Sales Growth$_{t+1}$		Cash Flow$_{t+1}$		IBES LTG$_{t+1}$		Return$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\beta^{\text{Core}}_{\text{Rank}} \times \text{IP}^{\text{Core}}_t$	0.196	0.177	0.178	0.142	0.109	0.145	−0.133	−0.155
	(3.69)	(3.11)	(3.76)	(3.09)	(2.24)	(2.76)	(−0.97)	(−1.14)
$\beta^{\text{Core}}_{\text{Rank}}$	0.002	0.002	0.001	0.003	−0.005	−0.003	0.001	0.001
	(0.62)	(0.71)	(0.34)	(1.48)	(−2.23)	(−1.38)	(0.31)	(0.39)
Log(Size)	−0.024	−0.093	0.198	0.119	−0.006	−0.001	−0.519	−0.476
	(−2.00)	(−7.11)	(13.76)	(8.46)	(−0.70)	(−0.16)	(−16.64)	(−16.63)
Y_t	−0.291	−0.337	0.384	0.341	−0.079	−0.079	−0.006	−0.013
	(−18.05)	(−20.38)	(26.02)	(21.06)	(−6.06)	(−6.04)	(−0.50)	(−1.00)
Asset Growth		0.199		0.027		0.008		0.002
		(16.55)		(5.90)		(3.33)		(0.67)
ME/BE		0.083		0.165		0.011		−0.013
		(9.93)		(17.29)		(2.19)		(−1.34)
Dividend Payout		0.006		−0.031		0.019		−0.025
		(1.32)		(−8.48)		(4.76)		(−4.92)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	167,559	150,573	168,021	150,917	137,358	124,181	173,512	152,867
Adj. R^2	10.9%	14.4%	58.6%	58.4%	2.7%	3.5%	29.8%	29.8%

Table 5. Inflation Beta Sorted Portfolios and Inflation Risk Premium

This table shows the performance of quintile portfolios sorted by core beta (β^{Core}, Panel A) and headline beta (β^{Head}, Panel B). The table reports the annualized excess returns (over the risk-free rate) and CAPM alpha for the full sample from January 1972 to December 2023, as well as for subsamples split around December 2002. Standard errors are adjusted for heteroskedasticity, and the t-stats are presented in parentheses.

Panel A. Core Beta (β^{Core}) Sorted Portfolios

	Whole Sample		Pre-2002		Post-2002	
	Ex.Ret.	α_{CAPM}	*Ex.Ret.*	α_{CAPM}	*Ex.Ret.*	α_{CAPM}
Q1 (Low)	8.45	0.52	7.04	1.23	10.52	−0.45
	(3.19)	(0.63)	(2.01)	(1.25)	(2.60)	(−0.31)
Q2	9.48	2.66	7.81	2.94	11.94	2.11
	(4.19)	(4.01)	(2.63)	(3.14)	(3.42)	(2.42)
Q3	9.21	2.51	7.69	2.98	11.46	1.54
	(4.13)	(3.57)	(2.66)	(2.97)	(3.26)	(1.79)
Q4	8.86	1.67	7.45	2.47	10.95	0.06
	(3.70)	(2.30)	(2.46)	(2.65)	(2.81)	(0.06)
Q5 (High)	9.63	1.22	7.68	1.72	12.52	0.22
	(3.41)	(1.31)	(2.13)	(1.65)	(2.76)	(0.12)
Q5 − Q1	1.19	0.70	0.63	0.48	2.00	0.67
(IP^{Core})	(1.06)	(0.62)	(0.61)	(0.47)	(0.87)	(0.28)

Panel B. Headline Beta (β^{Head}) Sorted Portfolios

	Whole Sample		Pre-2002		Post-2002	
	Ex.Ret.	α_{CAPM}	*Ex.Ret.*	α_{CAPM}	*Ex.Ret.*	α_{CAPM}
Q1 (Low)	9.82	1.89	8.90	3.08	11.18	0.24
	(3.68)	(2.08)	(2.49)	(2.52)	(2.81)	(0.18)
Q2	9.68	2.79	8.32	3.38	11.69	1.81
	(4.20)	(3.74)	(2.73)	(3.11)	(3.33)	(2.04)
Q3	9.23	2.49	7.50	2.77	11.78	1.77
	(4.10)	(3.52)	(2.57)	(2.73)	(3.32)	(2.08)
Q4	9.33	2.30	7.72	2.82	11.71	1.17
	(4.02)	(3.56)	(2.61)	(3.26)	(3.13)	(1.28)
Q5 (High)	7.63	−0.83	5.34	−0.59	11.00	−1.54
	(2.65)	(−0.78)	(1.46)	(−0.45)	(2.37)	(−0.85)
Q5 − Q1	−2.20	−2.72	−3.56	−3.66	−0.18	−1.79
(IP^{Head})	(−1.67)	(−1.98)	(−2.13)	(−2.11)	(−0.09)	(−0.81)

Table 6. Predicting Inflation Innovations Using Financial Assets

This table presents the predictive regressions of financial asset returns on core-CPI innovations and headline-CPI innovations, with returns estimated on a 10-day interval. For instance, the interval [-10,-1] denotes returns from 10 trading days before the CPI month to the last trading day before the CPI month. The predictors include IP^{Core}, IP^{Head}, GSCI, and TIPS-UST, all standardized with means of zero and standard deviations of one for ease of interpretation. The sample period is from January 1972 to December 2023, with the TIPS-UST sample spanning from May 1998 to December 2023. Standard errors are adjusted for heteroskedasticity, and the t-stats are presented in parentheses.

	Core-CPI Innovation$_{t+1}$				Headline-CPI Innovation$_{t+1}$			
	X=IP^{Core}	X=IP^{Head}	X=GSCI	X=TIPS-UST	X=IP^{Core}	X=IP^{Head}	X=GSCI	X=TIPS-UST
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X[-10,-1]	0.551	1.963	1.038	−0.233	3.319	4.568	8.407	7.707
	(0.92)	(2.42)	(1.41)	(−0.34)	(2.80)	(4.09)	(6.20)	(3.21)
X[-20,-11]	1.587	1.094	1.436	2.285	5.820	4.957	9.027	7.766
	(2.10)	(1.64)	(1.88)	(1.88)	(4.65)	(4.21)	(6.82)	(3.43)
X[-30,-21]	1.803	0.613	1.426	1.118	4.645	2.704	3.107	1.319
	(2.37)	(0.71)	(1.86)	(1.89)	(2.73)	(1.56)	(2.78)	(0.71)
X[-40,-31]	−0.571	0.273	0.340	0.812	−0.555	0.371	−0.992	−3.168
	(−0.94)	(0.41)	(0.54)	(1.37)	(−0.45)	(0.31)	(−0.88)	(−1.92)
Intercept	−0.072	−0.072	−0.072	−0.835	−0.012	−0.012	−0.012	−1.942
	(−0.12)	(−0.12)	(−0.12)	(−1.35)	(−0.01)	(−0.01)	(−0.01)	(−1.28)
Observations	624	624	624	308	624	624	624	308
Adj. R^2	1.9%	1.8%	1.8%	4.4%	8.9%	7.9%	24.2%	14.4%

Table 7. Predicting Inflation Innovations Using Core Beta-Sorted Portfolio

This table reports the ability of asset returns, observed at the end of month t, to predict the month-$t+1$ CPI innovation. The dependent variables are core-CPI innovations and headline-CPI innovations (in bps). IP^{Core} represents the cumulative return of the announcement-day core beta (β^{Core}) formed portfolio over the 30 days ([-30,-1]) preceding the end of month t. IP^{Head} is the 30-day cumulative return of the full-month headline beta (β^{Head}) formed portfolio before the end of month t. GSCI and TIPS-UST refer to the 30-day cumulative return for the Goldman Sachs Commodity Index and TIPS-UST, respectively, observed at the end of month t. All the independent variables are standardized with means of zero and standard deviations of one. The sample spans from January 1972 to December 2023, with the TIPS-UST sample ranging from May 1998 to December 2023. Standard errors are adjusted for heteroskedasticity, and the t-stats are reported in parentheses.

	Core-CPI Innovation_{t+1}						Headline-CPI Innovation_{t+1}					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IP^{Core}	2.235	1.653	2.591	2.394			7.901	4.476	8.858	5.556		
	(2.98)	(2.30)	(2.79)	(2.47)			(6.54)	(3.84)	(5.45)	(2.97)		
IP^{Head}					2.156	0.923					7.368	4.803
					(2.86)	(1.47)					(5.78)	(3.15)
GSCI		1.803		0.715		1.259		10.615		12.003		12.308
		(2.23)		(0.71)		(1.25)		(6.94)		(5.95)		(6.34)
TIPS-UST			1.352	1.014		1.005			8.021	2.348		2.154
			(1.75)	(1.30)		(1.33)			(2.63)	(0.74)		(0.69)
Intercept	−0.072	−0.072	−0.835	−0.835	−0.072	−0.835	−0.012	−0.012	−1.942	−1.942	−0.012	−1.942
	(−0.12)	(−0.12)	(−1.37)	(−1.37)	(−0.12)	(−1.35)	(−0.01)	(−0.01)	(−1.32)	(−1.42)	(−0.01)	(−1.42)
Observations	624	624	308	308	624	308	624	624	308	308	624	308
Adj. R^2	1.9%	2.9%	7.5%	7.5%	1.8%	4.1%	9.1%	24.0%	20.3%	31.3%	7.9%	30.4%

Table 8. Do Economists Update Inflation Expectations Using Market-Based Information?

This table reports the ability of asset returns to predict economists' forecasts of inflation growth as well as their forecasting errors. Change in forecast (in bps) is calculated as the Bloomberg economists' forecasting value of month-$t+1$ CPI growth minus the benchmark value predicted by the ARMA(1,1) model. Forecasting error (in bps) is calculated as the actual month-$t+1$ CPI growth minus the forecasting value by Bloomberg economists. The independent variables include IP^{Core}, IP^{Head}, GSCI, and TIPS-UST, all constructed at the end of month t. The independent variables are standardized to have means of zero and standard deviations of one. The sample period spans from May 1998 to December 2023. Standard errors are adjusted for heteroskedasticity, and the t-stats are reported in parentheses.

Panel A. Predicting Economist Forecasts of Core-CPI Growth

	Change in Forecast$_{t+1}$						Forecasting Error$_{t+1}$					
IP^{Core}	1.149	0.668	1.002	0.666			2.300	2.326	2.137	2.308		
	(2.31)	(1.72)	(2.38)	(1.73)			(3.10)	(2.72)	(2.85)	(2.70)		
IP^{Head}					1.241	0.754					0.422	0.063
					(3.13)	(2.42)					(0.72)	(0.10)
GSCI		1.278		1.229		1.203		−0.068		−0.626		0.196
		(2.73)		(2.66)		(2.45)		(−0.09)		(−0.67)		(0.23)
TIPS-UST			0.678	0.092		0.057			0.757	1.055		1.098
			(1.76)	(0.29)		(0.17)			(1.31)	(1.44)		(1.62)
Intercept	−0.548	−0.551	−0.546	−0.551	−0.549	−0.551	−0.23	−0.229	−0.227	−0.225	−0.229	−0.225
	(−1.80)	(−1.86)	(−1.81)	(−1.85)	(−1.81)	(−1.86)	(−0.38)	(−0.38)	(−0.37)	(−0.37)	(−0.37)	(−0.36)
Observations	307	307	307	307	307	307	307	307	307	307	307	307
Adj. R^2	4.2%	8.6%	5.3%	8.3%	4.9%	8.7%	4.1%	3.8%	4.3%	4.2%	−0.2%	0.3%

Panel B. Predicting Economist Forecasts of Headline-CPI Growth

	Change in Forecast$_{t+1}$						Forecasting Error$_{t+1}$					
IP^{Core}	7.579	3.620	6.207	3.588			3.786	2.583	3.594	2.597		
	(4.39)	(1.92)	(3.82)	(1.90)			(4.22)	(2.54)	(3.93)	(2.57)		
IP^{Head}					8.060	3.914					3.218	1.914
					(4.29)	(2.48)					(4.66)	(2.57)
GSCI		10.504		9.522		9.427		3.194		3.625		3.886
		(5.02)		(4.99)		(5.34)		(3.49)		(3.98)		(4.73)
TIPS-UST			6.370	1.869		1.692			0.893	−0.820		−0.889
			(2.71)	(0.75)		(0.69)			(0.84)	(−0.73)		(−0.81)
Intercept	−2.308	−2.308	−2.308	−2.308	−2.308	−2.308	0.097	0.097	0.097	0.097	0.097	0.097
	(−1.67)	(−1.82)	(−1.72)	(−1.82)	(−1.68)	(−1.82)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
Observations	308	308	308	308	308	308	308	308	308	308	308	308
Adj. R^2	8.6%	23.1%	14.3%	23.2%	9.8%	23.5%	8.2%	13.1%	8.3%	13.1%	5.8%	11.5%

Table 9. Time-Varying Predictability

Panel A reports the forecasting ability of the $\mathrm{IP}^{\mathrm{Core}}$ portfolio on core-CPI innovations and economists' forecasting errors during heightened inflation periods. The "2021 Episode" includes the 24 months before the peak of core inflation in September 2022 (i.e., from October 2020 to September 2022), and the "1973 Episode" includes the 24 months during the core-CPI run-up period from May 1973 to April 1975. Since TIPS are unavailable in the 1970s, we use the change in the 10-Year US Treasury yield as a substitute. Panel B reports the predictability of the $\mathrm{IP}^{\mathrm{Core}}$ portfolio for various subsamples. High and low uncertainty denote periods with above- and below-median last-month absolute CPI innovations. High and low disagreement are defined based on the median cutoff of CPI disagreement, calculated as the difference between the 75th percentile and the 25th percentile of quarterly CPI forecasts from the Survey of Professional Forecasters (SPF) database. "Behind the curve" refers to periods when the difference between the Taylor rule implied Fed funds rate and the actual Fed funds rate is higher than the 67% percentile cutoff, and "Other" refers to the rest. The federal funds rate implied by the Taylor rule is estimated as 2.5%+1.5*(Core-CPI YoY Growth-2%)+0.5*OutPut Gap. The standard errors are adjusted for heteroskedasticity, and the t-stats are reported in parentheses.

Panel A. Heightened Inflation Episodes

	2021 Episode				1973 Episode	
	Core Innovation$_{t+1}$		Forecasting Error$_{t+1}$		Core Innovation$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{IP}^{\mathrm{Core}}$	8.721	10.176	6.841	9.088	19.537	18.441
	(2.31)	(2.47)	(1.73)	(2.40)	(3.43)	(3.56)
GSCI		−5.171		−7.303		0.332
		(−1.07)		(−1.60)		(0.13)
TIPS-UST ($\Delta y^{10\mathrm{YR}}$)		6.824		10.665		7.865
		(0.85)		(1.44)		(1.10)
Observations	24	24	24	24	24	24
Adj. R^2	17.7%	15.0%	9.1%	12.3%	28.4%	26.1%

Panel B. Conditional on Inflation Risk and Noise from Treasury Market

	Core Innovation$_{t+1}$	Forecasting Error$_{t+1}$	Core Innovation$_{t+1}$	Forecasting Error$_{t+1}$
	High Uncertainty		Low Uncertainty	
$\mathrm{IP}^{\mathrm{Core}}$	3.918	2.900	0.442	1.815
	(3.34)	(2.39)	(0.70)	(2.38)
Adj. R^2	5.4%	5.1%	−0.2%	3.1%
	High Disagreement		Low Disagreement	
$\mathrm{IP}^{\mathrm{Core}}$	2.474	2.946	0.939	1.005
	(2.25)	(2.89)	(1.46)	(1.26)
Adj. R^2	3.3%	6.3%	0.6%	0.3%
	Behind the Curve		Other	
$\mathrm{IP}^{\mathrm{Core}}$	3.688	3.255	1.252	1.674
	(2.80)	(3.46)	(1.83)	(1.56)
Adj. R^2	5.6%	6.8%	0.4%	2.1%

Table 10. Out-of-Sample Forecastability

Panel A reports the out-of-sample incremental inflation forecasting power of inflation portfolios and other inflation forecasters. The forecasting period is from May 2003 to December 2023. In each month t, we estimate the forecasting model, $\pi_t = a + \sum_{k=1}^{N} b_k X_{t-1}^k + \epsilon_t$, using only information up to and including month t. We then use the estimated coefficients to forecast month-$t+1$ inflation growth. We include forecasting signals of inflation portfolios (IP^{Core}, IP^{Head}), financial assets (GSCI, TIPS-UST, VWRETD, $\Delta y^{2\text{YR}}$, and $\Delta y^{10\text{YR}}$), the latest survey forecasted inflation growth from SPF survey and Michigan survey, and macroeconomic variables (real GDP growth, output gap, unemployment rate (UNEMP), labor income share (Labor Share), and CFNAI). "Relative RMSE" reports the ratio of the root mean squared forecasting error estimated using the corresponding forecasting model, relative to that of the benchmark model of ARMA(1,1). The p-value is computed under the null that the RMSE for that model equals the RMSE for the ARMA(1,1), with the alternative hypothesis that the RMSE for the ARMA(1,1) exceeds the RMSE for that model. Panel B reports the out-of-sample forecasts for subsamples of high inflation importance defined in Table 9, including the 2021 episode, periods of high uncertainty, high disagreement, and behind-the-curve periods.

Panel A. Relative RMSE for the Whole Sample

	Core-CPI		Headline-CPI	
Forecasting Model	Relative RMSE	p-value	Relative RMSE	p-value
IP:				
IP^{Core}	96.37%	0.05	92.75%	0.00
IP^{Head}	99.67%	0.41	94.46%	0.00
Other Financial Assets:				
GSCI	97.59%	0.14	85.84%	0.00
TIPS-UST	101.18%	0.69	93.11%	0.11
VWRETD	100.99%	0.99	99.78%	0.38
$\Delta y^{2\text{YR}}$	99.49%	0.39	99.19%	0.06
$\Delta y^{10\text{YR}}$	99.46%	0.38	99.49%	0.26
Survey:				
SPF Survey	104.34%	0.92	98.33%	0.30
Michigan Survey	99.42%	0.27	100.47%	0.66
Macroeconomic Variables:				
Real GDP Growth	101.47%	0.79	101.09%	0.96
Output Gap	105.53%	0.97	101.34%	0.99
UNEMP	103.27%	0.99	100.99%	0.98
Labor Share	100.92%	0.88	100.75%	0.88
CFNAI	102.41%	0.60	103.51%	0.83

Panel B. Subsample Tests for the IP^{Core} Model

	Core-CPI		Headline-CPI	
Subsample	Relative RMSE	p-value	Relative RMSE	p-value
2021 Episode	93.56%	0.05	88.78%	0.07
High Uncertainty	95.15%	0.05	91.53%	0.00
High Disagreement	96.12%	0.07	91.28%	0.00
Behind the Curve	96.21%	0.09	91.67%	0.02

Table 11. Firm Information Environment and Inflation Forecastability

This table reports the predictability of $\mathrm{IP}^{\mathrm{Core}}$ conditional on the firm's information environment. The dependent variables are core-CPI innovations (Panel A) and headline-CPI innovations (Panel B) in bps. We use firm size, residual institutional ownership, and residual analyst coverage to measure the information environment. Residual institutional ownership and analyst coverage are computed by orthogonalizing them with respect to firm size. We sort stocks into 2×5 groups, first by their information environment proxy (X) and then by β^{Core}. The two size groups are defined by the median cutoff of NYSE market capitalization. The predictive regressors are the top-minus-bottom quintile portfolio returns within each group of X. $\mathrm{IP}^{\mathrm{Core}}$ returns are standardized with a mean of zero and a standard deviation of one. The sample spans from January 1972 to December 2023. The standard errors are adjusted for heteroskedasticity, and the t-stats are reported in parentheses.

Panel A. Predicting Month $t+1$ Core-CPI Innovation

	X = Size			X = Institutional Ownership			X = Analyst Coverage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathrm{IP}^{\mathrm{Core}}$ ($X >$ Median)	2.235		2.025	2.701		2.710	2.062		1.790
	(2.98)		(2.69)	(3.47)		(3.22)	(2.66)		(2.21)
$\mathrm{IP}^{\mathrm{Core}}$ ($X \leq$ Median)		1.359	0.488		1.204	−0.020		1.473	0.500
		(1.84)	(0.69)		(1.56)	(−0.03)		(2.36)	(0.90)
Observations	624	624	624	523	523	523	575	575	575
Adj. R^2	1.9%	0.6%	1.8%	3.4%	0.5%	3.2%	1.8%	0.9%	1.8%

Panel B. Predicting Month $t+1$ Headline-CPI Innovation

	X = Size			X = Institutional Ownership			X = Analyst Coverage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathrm{IP}^{\mathrm{Core}}$ ($X >$ Median)	7.901		7.636	5.580		4.597	4.468		3.060
	(6.54)		(6.20)	(4.18)		(3.29)	(3.68)		(2.47)
$\mathrm{IP}^{\mathrm{Core}}$ ($X \leq$ Median)		3.899	0.617		4.253	2.177		4.254	2.590
		(3.06)	(0.56)		(3.05)	(1.57)		(3.14)	(1.82)
Observations	624	624	624	523	523	523	575	575	575
Adj. R^2	9.1%	2.1%	9.0%	4.6%	2.6%	5.0%	3.0%	2.7%	3.5%

Table 12. Forecasting Inflation Swaps and Nominal Yields

This table reports the ability of IP^{Core}, observed at the end of month t, to predict changes in inflation swap rates (Panel A) and nominal yields (Panel B). Changes in swap rates and nominal yields are measured from the end of month t to the CPI announcement day of month-$t+1$ (released in month-$t+2$). IP^{Core} is standardized to have a mean of zero and a standard deviation of one. The sample period is from July 2004 to December 2023 in Panel A and from January 1972 to December 2023 in Panel B. The standard errors are Newey-West adjusted with two lags. The t-stats are in parentheses.

Panel A. Predicting Changes in Inflation Swap Rates (%)

	1 Year	2 Year	3 Year	5 Year	7 Year	10 Year	20 Year	30 Year
IP^{Core}	0.194	0.129	0.095	0.067	0.051	0.038	0.033	0.025
	(2.93)	(2.48)	(2.44)	(2.22)	(2.08)	(2.23)	(2.21)	(1.78)
Observations	234	233	233	233	233	234	233	233
Adj. R^2	7.6%	6.1%	5.6%	4.8%	3.8%	3.3%	3.0%	1.5%

Panel B. Predicting Changes in Nominal Yields (%)

	1 Year	2 Year	3 Year	5 Year	7 Year	10 Year	20 Year	30 Year
IP^{Core}	0.117	0.102	0.094	0.077	0.065	0.056	0.058	0.045
	(3.87)	(3.70)	(3.88)	(3.56)	(3.37)	(3.15)	(3.30)	(2.76)
Observations	624	571	624	624	624	624	542	563
Adj. R^2	2.4%	2.2%	2.2%	1.7%	1.4%	1.2%	1.5%	1.0%

Appendix A. Variable Definition

This table reports the definitions of the main variables used in the paper.

Variable	Definition
CPI growth	$\pi_t = log(P_t) - log(P_{t-1})$, where P_t is the level of CPI for month t
CPI innovation	CPI-Innov$_{t+1} = \pi_{t+1} - \widehat{\pi_{t+1}}$, where $\widehat{\pi_{t+1}}$ is estimated using all the historical observations on and before month t from ARMA(1,1) time series model: $\pi_{t+1} = \mu + \phi\pi_t + \varphi\varepsilon_t + \varepsilon_{t+1}$
IP$^{\text{Core}}$	The cumulative return of the announcement-day core beta (β^{Core}) formed portfolio in the 30 days ([-30,-1]) before the end of month t
IP$^{\text{Head}}$	The cumulative return of the full-month headline beta (β^{Head}) formed portfolio in the 30 days before the end of month t
GSCI	Goldman Sachs Commodity Index return in the 30 days before the end of month t
TIPS-UST	Return difference between Bloomberg U.S. Treasury Inflation Notes Index and Bloomberg U.S. Treasury Index in the 30 days before the end of month t
Change in Forecasts	The Bloomberg economists' forecasting value of CPI growth minus the value predicted under the ARMA(1,1) model
Forecasting Error	The actual MoM CPI growth minus the forecasting value by Bloomberg economists
CPI Uncertainty	The absolute value of last-month CPI innovations
CPI Disagreement	The difference between the 75th percentile and the 25th percentile of quarterly CPI forecasts from the Survey of Professional Forecasters database
Behind the curve	Periods when the difference between the Taylor rule implied Fed funds rate (2.5%+1.5*(Core-CPI YoY Growth-2%)+0.5*OutPut Gap) and the actual Fed funds rate is higher than the 67% percentile cutoff
Output Gap	Natural logarithm of real GDP, detrended using the Hodrick–Prescott filter
CFNAI	Chicago Fed National Activity Index
Log(Size)	The natural logarithm of a firm's market capitalization
Asset Growth	Growth rate of total asset: $atq_t/atq_{t-1} - 1$
Cash Flow	Income before extraordinary items plus depreciation and amortization, divided by total asset (Hennessy et al. (2007)): $\sum(ibq_t, dpq_t)/atq_t$
CF Beta	Cash flow betas, b_i^{Core} and b_i^{Head}, are estimated by regressing changes in quarterly cash flows on quarterly core and headline innovations, respectively, using a rolling 5-year window
ME/BE	The market value of equity divided by the book value of equity: ME_t/BE_t. ME: price ($prccq$)×common shares outstanding ($cshoq$). BE: stockholders' equity ($seqq$) + deferred tax and investment tax credit ($txditcq$), if not available, deferred taxes ($txdbq$) - book value of preferred/preference stock ($pstkrq$), if not available, pay value ($pstkq$)
Dividend Payout	Trailing 12-month dividends divided by income before extraordinary items: $dvc_t/ibadj_t$
CF Duration	Cash flow duration, constructed following Weber (2018)
Sales Growth	Change of gross sales divided by total asset: $(saleq_t - saleq_{t-1})/atq_{t-1}$

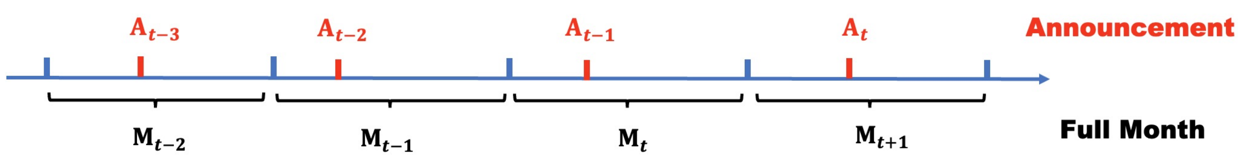
Internet Appendix for
"What Can Cross-Sectional Stocks Tell Us About Core Inflation Shocks"

Claire Yurong Hong, Jun Liu, Jun Pan, and Shiwen Tian

In this appendix, we provide additional results mentioned in the paper but not reported there for brevity. The appendix is organized as follows. Section I illustrates the timeline of beta estimation and inflation forecasting. In Section II, we provide detailed proof of model propositions. Section III provides additional tables and plots mentioned in the paper.

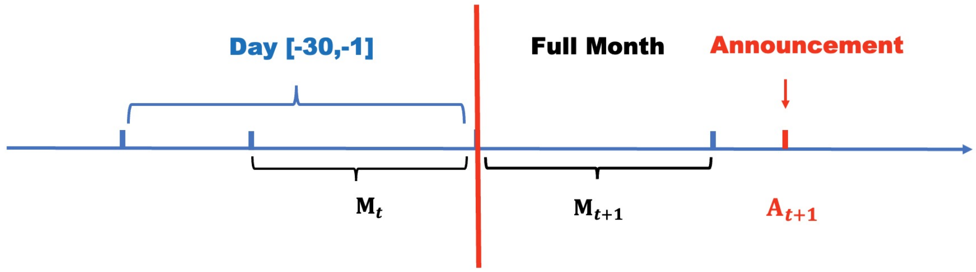
I. Illustration of the Time Line

Beta Estimation – We use two approaches to estimate the inflation exposure for individual stocks as well as for various assets. The first approach provides an information-based, announcement-day focused inflation beta. This is constructed by regressing a firm i's announcement-day returns against the CPI innovations released on those days. In particular, after the announcement of CPI data on day A_t, we measure the headline- and core-inflation exposure for firm i using a rolling 60-month window. We update the estimation of inflation betas on each CPI announcement days, as we need to wait until announcement day A_t to obtain the CPI innovation for month M_t.



As shown in the graph above, on announcement day A_t, firm i 's announcement-day beta is estimated using announcement-day returns from A_{t-59} to A_t following the regression specification in equation (4). For instance, after the CPI announcement on May 11, 2022, we estimate the announcement-day beta using all CPI announcements from June 14, 2017 (for May 2017) to May 11, 2022 (for April 2022).

The second approach, known as the full-month approach, estimates inflation exposure by the sensitivity of monthly security returns to the contemporaneous-month inflation innovations. Standing at announcement day A_t, firm i 's full-month beta is estimated using monthly returns from month M_{t-59} to M_t. We again update the full-month beta on each announcement day, as we wait for the CPI value for month t to be released publicly, thus avoiding look-ahead bias. For example, when estimating the inflation beta on May 11, 2022, which is the CPI announcement day for April 2022, we use the monthly returns and CPI innovations from May 2017 to April 2022.



Forecasting with IP – To examine the predictive power of inflation portfolio returns for inflation shocks, we use the 30-day inflation portfolio returns observed by the end of month t (M_t) to predict the CPI innovations realized in month $t+1$ (M_{t+1}) and announced in day A_{t+1}. For example, to predict the CPI for month April 2022, i.e., M_{t+1} is April 2012, we construct our signal using the 30-day cumulative return from February 18, 2022 to March 31, 2022 (total 30 trading days). The predicted CPI is then materialized in month April 2022 and announced on day May 11, 2022. Essentially, we are predicting the actual CPI release value around one and a half months in advance.

II. Model Proof

Derivations of formulas for the illustrative model are given below.

Stock Price

The stock price is given by

$$S_t^i = \mathrm{E}_t[\sum_{v=1}^{\infty} \exp(-\sum_{u=0}^{v-1} r_{t+u}) D_{t+v}^i].$$

Data suggests that the risk premium of stocks does not dependent on y_t, we take risk premium to be zero so risk-neutral measure is the same as physical measure. Alternatively, the constant risk premium for y_t risk is absorbed in the constant μ_r. Given our assumption of r_t and D_t^i, we get

$$S_t^i = D_t^i \sum_{v=1}^{\infty} \mathrm{E}_t[e^{-\mu_r v - \sum_{u=0}^{v-1}(\alpha y_{t+u} + \sigma_r \epsilon_{t+u}^r) + \mu_i v + b_i \sigma_\pi \sum_{u=0}^{v-1}(y_{t+u} + \epsilon_{t+u+1}) - \frac{\sigma_i^2}{2} v + \sigma_i \sum_{u=0}^{v-1} \epsilon_{t+u+1}^i}],$$

where the first two terms in the exponential are constant and conditional components of the discount rate respectively, the middle two terms are constant and conditional components of the dividend growth rate respectively, and the last two terms are the dividend shocks. This leads to

$$S_t^i = D_t^i \sum_{v=1}^{\infty} e^{-(\mu_r-\mu_i)-(\mu_r-\mu_i-\frac{1}{2}(\sigma_r^2+b_i^2\sigma_\pi^2+(b_i\sigma_\pi-\alpha)^2\sigma_y^2)(v-1)-\sigma_r\epsilon_t^r+(b_i\sigma_\pi-\alpha)y_t+\frac{1}{2}b_i^2\sigma_\pi^2}$$

$$= D_t^i \frac{e^{-(\mu_r-\mu_i)-\alpha y_t-\sigma_r\epsilon_t^r+b_i\sigma_\pi y_t+\frac{1}{2}b_i^2\sigma_\pi^2}}{1-e^{-(\mu_r-\mu_i-\frac{1}{2}(\sigma_r^2+b_i^2\sigma_\pi^2+(b_i\sigma_\pi-\alpha)^2\sigma_y^2))}} = D_t^i \frac{e^{-r_t+\mu_i+b_i\sigma_\pi y_t+\frac{1}{2}b_i^2\sigma_\pi^2}}{1-e^{-(\mu_r-\mu_i-\frac{1}{2}(\sigma_r^2+b_i^2\sigma_\pi^2+(b_i\sigma_\pi-\alpha)^2\sigma_y^2))}}.$$

Stock Returns

The capital gains return from time $t-1$ to t is

$$\frac{S_{t+1}^i}{S_t^i} = \frac{f_i(y_{t+1},\theta_i)D_{t+1}^i}{f_i(y_t,\theta_i)D_t^i} = e^{(b_i\sigma_\pi-\alpha)(y_{t+1}-y_t)-\sigma_r(\epsilon_{t+1}^r-\epsilon_t^r)+\mu_i+b_i\sigma_\pi(y_t+\epsilon_{t+1})-\frac{1}{2}\sigma_i^2+\sigma_i\epsilon_{t+1}^i}$$

$$= e^{(b_i\sigma_\pi-\alpha)y_{t+1}-\sigma_r\epsilon_{t+1}^r+\mu_i+\alpha y_t+\sigma_r\epsilon_t^r+b_i\sigma_\pi\epsilon_{t+1}-\frac{1}{2}\sigma_i^2+\sigma_i\epsilon_{t+1}^i}.$$

The log capital-gains return is

$$\ln S_{it+1}/S_{it} = (b_i\sigma_\pi-\alpha)y_{t+1}-\sigma_r\epsilon_{t+1}^r+\mu_i+\alpha y_t+\sigma_r\epsilon_t^r+b_i\sigma_\pi\epsilon_{t+1}-\frac{1}{2}\sigma_i^2+\sigma_i\epsilon_{t+1}^i. \tag{8}$$

A hedging portfolio is a portfolio that longs \$1 of stock i and shorts \$1 of stock j for $i \neq j$, with following log capital-gains return

$$\begin{aligned}\ln\frac{S_{it+1}}{S_{it}} - \ln\frac{S_{jt+1}}{S_{jt}} &= (b_i-b_j)\sigma_\pi y_{t+1} + (\mu_i-\mu_j) + (b_i-b_j)\sigma_\pi\epsilon_{t+1} \\ &\quad - \frac{1}{2}(\sigma_i^2-\sigma_j^2) + (\sigma_i\epsilon_{t+1}^i - \sigma_j\epsilon_{t+1}^j).\end{aligned} \tag{9}$$

In the above expression, the y_{t+1} term dependence is due to the price-dividend ratio and represents the pricing effect, while the ϵ_{t+1} term is due to inflation exposure in the dividend growth rates, and the ϵ_{t+1}^i and ϵ_{t+1}^j terms are "real" shocks from dividend growth rates.

Consider the regression of log-capital-gains-return on inflation innovation,

$$\ln S_{it+1}/S_{it} = \alpha_i + \beta_i\sigma_\pi\epsilon_{t+1}^\pi + u_{it+1},$$

the population estimate of β_i is

$$\beta_i = \frac{\mathrm{E}[\ln S_{it+1}/S_{it}\sigma_\pi\epsilon_{t+1}^\pi]}{\mathrm{var}[\sigma_\pi\epsilon_{t+1}^\pi]} = \frac{\sigma_\pi\mathrm{E}[(\alpha y_t+b_i\sigma_\pi\epsilon_{t+1})(y_t+\epsilon_{t+1})]}{\mathrm{var}[\sigma_\pi\epsilon_{t+1}^\pi]} = \frac{\sigma_\pi(\alpha\sigma_y^2+b_i\sigma_\pi)}{\sigma_\pi^2(\sigma_y^2+1)}.$$

The beta β_{ij} of the hedging portfolio is given by $\beta_i - \beta_j$:

$$\beta_{ij} = \frac{\mathrm{E}[(\ln S_{it+1}/S_{it} - \ln S_{it+1}/S_{it})\sigma_\pi \epsilon^\pi_{t+1}]}{\mathrm{var}[\sigma_\pi \epsilon^\pi_{t+1}]} = \frac{b_i - b_j}{\sigma_y^2 + 1}.$$

Now consider the predictive regression of inflation innovation on hedging portfolio,

$$\sigma \epsilon^\pi_{t+1} = \gamma_{ij0} + \gamma_{ij}\Big(\ln S_{it}/S_{it-1} - \ln S_{jt}/S_{jt-1}\Big) + u_{ijt+1}$$

$$= \gamma_{ij0} + \gamma_{ij}\Big((b_i - b_j)\sigma_\pi y_t + (b_i - b_j)\sigma_\pi \epsilon_t + (\sigma_i \epsilon^i_t - \sigma_j \epsilon^j_t) + (\mu_i - \mu_j) - \frac{1}{2}(\sigma_i^2 - \sigma_j^2)\Big) + u_{ijt+1}.$$

The population estimate of γ_{ij} is

$$\gamma_{ij} = \sigma_\pi \frac{\mathrm{E}[(y_t + \epsilon_{t+1})\Big((b_i - b_j)\sigma_\pi y_t + (b_i - b_j)\sigma_\pi \epsilon_t + (\sigma_i \epsilon^i_t - \sigma_j \epsilon^j_t)\Big)]}{\mathrm{var}[\Big((b_i - b_j)\sigma_\pi y_t + (b_i - b_j)\sigma_\pi \epsilon_t + (\sigma_i \epsilon^i_t - \sigma_j \epsilon^j_t)\Big)]}$$

$$= \frac{(b_i - b_j)\sigma_\pi^2}{(b_i - b_j)^2 \sigma_\pi^2 (1 + 1/\sigma_y^2) + (\sigma_i^2 + \sigma_j^2 - 2\rho_{ij}\sigma_i\sigma_j)/\sigma_y^2},$$

where ρ_{ij} is the correlation coefficient between ϵ^i_t and ϵ^j_t.

III. Additional Results

Figure IA1. Persistence of Inflation Beta

This figure shows the persistence of core beta (β^{Core}, upper graph) and headline beta (β^{Head}, lower graph). For each month t, we form quintile portfolios by ranking stocks based on their core beta and headline beta. The figures report the probability that stocks in the top (bottom) quintile group will remain in the top (bottom) quintile group over the 24 months following the portfolio formation month t.

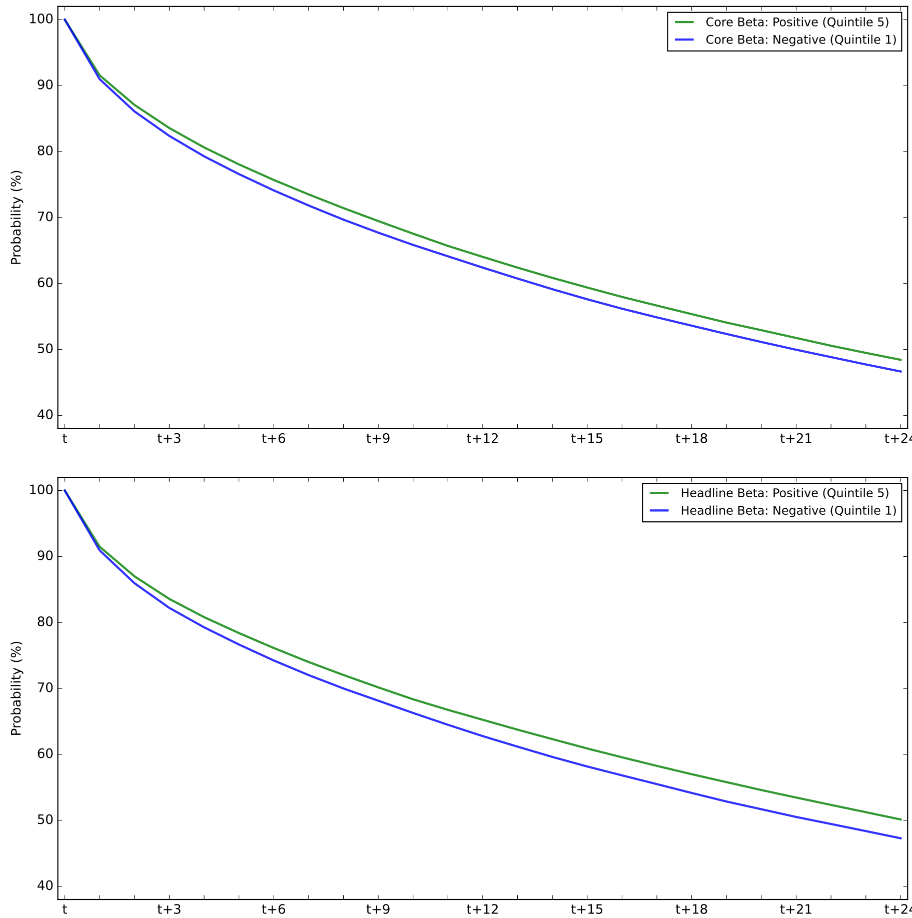


Figure IA2. Predicting CPI Shocks using IP^{Core}, R-Squared

The upper and lower graphs display the predictive regression R-squared, estimated using a rolling five-year window for core CPI and headline CPI, respectively. For each time t, we estimate the model: CPI $\text{Shock}_{t+1} = \alpha + \gamma^{IP} \times IP_t^{Core} + \varepsilon_{t+1}$, using observations from $t-59$ to t. We require at least 24 months of data for estimations. The sample period spans from December 1973 to December 2023. The red solid line shows the regression R-squared with shocks measured by CPI innovations, while the blue dotted line represents CPI shocks measured by Bloomberg economist forecasting errors.

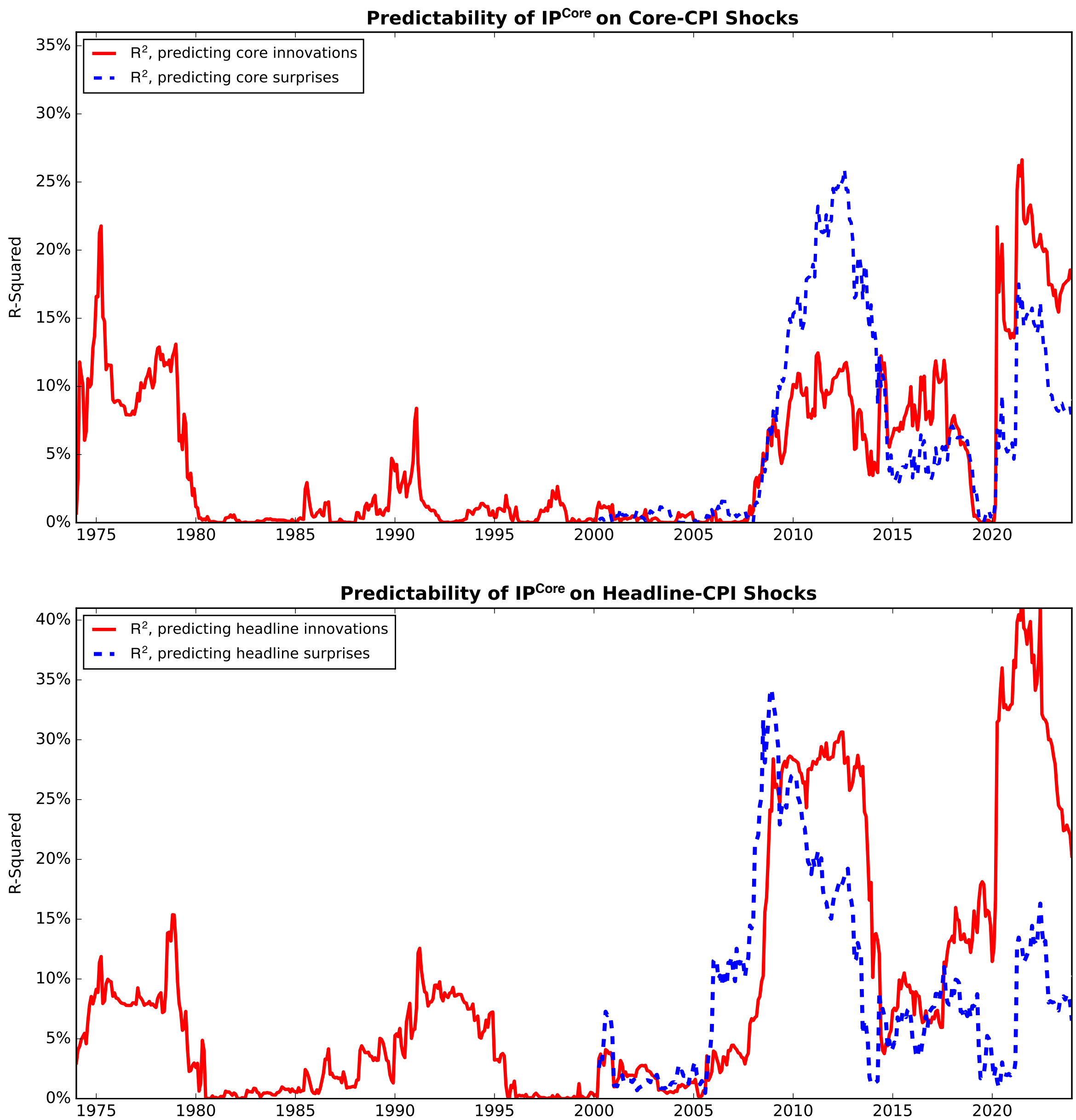


Table IA1. Summary Statistics

This table reports the monthly summary statistics for our main variables. CPI innovations for month $t+1$ (Head-Innov$_{t+1}$ and Core-Innov$_{t+1}$) are computed as the actual CPI monthly growth minus the value predicted by the time-series model of ARMA(1,1). Economists' inflation forecasting errors, Head-Surprise$_{t+1}$ and Core-Surprise$_{t+1}$, are constructed as the actual CPI monthly growth minus the median forecast by Bloomberg economists survey. IP^{Core} and IP^{Head} are the 30-day cumulative returns of the β^{Core} and β^{Head} sorted portfolios observed at the end of month t. We also include statistics for asset returns, including the aggregate stock market return (VWRETD), changes in two-year and ten-year U.S. Treasury yields (Δy^{2YR} and Δy^{10YR}), the Goldman Sachs Commodity Index return (GSCI), and the return difference between the Bloomberg TIPS index and the U.S. Treasury index (TIPS-UST). The sample period is from January 1972 to December 2023.

Variable	N	Mean	Median	Q1	Q3	STD
Head-Innov$_{t+1}$ (bps.)	624	−0.01	−0.47	−12.29	12.61	25.97
Core-Innov$_{t+1}$ (bps.)	624	−0.07	−0.51	−7.34	5.66	15.58
Head-Surprise$_{t+1}$ (bps.)	308	0.10	0.00	−10.00	10.00	13.00
Core-Surprise$_{t+1}$ (bps.)	307	−0.23	0.00	−10.00	10.00	10.92
IP^{Core} (%)	624	0.19	0.12	−1.06	1.42	2.56
IP^{Head} (%)	624	−0.24	−0.25	−1.72	1.52	3.22
VWRETD (%)	624	1.23	1.70	−1.42	4.43	5.21
Δy^{2YR} (%)	571	−0.01	−0.01	−0.25	0.18	0.53
Δy^{10YR} (%)	624	0.00	−0.01	−0.21	0.20	0.40
GSCI (%)	624	0.95	1.42	−3.06	5.00	6.74
TIPS-UST (%)	308	0.17	0.19	−0.33	0.88	1.43

Table IA2. Inflation Risk Premium Conditional on Nominal-Real Covariance

This table presents time-series regressions of inflation beta-sorted portfolios on the lagged nominal-real covariance following Boons et al. (2020). The nominal-real covariance is proxied by the time-varying relation between current inflation and future 12-month consumption growth. The left-hand side returns are compounded over horizons of one, three, and 12 months. The standard errors are Newey-West adjusted with K lags. The t-stats are in parentheses.

Panel A. Core Beta (β^{Core}) Sorted Portfolios

	$K=1$		$K=3$		$K=12$	
	Intercept	β^{NRC}	Intercept	β^{NRC}	Intercept	β^{NRC}
Q1 (Low)	12.75	−1.83	12.89	−1.68	13.36	−1.87
	(4.65)	(−0.69)	(5.39)	(−0.69)	(5.91)	(−0.79)
Q2	13.78	−1.82	13.92	−1.84	14.45	−2.27
	(5.92)	(−0.77)	(6.85)	(−0.84)	(7.57)	(−1.15)
Q3	13.51	−1.60	13.61	−1.68	14.04	−2.15
	(5.94)	(−0.69)	(6.98)	(−0.80)	(8.07)	(−1.18)
Q4	13.16	−2.63	13.28	−2.67	13.74	−3.02
	(5.40)	(−1.04)	(6.30)	(−1.16)	(7.07)	(−1.53)
Q5 (High)	13.93	−2.14	14.04	−2.03	14.42	−2.31
	(4.85)	(−0.75)	(5.65)	(−0.78)	(6.51)	(−1.06)
Q5 − Q1	1.19	−0.32	1.21	−0.48	1.29	−0.44
(IP^{Core})	(1.05)	(−0.30)	(1.16)	(−0.50)	(1.23)	(−0.43)

Panel B. Headline Beta (β^{Head}) Sorted Portfolios

	$K=1$		$K=3$		$K=12$	
	Intercept	β^{NRC}	Intercept	β^{NRC}	Intercept	β^{NRC}
Q1 (Low)	14.12	−2.90	14.31	−2.86	14.82	−3.17
	(5.10)	(−1.08)	(5.95)	(−1.15)	(6.63)	(−1.46)
Q2	13.98	−2.34	14.14	−2.44	14.71	−2.98
	(5.90)	(−0.98)	(6.86)	(−1.12)	(7.63)	(−1.52)
Q3	13.53	−1.83	13.64	−1.84	14.16	−2.17
	(5.89)	(−0.78)	(6.90)	(−0.86)	(7.73)	(−1.14)
Q4	13.63	−1.85	13.74	−1.84	14.23	−2.22
	(5.78)	(−0.75)	(6.71)	(−0.82)	(7.45)	(−1.09)
Q5 (High)	11.93	−1.17	12.04	−1.00	12.30	−1.24
	(4.05)	(−0.40)	(4.70)	(−0.37)	(5.27)	(−0.51)
Q5 − Q1	−2.20	1.73	−2.10	1.61	−1.94	1.76
(IP^{Head})	(−1.58)	(1.19)	(−1.65)	(1.21)	(−1.42)	(1.36)

Table IA3. Industry vs. Stock-Level Inflation Exposure

Panel A lists the top 10 and bottom 10 industries that are the most and least sensitive to announcement-day core-CPI innovations and full-month headline-CPI innovations, respectively. We construct industry CPI betas in a similar manner to individual stock CPI betas, by regressing Fama and French 48 Industry returns (%) on CPI innovations (standardized) under the "CAPM Model". We report the time series average industry betas beside the industry names. Panel B compares the predictability of industry- and stock-constructed inflation portfolios on CPI innovations. $\mathrm{IP}^{\mathrm{Core}}_{\mathrm{Ind}}$ and $\mathrm{IP}^{\mathrm{Head}}_{\mathrm{Ind}}$ are the 30-day cumulative returns for the industry-constructed inflation portfolios, with a long position in top-quintile CPI beta industries and a short position in bottom-quintile CPI beta industries. $\mathrm{IP}^{\mathrm{Core}}$ and $\mathrm{IP}^{\mathrm{Head}}$ are the 30-day cumulative returns for the stock-constructed inflation portfolios as in Table 7. All the IP returns are standardized with means of zero and standard deviations of one.

Panel A. Most and Least Inflation-Sensitive Industries

	β^{Core}				β^{Head}			
Rank	Top 10		Bottom 10		Top 10		Bottom 10	
1	Precious Metals	0.131	Candy & Soda	-0.060	Oil & Natural Gas	1.101	Candy & Soda	-0.356
2	Ship building	0.115	Communication	-0.040	Mining	1.010	Restaurants & Hotels	-0.316
3	Coal	0.108	Beer & Liquor	-0.039	Precious Metals	0.733	Tobacco Products	-0.271
4	Oil & Natural Gas	0.102	Recreation	-0.036	Agriculture	0.697	Construction	-0.196
5	Mining	0.069	Entertainment	-0.033	Coal	0.630	Apparel	-0.189
6	Defense	0.044	Apparel	-0.028	Steel Works	0.479	Insurance	-0.185
7	Business Supplies	0.032	Insurance	-0.020	Fabricated Products	0.460	Rubber & Plastic	-0.163
8	Shipping Containers	0.030	Business Services	-0.020	Machinery	0.302	Automobiles & Trucks	-0.158
9	Machinery	0.027	Retail	-0.019	Ship building	0.284	Utilities	-0.151
10	Measuring Equipment	0.023	Personal Services	-0.018	Pharmaceutical	0.283	Shipping Containers	-0.142

Panel B. Predictability of Industry vs. Stock Portfolios

	Core-CPI Innovation$_{t+1}$						Headline-CPI Innovation$_{t+1}$					
$\mathrm{IP}^{\mathrm{Core}}_{\mathrm{Ind}}$	1.009		0.057				5.621		2.725			
	(1.69)		(0.10)				(4.32)		(2.18)			
$\mathrm{IP}^{\mathrm{Core}}$		2.235	2.210					7.901	6.729			
		(2.98)	(2.81)					(6.54)	(5.59)			
$\mathrm{IP}^{\mathrm{Head}}_{\mathrm{Ind}}$				1.505		0.436				5.820		2.476
				(2.69)		(0.71)				(4.53)		(1.87)
$\mathrm{IP}^{\mathrm{Head}}$					2.156	1.912					7.368	5.984
					(2.86)	(2.17)					(5.78)	(4.38)
Intercept	−0.072	−0.072	−0.072	−0.072	−0.072	−0.072	−0.012	−0.012	−0.012	−0.012	−0.012	−0.012
	(−0.12)	(−0.12)	(−0.12)	(−0.12)	(−0.12)	(−0.12)	(−0.01)	(−0.01)	(−0.01)	(−0.01)	(−0.01)	(−0.01)
Observations	624	624	624	624	624	624	624	624	624	624	624	624
Adj. R^2	0.3%	1.9%	1.7%	0.8%	1.8%	1.7%	4.5%	9.1%	9.9%	4.9%	7.9%	8.4%

Table IA4. Predicting Inflation Growth Using Core Beta-Sorted Portfolio

This table reports the ability of asset returns observed at the end of month t to predict month-$t+1$ CPI growth and the next 3-month CPI growth (in bps). The independent variables are IP^{Core}, IP^{Head}, GSCI, and TIPS-UST returns. All of the independent variables are standardized with means of zero and standard deviations of one. The sample is from January 1972 to December 2023. The TIPS-UST sample is from May 1998 to December 2023. The standard errors are adjusted for heteroskedasticity. The t-stats are in parentheses.

Panel A. Predicting Month t+1 CPI Growth

	Core-CPI Growth						Headline-CPI Growth					
IP^{Core}	1.998	1.490	2.561	2.537			6.493	3.806	8.114	4.390		
	(2.93)	(2.13)	(3.01)	(2.76)			(5.72)	(3.36)	(5.39)	(2.76)		
IP^{Head}					1.442	0.751					5.506	2.450
					(1.88)	(1.18)					(4.67)	(1.94)
GSCI		1.574		0.085		0.738		8.999		14.776		15.511
		(1.99)		(0.09)		(0.78)		(5.72)		(8.18)		(8.66)
TIPS-UST			1.254	1.214		1.221			8.413	3.189		3.127
			(1.84)	(1.74)		(1.71)			(3.08)	(1.18)		(1.15)
Lag (Y)	0.750	0.746	0.580	0.579	0.746	0.582	0.614	0.543	0.319	0.163	0.607	0.162
	(16.56)	(16.64)	(11.13)	(10.88)	(16.52)	(10.09)	(13.51)	(11.49)	(4.88)	(2.54)	(13.17)	(2.42)
Observations	624	624	308	308	624	308	624	624	308	308	624	308
Adj. R^2	56.6%	56.9%	39.1%	38.9%	56.3%	36.1%	43.5%	49.5%	37.2%	50.5%	42.4%	49.2%

Panel B. Predicting Next 3-Month CPI Growth

	Core-CPI Growth						Headline-CPI Growth					
IP^{Core}	7.349	5.931	7.833	7.277			15.616	9.911	15.997	10.269		
	(4.03)	(3.13)	(3.62)	(3.10)			(4.69)	(2.96)	(4.27)	(2.67)		
IP^{Head}					3.868	1.820					15.020	4.945
					(1.97)	(1.26)					(3.87)	(1.07)
GSCI		4.390		2.012		3.995		17.861		20.447		22.383
		(2.33)		(0.84)		(1.64)		(5.39)		(4.52)		(4.87)
TIPS-UST			3.742	2.798		2.800			21.078	12.351		12.199
			(2.54)	(1.74)		(1.54)			(4.01)	(2.41)		(2.41)
Lag (Y)	0.804	0.801	0.495	0.491	0.799	0.491	0.615	0.582	0.131	0.081	0.611	0.082
	(19.16)	(19.07)	(6.57)	(6.45)	(18.78)	(6.16)	(14.32)	(12.97)	(1.96)	(1.17)	(13.89)	(1.13)
Observations	622	622	306	306	622	306	622	622	306	306	622	306
Adj. R^2	65.1%	65.5%	31.8%	31.8%	64.3%	28.0%	41.2%	45.1%	21.4%	26.8%	41.0%	25.3%

Table IA5. Inflation Beta Constructed using Ann-Day Surprise

Panel A presents the post-ranking announcement-based inflation betas using different measures of inflation surprises. These measures include economists' forecasting errors of Core CPI (β^{Surp}), changes in 2-year Inflation Swap Rates (β^{ISWAP2YR}), changes in 5-year Inflation Swap Rates (β^{ISWAP5YR}), changes in 2-year UST yield (β^{UST2YR}) and changes in 5-year UST yield (β^{UST5YR}). The post ranking announcement-day inflation beta, estimated under the the "CAPM Model", is reported for each quintile portfolio sorted based on their corresponding pre-ranking beta. Panel B examines the predictability of month-t inflation portfolios, including IP^{Surp}, $\text{IP}^{\text{ISWAP2YR}}$, $\text{IP}^{\text{ISWAP5YR}}$, $\text{IP}^{\text{UST2YR}}$ and $\text{IP}^{\text{UST5YR}}$, constructed based on Panel A's betas, to predict month-$t+1$ core-CPI innovations. Standard errors are adjusted for heteroskedasticity, and the t-stats are in parentheses.

Panel A. Post-Ranking Inflation Beta

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q5 − Q1
β^{Surp}	−9.18	−3.77	0.37	2.09	1.20	10.38
t-stat	(−2.32)	(−1.42)	(0.12)	(0.60)	(0.30)	(2.24)
β^{ISWAP2YR}	−9.62	−4.15	−1.10	3.90	14.25	23.87
t-stat	(−1.97)	(−1.22)	(−0.38)	(1.21)	(2.38)	(3.44)
β^{ISWAP5YR}	−9.75	−6.42	−2.62	1.96	15.05	24.81
t-stat	(−1.72)	(−1.76)	(−0.68)	(0.50)	(2.90)	(4.28)
β^{UST2YR}	−2.82	−0.45	1.38	2.94	6.61	9.43
t-stat	(−0.69)	(−0.17)	(0.61)	(1.20)	(2.14)	(2.69)
β^{UST5YR}	−1.89	0.13	1.18	2.29	4.96	6.85
t-stat	(−0.52)	(0.05)	(0.55)	(1.10)	(1.72)	(2.58)

Panel B. Predicting Month $t+1$ CPI Innovation

	Core-CPI Innovation					Headline-CPI Innovation				
IP^{Surp}	1.811					7.824				
	(2.22)					(3.68)				
$\text{IP}^{\text{ISWAP2YR}}$		2.381					13.895			
		(2.36)					(4.99)			
$\text{IP}^{\text{ISWAP5YR}}$			2.094					14.215		
			(1.79)					(5.37)		
$\text{IP}^{\text{UST2YR}}$				1.536					0.899	
				(2.34)					(0.77)	
$\text{IP}^{\text{UST5YR}}$					1.857					0.016
					(2.76)					(0.01)
Observations	248	207	208	511	624	248	207	208	511	624
Adj. R^2	2.1%	3.5%	2.6%	1.2%	1.3%	6.1%	22.4%	23.1%	−0.1%	−0.2%

Table IA6. Inflation Beta Constructed Using All Historical Observations

Panel A reports the post-ranking inflation betas of cross-sectional stocks, where the pre-ranking inflation betas are estimated using a weighted least squares (WLS) regression with exponential weights over an expanding window that encompasses all historical observations. Following the methodology in Boons et al. (2020), firm i's announcement-day inflation beta ($\beta_{i,A_t}^{\text{Ann}}$) is given by: $\min_{\alpha_{i,A_t},\beta_{i,A_t}^{\text{Ann}}} \sum_{\tau=1}^{t} w(\tau)(R_{i,A_\tau} - \alpha_{i,A_t} - \beta_{i,A_t}^{\text{Ann}}\text{CPI-Innov}_{A_\tau})^2$, where R_{i,A_τ} denotes firm i's excess return on the announcement day A_τ. The weight is given by $w(\tau) = \frac{\exp(-|t-\tau|/h)}{\sum_{\tau=1}^{t-1}\exp(-|t-\tau|/h)}$. Using $h = \log(2)/60$ means the half-life of the weights $w(\tau)$ converges to 60 months for large t. The full-month inflation betas are estimated similarly. Following Boons et al. (2020), the betas are further transformed using the Vasicek (1973) adjustment: $\widehat{\beta_{i,t}^{v}} = \widehat{\beta_{i,t}} + \frac{\text{var}_{TS}(\widehat{\beta_{i,t}})}{\text{var}_{TS}(\widehat{\beta_{i,t}})+\text{var}_{CS}(\widehat{\beta_{i,t}})} \times (\text{mean}_{CS}(\widehat{\beta_{i,t}}) - \widehat{\beta_{i,t}})$, where each $\widehat{\beta_{i,t}^{v}}$ represents a weighted average of the stock's beta derived from time-series data ($\widehat{\beta_{i,t}}$) and the cross-sectional beta average ($\text{mean}_{CS}(\widehat{\beta_{i,t}})$). We control for market returns in estimating the betas. Panel B reports the inflation predictability of IP^{Core}, which is constructed based on the β^{Core} estimated in Panel A. The standard errors are adjusted for heteroskedasticity. The t-stats are in parentheses.

Panel A. Post-Ranking Inflation Beta, CAPM Model

	β^{Ann}			β^{Full}		
	Core	*Headline*	*Energy*	*Core*	*Headline*	*Energy*
Q1 (Low)	−2.20	−0.59	−0.61	−10.70	−7.45	−6.79
	(−1.20)	(−0.28)	(−0.31)	(−0.85)	(−0.61)	(−0.51)
Q2	0.52	2.07	−0.14	−12.46	−5.80	−1.96
	(0.29)	(1.10)	(−0.09)	(−1.39)	(−0.67)	(−0.21)
Q3	1.15	0.93	1.37	−14.32	3.33	−0.56
	(0.62)	(0.46)	(0.62)	(−1.71)	(0.39)	(−0.06)
Q4	2.79	1.85	−0.35	−11.71	7.54	5.92
	(1.31)	(0.84)	(−0.18)	(−1.27)	(0.77)	(0.56)
Q5 (High)	2.53	1.09	−1.58	−5.27	35.92	37.64
	(1.08)	(0.36)	(−0.69)	(−0.47)	(2.65)	(2.37)
Q5 − Q1	4.73	1.68	−0.96	5.43	43.37	44.43
	(2.38)	(0.55)	(−0.37)	(0.45)	(2.89)	(2.47)

Panel B. Predicting Month $t+1$ Inflation

	Core-CPI				Headline-CPI			
	Innovation		Forecasting Error		Innovation		Forecasting Error	
IP^{Core}	2.669	2.499	2.009	2.006	7.466	4.617	3.588	2.368
	(3.40)	(2.56)	(2.70)	(2.38)	(6.83)	(2.06)	(4.06)	(2.36)
GSCI		0.637		−0.543		12.272		3.670
		(0.64)		(−0.59)		(5.74)		(4.04)
TIPS-UST		1.149		1.166		2.62		−0.686
		(1.43)		(1.57)		(0.81)		(−0.60)
Intercept	−0.072	−0.835	−0.232	−0.228	−0.012	−1.942	0.097	0.097
	(−0.12)	(−1.37)	(−0.38)	(−0.37)	(−0.01)	(−1.41)	(0.14)	(0.14)
Observations	624	308	307	307	624	308	308	308
Adj. R^2	2.8%	7.9%	3.1%	3.3%	8.1%	30.3%	7.3%	12.5%

Table IA7. The Predictability of Fama French 5-Factor Adjusted IP^{Core} Alpha

Panel A reports the beta loading of monthly IP^{Core} and IP^{Head} on Fama-French 5 factors. Panel B reports the predictability of Fama-French 5-factor adjusted 30-day IP^{Core} and IP^{Head} on Month t+1 CPI innovation (in bps). All independent variables are standardized with means of zero and standard deviations of one. The standard errors are adjusted for heteroskedasticity. The t-stats are in parentheses.

Panel A. FF5F Loading

		Mktrf	SMB	HML	CMA	RMW	Obs.	Adj. R^2
IP^{Core}	Coeff.	0.050	0.091	0.120	−0.090	0.004	624	3.6%
	t-stat	(1.83)	(2.01)	(1.78)	(−1.01)	(0.07)		
IP^{Head}	Coeff.	0.036	−0.053	0.033	−0.241	−0.320	624	8.9%
	t-stat	(1.03)	(−1.07)	(0.44)	(−2.55)	(−4.40)		

Panel B. Predicting Month t+1 CPI Innovation

	Core-CPI Innovation						Headline-CPI Innovation					
IP^{Core} α	1.971	1.398	2.154	1.918			7.290	4.055	8.153	5.036		
	(2.87)	(2.12)	(2.58)	(2.21)			(6.33)	(3.58)	(5.01)	(2.84)		
IP^{Head} α					2.595	1.309					7.781	5.187
					(3.31)	(1.91)					(6.24)	(3.36)
GSCI		1.919		0.93		1.085		10.851		12.300		12.031
		(2.34)		(0.91)		(1.08)		(6.93)		(6.20)		(6.13)
TIPS-UST			1.574	1.116		0.987			8.655	2.6		2.158
			(1.90)	(1.42)		(1.30)			(2.80)	(0.82)		(0.69)
Observations	624	624	308	308	624	308	624	624	308	308	624	308
Adj. R^2	1.4%	2.7%	6.0%	6.2%	2.6%	4.6%	7.7%	23.5%	19.1%	30.8%	8.8%	30.8%