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

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.

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 in predicting inflation, and why does the aggregate stock market miss this information?

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, the information contained in cross-sectional stocks can add value, especially when the pricing of U.S. Treasury bonds is influenced by factors unrelated to inflation risk.[3] Relative to the commodity market, which typically contains rich information about energy prices, cross-sectional stocks can offer additional information 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

[1]Fama and Schwert (1977) demonstrates that the aggregate stock market poorly hedges against inflation, and more recently, Fang et al. (2021) 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]For example, expectations of monetary policy, episodes of flight-to-safety, and Fed's interventions (e.g., QE) can distort the bond pricing and thereby mask inflation expectations. Moreover, the illiquidity of the market for TIPS can add noise to the break-even inflation forecasts.

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 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 for the central Florida region where most juice oranges are grown.

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 – Another 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

[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, while our focus is on the predictability of inflation via cross-sectional differences in realized stock returns.

inflation innovations.[5]

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 less observable in real-time and often lead to surprises on CPI announcement days, 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.

By sorting stocks based on their pre-ranking beta, estimated using a 60-month rolling window, we form monthly rebalanced top-minus-bottom quintile inflation portfolios – 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; that is, their quarterly cash flows increase with positive inflation shocks. This indicates a significant alignment between

[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.

[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.

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 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-2000 period (Boons et al. (2020)), the returns of IP^{Core} are insignificant both before and after 2000. 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, which are unexpected by both econometricians and economists. 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.

When comparing 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 portfolio return between real

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

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 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 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. When investors have limited capacity or face constraints on arbitrage, inflation expectations may not be quickly reflected in individual stock prices. As a result, we anticipate stronger price discovery in firms with superior information environments. Supporting this, our findings show that IP^{Core} exhibits stronger predictive power when constructed using firms with better information environments, such as larger firms, those with greater analyst coverage, and higher institutional ownership.

In analyzing the time-varying predictability, we find IP^{Core} becomes more informative during periods when inflation poses a significant risk and when there is heightened disagree-

[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.

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

ment 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} successfully signaled a series of alerts. 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 from 1973 and 2021 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}

[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.

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-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. Using survey-based forecasts, 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 examined in their studies. Through the construction of the 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 cross-sectional method, which relies exclusively on stock returns, has the advantage of tracking inflation movements over an extended historical period, making it particularly valuable for markets that lack access to survey-based forecasts and inflation-linked securities. This is especially relevant during the early stages of inflation surges, when traditional measures may be less informative.

Moreover, 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 conditions.

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),

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

and Boudoukh, Richardson, and Whitelaw (1994) have shown that inflation betas, estimated using the traditional approach, vary significantly across industries and over time.[12] Methodologically, we contribute by proposing two distinct approaches for estimating headline and 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 (2021), who examine aggregate asset classes. Consistent with Fang, Liu, and Roussanov (2021), we find that negative inflation exposure is generally more pronounced for core CPI than for headline CPI. However, 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 motivated by the post-COVID inflation surge.[13] Focusing on belief formation and distortion in the context of inflation, 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 side of inflation, Feng et al. (2024) investigate the predictability of supply-chain inflation on stock returns, while Cieslak, Li, and Pflueger (2024) explore its connection to the Treasury convenience yield. In the context of firm-level impacts, Bhamra et al. (2023) and Bonelli, Palazzo, and Yamarthy (2024) study how inflation affects firm default risk and credit spreads. Additionally, Andrei and Hasler (2023) examine the Fed's ability to control inflation, highlighting the role of learning about the Fed's inflation management in shaping financial markets.

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.

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

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

2 Data

We obtain monthly data on the Consumer Price Index (CPI), including Headline, Core, and Energy CPI from the U.S. Bureau of Labor Statistics (BLS).[14] 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 $\widehat{\pi}_t$. 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

[14] The BLS CPI data series are as follows: Headline (CPIAUCSL), Core (CPILFESL), and Energy (CPI-ENGSL).

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).[15]

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

The financial market incorporates inflation-relevant news both during the month when inflation is realized and on the CPI announcement day when the unexpected component of inflation arrives. Previous research has primarily focused on the sensitivity of asset returns to contemporaneous-month CPI innovations, neglecting the information from CPI

[15]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.

announcement days (e.g., Chen, Roll, and Ross (1986), Boons et al. (2020), Fang, Liu, and Roussanov (2021)). Since announcement days contain rich information about unexpected inflation shocks, using a narrow window to identify an asset's inflation exposure could provide additional insights beyond the traditional full-month approach.

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 CPI innovations released on the announcement days. Given that different CPI components (e.g., core vs. non-core) may affect the financial market at different times and with varying intensities, we estimate securities' sensitivities to core, headline, and energy CPI innovations separately using the following regression specification:

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

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 security i's sensitivity to inflation shocks on the CPI announcement days.

The full-month inflation beta is constructed by the sensitivity of securities' monthly excess returns to contemporaneous-month CPI innovations, following the methodology in Chen, Roll, and Ross (1986), Boons et al. (2020), and Fang, Liu, and Roussanov (2021):

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

where t denotes the calendar month, and $R_{i,t}$ denotes security i's excess return in month t.[16]

3.2 Inflation Exposures in Cross-Sectional Stocks

We first estimate individual stocks' pre-ranking inflation betas using a rolling five-year window, as specified by equations (3) and (4). Section II of Internet Appendix details the timeline for the estimations. Each month, after the CPI announcement A_t, we construct

[16]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.

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 data on CPI innovations start from 1967, with five-year estimation periods, the individual stocks' CPI beta estimates begin in 1972.[17]

We construct the announcement-day and full-month (pre-ranking) inflation betas for each individual stock using different components of inflation (core, headline, energy) innovations. We then form 2×5 equal-weighted portfolios by two-way sorting all stocks at the intersection of two size groups (Small and Large) and five inflation beta quintiles. 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). We hold the portfolio until the next CPI announcement day, at which point the new CPI innovation becomes available, allowing us to update the estimates of each stock's inflation exposure.

Table 1 reports the post-ranking announcement-day and full-month inflation betas for the pre-ranking beta sorted cross-sectional stock portfolios, with the two size groups combined. We find that cross-sectional stocks' core-inflation betas are significantly more negative than their headline betas, consistent with Fang, Liu, and Roussanov (2021). Additionally, core CPI has a much larger impact on stock returns on announcement days compared to headline and energy components. 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. In contrast, the same increase in headline- and energy-CPI innovations has a positive and trivial impact of 1.6 bps (t-stat=0.19) and 4.5 bps (t-stat=0.57), respectively.

As our focus is on the cross-sectional dispersion in individual stocks' inflation exposure, Panel B of Table 1 further reports the beta estimates while controlling for the aggregate stock market return, i.e., controlling for announcement-day market return and full-month market 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. However, we can still observe significant dispersion in cross-sectional stocks' post-ranking

[17] Appendix Figure IA1 shows that the individual stocks inflation beta estimation 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.

core-beta when estimated using announcement days. 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, with firms showing strong sensitivity to core-CPI innovations on past announcement days continuing to respond significantly to core innovations in future announcements.

The full-month inflation betas, on the other hand, exhibit significant and persistent sensitivity to headline inflation, particularly the energy component, but not to the core component. In the version controlling for market returns, the post-ranking headline beta increases monotonically from the lowest value of -1.5 bps to the highest value of 40.8 bps for the quintile portfolios sorted based on stocks' pre-ranking full-month headline betas. The core-, headline-, and energy-inflation exposure for the top-minus-bottom portfolios sorted based on the corresponding pre-ranking betas are 3.9 (t-stat=0.35), 42.3 (t-stat=2.96), and 37 (t-stat=2.23), respectively, suggesting a stronger response of monthly returns to the energy component but not the core component.

Overall, the cross-sectional stocks' inflation exposure suggests persistent cross-firm variations in inflation exposure, with the information-based announcement-day approach being most effective in capturing the core-inflation exposure and the contemporaneous approach most effective in capturing the headline exposure. This contrast is consistent with the intuition that non-core inflation components (like energy and food) are more observable and can be hedged using commodity instruments as investors experience inflation throughout the month. In contrast, core components (such as goods and services) are harder to observe and tend to cause larger surprises on CPI announcement days. Therefore, we refer to the 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

Estimating the inflation betas for a wide range of inflation-sensitive assets, we observe a consistent contrast between announcement-day and full-month approaches. 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 means of zero and standard deviations 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 for 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, compared to only a 5% (t-stat = 0.70) increase for the same rise in core-CPI innovation.

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).[18] Comparing the two, it is evident that the IP portfolio 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

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

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.[19]

3.4 Determinants of Inflation Beta

To better understand the variations in inflation exposure among different firms, we next examine the factors that determine a firm's inflation exposure. Specifically, we analyze the relationship between return-based inflation betas, as estimated in Section 3.2, and firms' cash flows and cash flow betas, which reflect the sensitivity of cash flows to inflation.

We estimate each firm's cash flow inflation beta (b^{Core} and b^{Head}) 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 inflation betas and their corresponding cash flow 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 ratio (ME/BE), cash flow, dividend payout ratio, and the cash flow duration from Weber (2018) to capture the distribution of cash flows.[20] Table 3 suggests that firms with more positive β^{Core} tend to have 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, leading to a shorter cash flow duration. In contrast, firms with more negative core betas exhibit longer cash flow duration and are typically growth firms.

[19]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.

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

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

This section presents a model illustrating how inflation expectations among financial market participants can influence asset prices through the cash flow channel and how cross-sectional stock returns can be used to predict inflation movements. We provide empirical evidence supporting this cash flow mechanism.

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

$\sigma_\pi\,\epsilon^\pi_t$. 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^i_t, 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

$$S^i_t = \mathrm{E}_t\left[\sum_{v=1}^{\infty} \exp\left(-\sum_{u=0}^{v-1} r_{t+u}\right) D^i_{t+v}\right] = D^i_t\, f(y_t, \theta_i)\,,$$

where, excluding the risk premium channel from the valuation problem, we take the expectation under the physical measure.[21] The price-dividend ratio can be further calculated as

$$f(y_t,\theta_i) = \frac{S^i_t}{D^i_t} = \frac{\exp\left(\mu_i - \mu_r + (b_i\sigma_\pi - \alpha)y_t - \sigma_r\epsilon^r_t + \frac{1}{2}b_i^2\sigma_\pi^2\right)}{1-\exp\left(\mu_i - \mu_r + \frac{1}{2}(\sigma_r^2 + b_i^2\sigma_\pi^2 + (b_i\sigma_\pi-\alpha)^2\sigma_y^2)\right)}\,, \tag{5}$$

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 across firms via $b_i\sigma_\pi - \alpha$, where b_i enters via the cashflow channel and differs cross-sectionally, while α enters via the riskfree rate channel and is the same for all firms.[22]

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

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

The bond price of a consol is a special case of $D^i_t = 1$ 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*

[21] 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.

[22] 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.

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:

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

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

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

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:

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

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.

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 relation between quarter-t β^{Core} and the quarter-$t+1$ firm fundamentals, captured by 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 (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 positively affects sales growth, cash flow, and the IBES long-term growth forecast more for firms with more positive β^{Core}. Focusing on sales growth in the first two columns, the coefficients of the interaction term are significantly positive. A 10% increase in IP^{Core} leads to a 7.8% standard deviation increase in sales growth when the quintile ranks of β^{Core} move from the bottom to the top quintile. After taking into account operational costs, we observe a similar magnitude of IP^{Core} on cash flows: A 10% increase in IP^{Core} at the end of quarter t predicts a 7.1% standard deviation increase in quarter-$t+1$ cash flow. A similar pattern is observed for the IBES long-term growth forecast of firm EPS, suggesting that analysts are potentially informed about the impact of inflation on firm cash flows, or they promptly update their beliefs about firm long-term earnings growth upon observing a high y_t.

Figure 1 offers a more intuitive graphical illustration. At the beginning of each quarter t, we sort all stocks into quintile groups based on their core beta (β^{Core}) 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^{Core} return in quarter t. We observe a comovement between the return and cash flow of IP^{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^{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 its normal levels. Overall, these visualizations 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 are driven by the inflation risk premium. If the variations in IP^{Core} are driven by the time-varying inflation risk premium, we would expect firms with higher β^{Core} to face lower required rates of return in the context of elevated inflation expectations, assuming that inflation is negatively priced. However, we do not find evidence in support of 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 from January 1972 to December 2023, as well as for subsamples split around December 2002.[23] As shown in Panel A, over the full sample, there is no monotonic pattern in returns for β^{Core} sorted portfolios. The return dispersion of the top and bottom portfolios

[23]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)).

(IP^{Core}) is 1.2% (t-stat=1.06). The subsample analysis yields similar results: both in the pre-2002 and post-2002 subsamples, the return difference between the top and bottom portfolios is positive and insignificant. However, for the β^{Head} sorted 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 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 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 provide evidence that the cross-sectional IP portfolio contains unique predictive information about future inflation shocks that is not yet fully incorporated by econometricians and economists.

5.1 Predicting Inflation Innovations

We use the monthly rebalanced top-minus-bottom quintile inflation portfolios from Section 3.2 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 discussed in Proposition 2, stocks in the bottom-ranked portfolio, whose inflation betas are ranked the lowest, suffer the most when inflation increases. Therefore, in anticipation of heightened inflation, sophisticated investors would underprice stocks in the bottom portfolio more severely than those in the top portfolio, leading to a positive return for the inflation portfolios. In other words, a higher-than-usual return for the inflation portfolio 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 begin by tracking the performance of inflation portfolios around extreme CPI events to understand the timing of price discovery. According to Lo and MacKinlay (1990), large stocks have better liquidity and often lead small stocks in incorporating market-wide information, so we focus on inflation portfolios constructed using large stocks.[24] We categorize all CPI events into quintiles based on headline- and core-CPI innovations, with the top (bottom) quintile capturing the events with very positive (negative) surprises. We then plot the cumulative performance of inflation portfolios (IP^{Core} and IP^{Head}) from $t = -50$ trading days before the start of the CPI month to $t = 50$ days afterward in Figure 2, with $t = 0$ marking the start of the CPI month.

Focusing first on the upper graph, the performance of inflation portfolios remains flat during the CPI month, regardless of whether the headline-CPI innovations are extremely high or low. However, inflation portfolios start to drift upwards around 30 days before the start of higher-than-expected headline-CPI innovations. The red line lies above the yellow line, suggesting that the core-focused inflation portfolio (IP^{Core}) discovers heightened inflation information faster than the headline-focused portfolio (IP^{Head}). The lower graph, conditional on core-CPI innovations, shows similar pattern.

[24] We contrast the forecastability of large stocks with small stocks in Section 6.1.

To pinpoint when the equity market starts incorporating next-month inflation expectations, Table 6 reports the predictability of inflation portfolio returns on CPI innovations, with returns estimated 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 compare with information discovery in other asset markets, we also include TIPS-UST returns to capture Treasury market dynamics, and GSCI returns for the commodity market. All regressors are standardized with means of zero and standard deviations of one for ease of interpretation.

Inflation portfolios demonstrate robust predictive power for both core-CPI and headline-CPI innovations, initiating 30 days before the CPI month. For instance, within the [-30,-20] day window, a one standard deviation increase in the 10-day return of $\mathrm{IP}^{\mathrm{Core}}$ predicts a 1.8 bps (t-stat=2.37) and 4.6 bps (t-stat=2.73) rise in core and headline-CPI innovations, respectively. Despite noise in returns, coefficient estimates are consistently positive during this 30-day period but become insignificant and even shift sign for the [-40,-30] window preceding it. 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 actual CPI month begins. Our findings align with Downing, Longstaff, and Rierson (2012), highlighting asset prices' forward-looking nature regarding future inflation expectations.

5.1.2 Predictability of Core-Focused Inflation Portfolio

Building on the event window analysis in Section 5.1.1, we assess the performance of inflation portfolios in the 30-day period before the CPI month to predict upcoming inflation changes. We focus on the additional forecasting ability of $\mathrm{IP}^{\mathrm{Core}}$, comparing it with the headline-inflation portfolio and market-based signals from Treasury bond and commodity markets. Specifically, as shown in Section II of the Internet Appendix, at the end of month t (M_t), we use the 30-day returns observed by the end of month t to forecast CPI changes for month $t+1$ (M_{t+1}), which are announced on day A_{t+1}, using the following regression specification:

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

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$^{\text{Core}}$ on inflation innovations. A one standard deviation increase in the 30-day core beta inflation portfolio (IP$^{\text{Core}}$) observed at the end of month t predicts a 2.2 bps increase (t-stat=2.98) in core-CPI innovations and a 7.9 bps increase (t-stat=6.54) 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$^{\text{Core}}$ is non-trivial. This evidence confirms our finding in Section 5.1.1 that a significant portion of future inflation expectations is incorporated into cross-sectional stocks well before the start of the actual CPI month.

The predictability of IP$^{\text{Core}}$ remains strong even 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.[25] Including GSCI with IP$^{\text{Core}}$ 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$^{\text{Core}}$ remains robust both economically and statistically.

While TIPS-UST and GSCI can predict headline-CPI innovations, their ability to forecast core-CPI innovations is limited. According to the estimates in column (4), a one standard deviation increase in IP$^{\text{Core}}$ 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 can still add significant value, especially in terms of core-CPI shocks.

[25] Based on the index composition in 2023, the GSCI index was composed of 61% energy, 24% food, and 15% metals.

Finally, columns (5)-(6) and (11)-(12) analyze the headline-focused portfolio (IP^{Head}) for predicting inflation. The forecastability of IP^{Head} on headline inflation is similar to that of IP^{Core}. A one standard deviation increase in IP^{Head} predicts a 7.4 bps (t-stat=5.78) increase in headline-CPI innovations, close to the 7.9 bps (t-stat=6.54) increase predicted by IP^{Core}. However, IP^{Head} is less effective for core-CPI innovations. When controlling for TIPS-UST and GSCI in column (6), the coefficient for IP^{Head} is an insignificant 0.9 bps (t-stat=1.47), as the headline portfolio's information is largely absorbed by Treasury and commodity market signals. Thus, compared to IP^{Head}, the core-focused IP^{Core} excels in forecasting both headline- and core-inflation changes. Given the core CPI's influence on Fed policy, the unique predictability from cross-sectional stocks is crucial.[26]

5.2 Do Economists Update Beliefs about Inflation?

Our IP^{Core} forecaster 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 results in a lag of over one month between the signal formation and the CPI announcement. This situation raises an intriguing question: Do economists update their inflation expectations based on market-based information, particularly that embedded in cross-sectional stock data? Alternatively, 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 market economists' expectations for month-$t+1$ inflation growth, we utilize Bloomberg Economists' survey forecasts for headline- and core-CPI month-over-month growth. These surveys provide the most current consensus view of inflation just prior to the announcement. We define the change in forecasts as the difference between economists' estimated value for month-$t+1$ inflation growth and the value predicted by the ARMA (1,1) model. The announcement-day forecasting error is then defined as the actual inflation growth for month $t+1$ minus the value estimated by Bloomberg economists.

Table 8 shows that although economists are generally responsive to market-based inflation signals, particularly the one from the commodity market, they do not adequately update their

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

beliefs regarding IP^{Core}. Consequently, IP^{Core} can significantly predict announcement-day forecasting errors with considerable magnitude. Specifically, we use the inflation portfolios alongside GSCI and TIPS-UST to jointly predict changes in forecasts and the forecasting errors for both core and headline inflation by economists. 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. Once we control for GSCI return, there is no statistically significant evidence that economists use the information contained in IP^{Core} to update their inflation expectations. This suggests that the uniquely important core-focused inflation portfolio is not in their information set.

The economists' failure to utilize information from the cross-sectional stock market implies that IP^{Core} might predict announcement-day forecasting errors or survey-based announcement surprises. Consistently, the right panel shows that our core-focused inflation portfolio can predict announcement-day errors for both headline- and core-CPI, beyond what other market-based predictors can achieve. A one standard deviation increase in IP^{Core} predicts an increase of 2.3 bps (t-stat=3.1) and 3.8 bps (t-stat=4.22) in the core and headline CPI, respectively, which economists do not anticipate. 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 incorporated into the economists' forecasts.

5.3 Time-Varying Predictability

The influence of inflation on the economy and its effect on asset prices fluctuates over time (Cieslak and Pflueger (2023) and Bauer, Pflueger, and Sunderam (2024)). When inflation is low, it has a minimal impact on firms' fundamentals, and the predictive power of our inflation portfolio can be quite limited. However, when inflation becomes a significant risk factor in the capital market, the price discovery of inflation-related news among assets intensifies. This section examines the role of core-focused inflation portfolios during key inflation episodes, considering inflation uncertainty and government interventions.

The Episode of 2021 – In 2021, the global economy saw a significant surge in inflation, driven by supply chain disruptions from COVID-19, increased demand from fiscal and monetary stimulus, and rising energy prices. After surpassing the 2% Fed target in April 2021, core CPI continuously increased, reaching a 40-year high of 6.6% year-over-year growth by 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.[27]

In contrast to the failure of economists, the inflation portfolio (IP^{Core}) appeared to correctly anticipate the inflation surge during this period. 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). We observe a tremendous increase in IP^{Core} just before the rapid surge of core CPI in April 2021. The magnitude of IP^{Core} observed at the end of March 2021 is 3.7 times of its sample standard deviation. Meanwhile, IP^{Core} co-moves well with the ups and downs of core CPI, successfully catching the local trough in July 2021 and the local peaks in April 2021 and June 2022.

In the form of a scatter plot, the upper left graph of Figure 4 further demonstrates the capability of IP^{Core} in predicting core-CPI innovations during this crucial period. A 10% increase in the 30-day IP^{Core} observed at the end of month-t predicts a 26.3 bps (t-stat=2.31) increase in core-CPI innovations for month $t+1$, with an R-squared of 17.7%. Amid doubts about the persistence of the inflation shock, possibly driven by temporary supply-chain disruptions post-COVID-19, IP^{Core} effectively captured the month-over-month movements of core CPI that were largely missed by policymakers and economists.

Turning to other market-based predictors, we find their performance in predicting this surge in inflation to be rather disappointing. Conducting the same analysis using signals

[27]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.

from the bond market, the upper right graph of Figure 4 shows that TIPS-UST fails to predict core-CPI innovations and even exhibits 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. IP^{Core} emerges as the only significant predictor, with both economic and statistical significance far surpassing other predictors.[28] Importantly, the coefficient estimates of IP^{Core} on core-CPI innovation and survey-based forecasting error are more than three times larger than the full-sample estimates, highlighting the importance of the core-focused inflation portfolio in the price discovery of inflation 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. This surge was driven by stimulative fiscal policies under Nixon's presidency, excessive government spending for the Vietnam War, and the Arab oil shock. Both periods experienced highly accommodative monetary policies leading up to their respective inflationary episodes. In 1973, inflation persisted at elevated levels until Paul Volcker's appointment as Chair of the Federal Reserve in 1979, when he initiated a stringent monetary tightening campaign.

Similar to the 2021 scenario, economists and policymakers in the early 1970s severely underestimated the rate of inflation. 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 by our IP^{Core}, mirroring the results observed in the 2021 episode. Columns (5) and (6) of Ta-

[28] 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.

ble 9 further report the predictability of bond and commodity-based forecasters together with $\mathrm{IP}^{\mathrm{Core}}$.[29] Among all these forecasters, $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$, 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.[30] Panel B of Table 9 reports the predictability of $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$ 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.[31] Overall, the evidence suggests that $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$. 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 inflation preemptively, inflation can be effectively contained, reducing the predictability of

[29] 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.

[30] 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.

[31] 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.

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).[32] 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 $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$. 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.[33] 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 consistently stronger at the beginning of the inflation run-up when the Fed is behind the

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

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

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.

At the end of 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 publicly available information up to month t. Here, X_{t-1}^k represents the forecasting signal k observed at the end of month $t-1$, and π_t represents 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.[34] 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 $\mathrm{IP}^{\mathrm{Core}}$ for subsamples when inflation is particularly significant to the economy. Consistent with Section 5.3, the forecasting power of $\mathrm{IP}^{\mathrm{Core}}$ 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, $\mathrm{IP}^{\mathrm{Core}}$ provides unique information about inflation both in-sample and out-of-sample, particularly during heightened inflation periods.

[34] 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).[35] 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

[35]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. Our findings align with previous studies by Boudoukh, Richardson, and Whitelaw (1994) and Ang, Brière, and Signori (2012), showing 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, consistent with the notion that oil and gas stocks benefit from rising commodity prices. In contrast, cyclical industries like soda, restaurants, hotels, and insurance are more negatively impacted by unexpected inflation shocks.

The distribution of announcement-day core-based inflation betas is less documented in the literature. The core beta ranking reveals that β^{Core} captures distinct information compared to β^{Head}. 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: while rising commodity prices are costly for firms running shipping containers, price increases for providing shipping services benefit them.

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 primary analysis, 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 $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$ 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.[36] 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

[36] 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. In line with the results from Table 3, IP^{Core} exhibits a positive loading on HML, although the t-stat is only marginally significant. Panel B additionally reports the predictability of the Fama-French five-factor adjusted inflation portfolio alphas in response to inflation shocks. The findings are robust and exhibit similar economic magnitudes.

7 Conclusions

In this paper, we explore the price discovery of inflation news among cross-sectional stocks. To understand the cross-firm variations in inflation exposure, we observe that cross-sectional stock returns exhibit persistent sensitivity to headline inflation shocks during the calendar month of the CPI release and to core inflation news on CPI announcement days. Both headline and core betas are effective in capturing individual stocks' exposure to inflation, but they convey different information. The headline beta is more attuned to variations in headline exposure and inflation risk premiums across firms, while the core beta is better at detecting core inflation shocks. Furthermore, we provide evidence that the relative pricing between stocks with high and low inflation exposure can predict inflation shocks, driven by the cash flow effect of inflation on firm pricing.

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. The strong predictability documented in our paper suggests that much can be gained from the cross-section. Our analysis shows that the predictability of inflation portfolios increased significantly, with an R-squared of 17.7% and 28.4% during the inflationary periods of 2021 and 1973, respectively. 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 commonly used for forecasting inflation, our results indicate that the information contained in cross-sectional stocks can add value, especially for the core component.

Focusing on economists' forecasting errors, we find that they do not incorporate the information contained in the inflation portfolio, and their room for improvement is especially large 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 (β^{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.

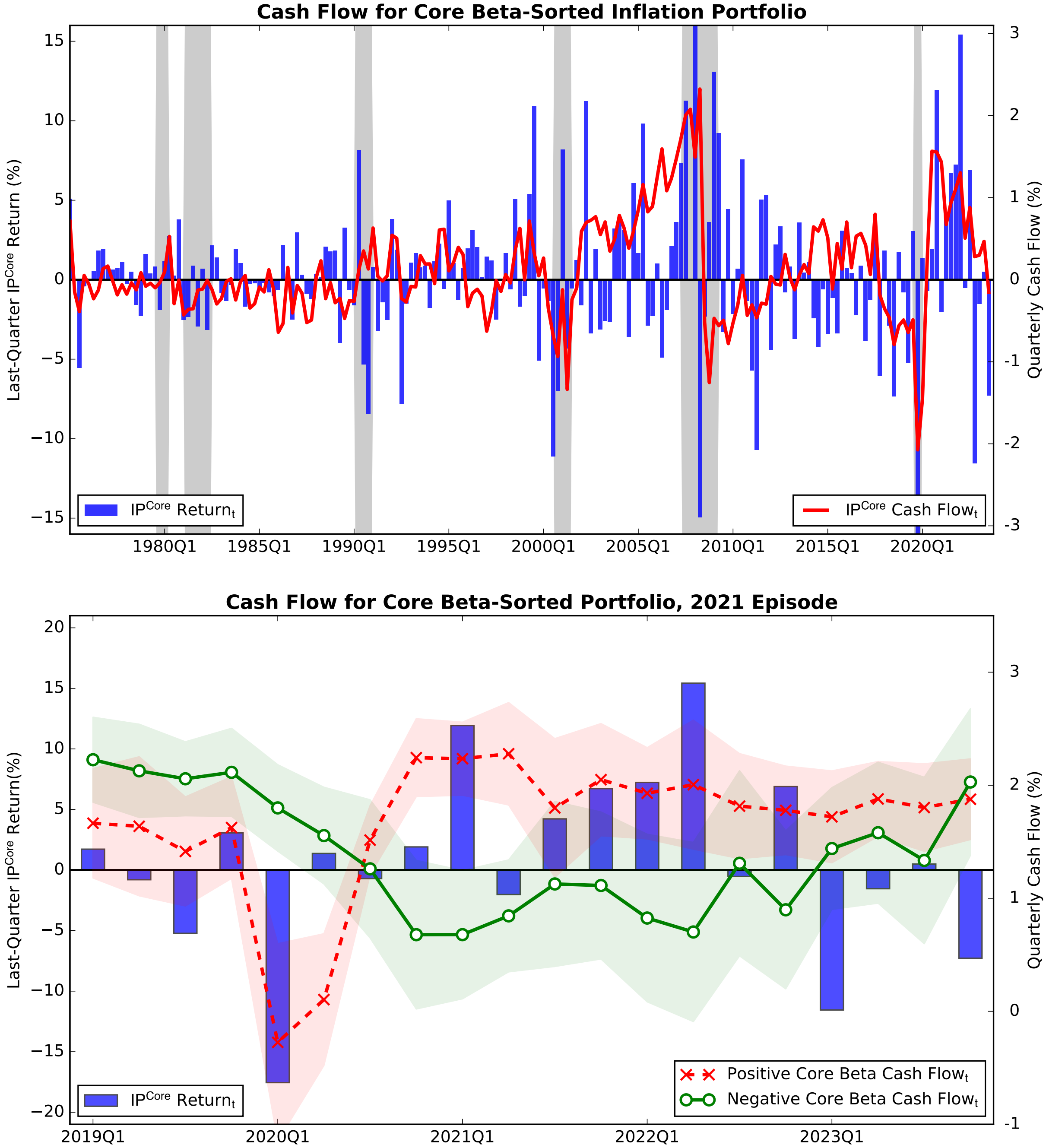
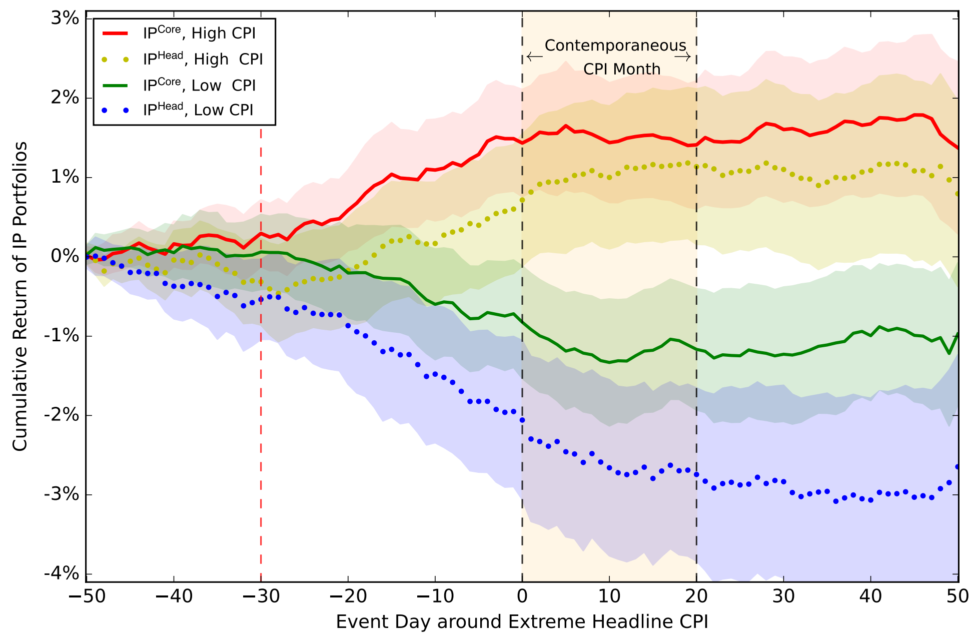


Figure 2. Performance of Inflation Portfolios around Extreme CPI Months

The upper graph illustrates 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. High (low) CPIs are categorized as those falling within the top (bottom) quintile among all CPI values. The lower graph depicts the corresponding performance of inflation portfolios when extreme CPI events are defined based on core-CPI innovations.



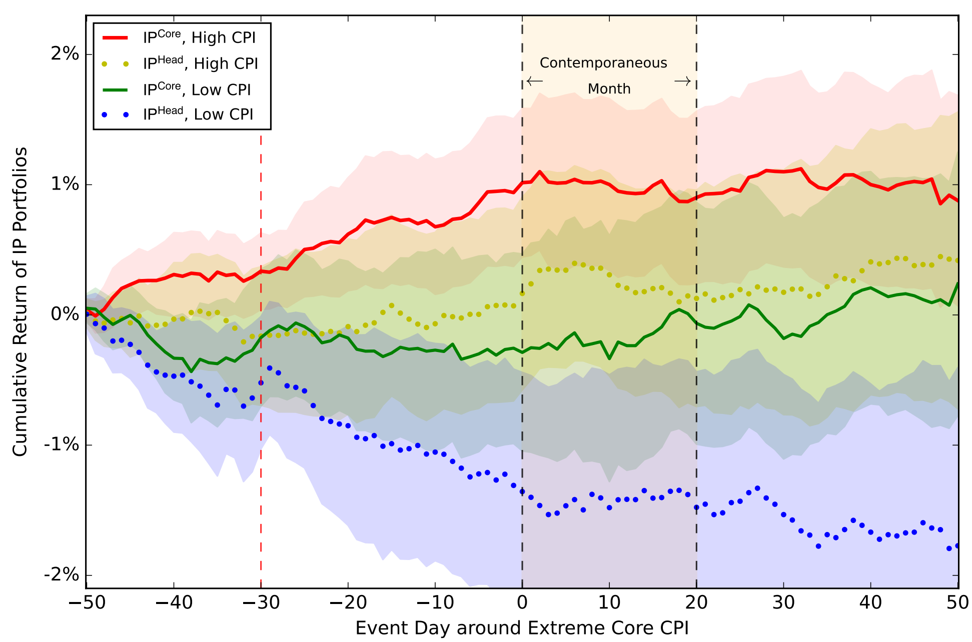


Figure 3. Economists' Forecasts and IP^{Core} in the 2021 Episode

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 IP^{Core} and TIPS-UST during the same period.

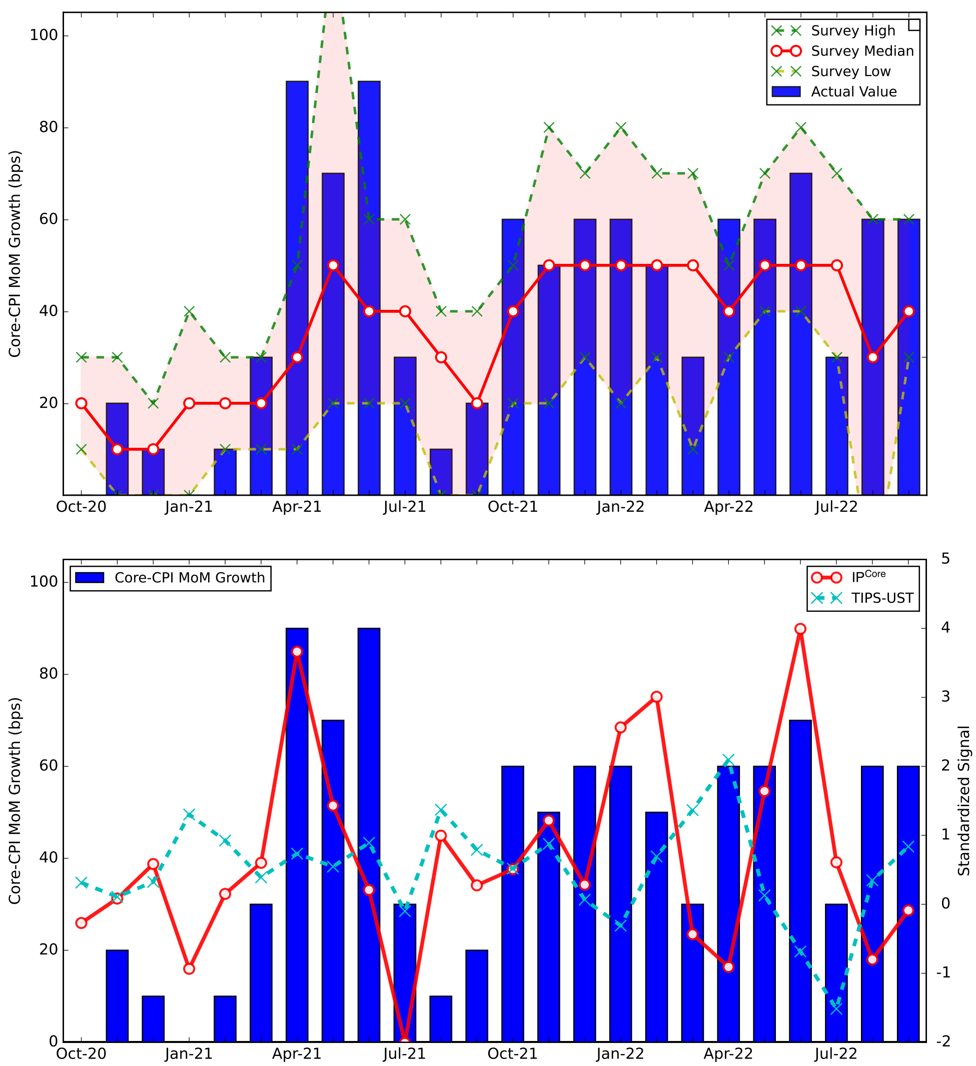


Figure 4. Predictability During Heightened Inflation Periods

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.

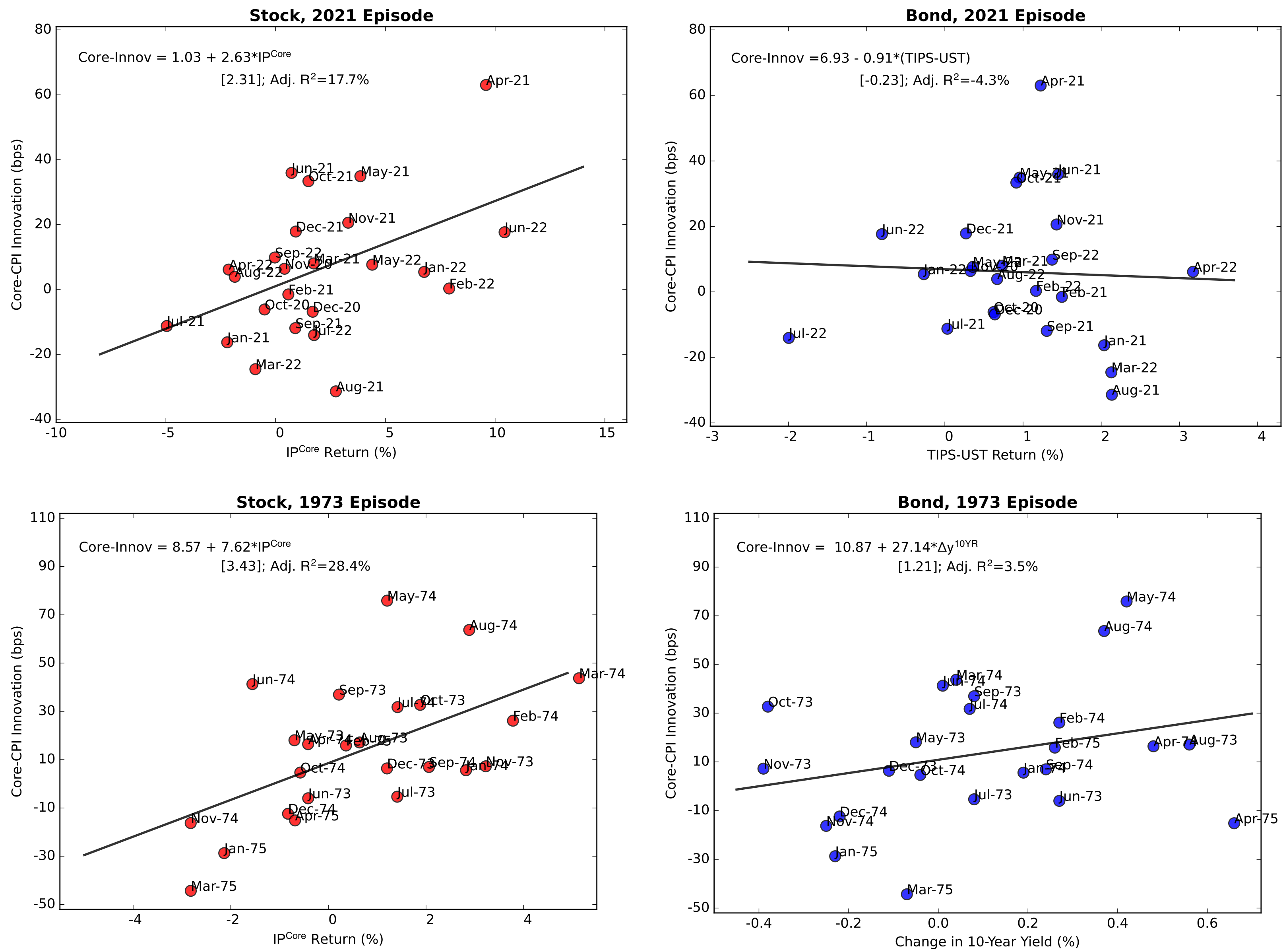
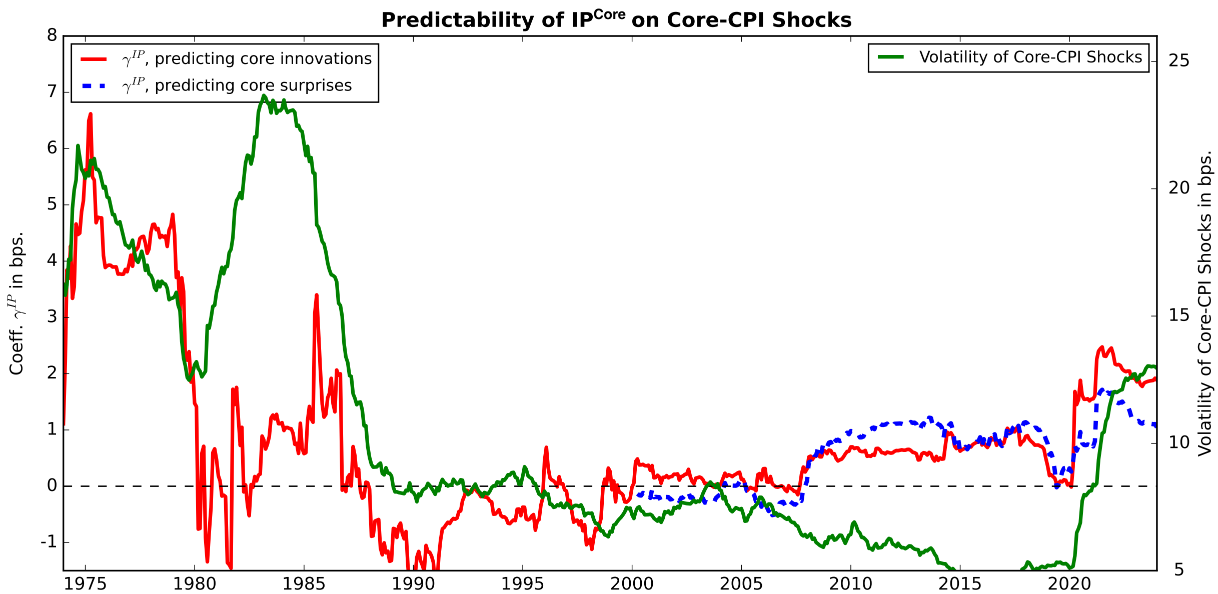


Figure 5. Predicting CPI Shocks using IP^{Core}

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: $\text{CPI Shock}_{t+1} = \alpha + \gamma^{\text{IP}} \times \text{IP}_t^{\text{Core}} + \varepsilon_{t+1}$, 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.



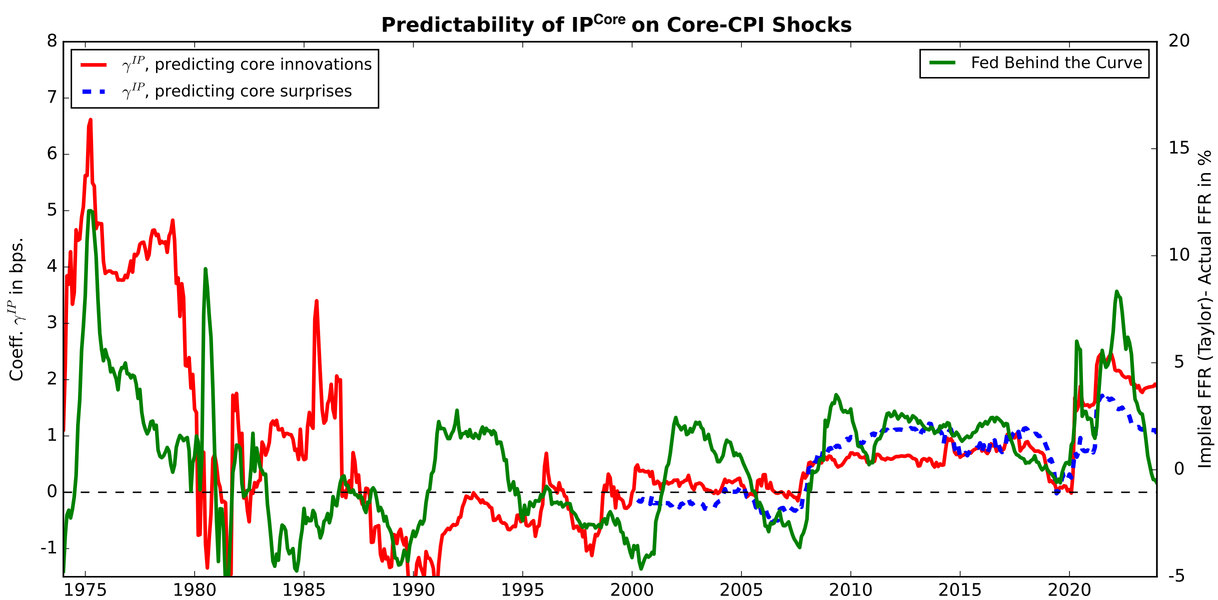


Table 1. Inflation Beta in Cross-Sectional Stocks: Ann-Day vs. Full-Month

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. 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 spans from January 1972 to December 2023. Standard errors are adjusted for heteroskedasticity, and the t-stats are presented in parentheses.

	Announcement-Day (β^{Ann})			Full-Month (β^{Full})		
	Core	*Headline*	*Energy*	*Core*	*Headline*	*Energy*
$\Delta y^{2\mathrm{YR}}$	0.120	0.037	0.019	0.120	0.140	0.068
	(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
	(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
	(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
	(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
	(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
	(−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
	(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. 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	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. 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$^{\text{Core}}$	X=IP$^{\text{Head}}$	X=GSCI	X=TIPS-UST	X=IP$^{\text{Core}}$	X=IP$^{\text{Head}}$	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 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 $\mathrm{IP}^{\mathrm{Core}}$, $\mathrm{IP}^{\mathrm{Head}}$, 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$_{t+1}$					
$\mathrm{IP}^{\mathrm{Core}}$	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)		
$\mathrm{IP}^{\mathrm{Head}}$					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$_{t+1}$					
$\mathrm{IP}^{\mathrm{Core}}$	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)		
$\mathrm{IP}^{\mathrm{Head}}$					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 IP^{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 IP^{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)
IP^{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 (Δy^{10YR})		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	
IP^{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	
IP^{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	
IP^{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 basis points. 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 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 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 CPI growth minus the forecasting value by Bloomberg economists
CPI Uncertainty	Last-month absolute 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
QE	Periods of Quantitative Easing: November 2008 to March 2010, November 2010 to June 2011, September 2012 to October 2014, and March 2020 to March 2022
Output Gap	Log real GDP, detrended using the Hodrick–Prescott filter
CFNAI	A monthly index designed to gauge overall economic activity and related inflationary pressure
Log(Size)	The natural logarithm of a firm's market capitalization
Asset Growth	Growth rate of total asset: $AT_t/AT_{t-1} - 1$
Cash Flow	Income before extraordinary items plus depreciation and amortization, divided by total asset (Hennessy et al. (2007)): $\sum(IB_t, DP_t)/AT_t$
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 window of 5-year
ME/BE	The market value of total assets divided by the book value of total assets: ME_t/BE_t
Dividend Payout	Dividends divided by income: DVC_t/IB_t
CF Duration	Cash flow duration, constructed following Weber (2018)
Sales Growth	Change of gross sales divided by total asset: $(Sales_t - Sales_{t-1})/AT_{t-1}$

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. In Section I, we provide detailed proof of model propositions. Section II illustrates the timeline of beta estimation and inflation forecasting. Section III provides additional tables and plots mentioned in the paper.

I. 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

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

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 $\beta_i - \beta_j$:

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

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

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

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

The population estimate of γ_{ij} is

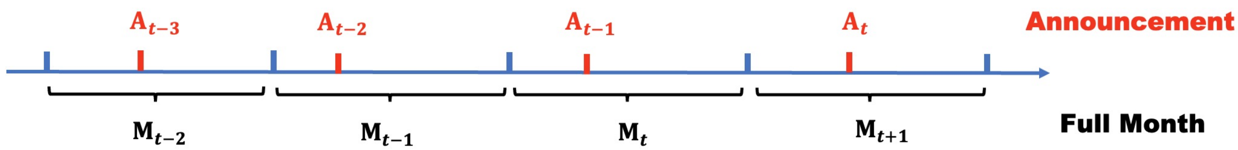
$$\gamma_{ij} = \sigma_\pi \frac{\mathrm{E}[(y_t + \epsilon_{t+1})\Big((b_i - b_j)\sigma_\pi y_t + (b_i - b_j)\sigma_\pi \epsilon_t + (\sigma_i \epsilon_t^i - \sigma_j \epsilon_t^j)\Big)]}{\mathrm{var}[\Big((b_i - b_j)\sigma_\pi y_t + (b_i - b_j)\sigma_\pi \epsilon_t + (\sigma_i \epsilon_t^i - \sigma_j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

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

where ρ_{ij} is the correlation coefficient between ϵ_t^i and ϵ_t^j.

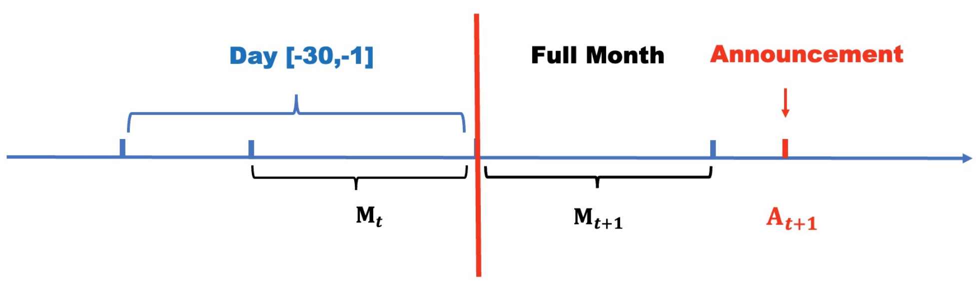
II. Illustration of the Time Line

Beta Estimation – To capture the inflation exposure of individual stocks as well as different assets, we adopt two approaches. The first approach estimates an information-based inflation beta, constructed by regressing firm i's announcement-day returns on announcement-day released CPI innovations. Each month after the announcement of CPI (A_t), we measure the headline- and core-inflation exposure for firm i using a rolling window of 60 months. We dynamically update the estimation of inflation beta on the CPI announcement days, as we need to wait until announcement day A_t to get the CPI innovation for month M_t.



As illustrated in the above graph, standing at announcement day A_t, firm i 's announcement-day beta is estimated using announcement-day returns from A_{t-59} to A_t under the equation (4). Taking the announcement day of May 11, 2022 as an example, A_{t-59} refers to June 14, 2017, which is the announcement day for CPI month of May 2017.

The second approach estimates the inflation risk exposure by the sensitivity of monthly asset 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. For example, if we are estimating inflation beta on May 11, 2022, which is the CPI announcement day for April 2022, we use the monthly returns and monthly CPI innovations from May 2017 to April 2022 to estimate.



Forecasting with IP – To examine the forecastability of inflation portfolio returns, standing at the end of month t (M_t), 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.

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.

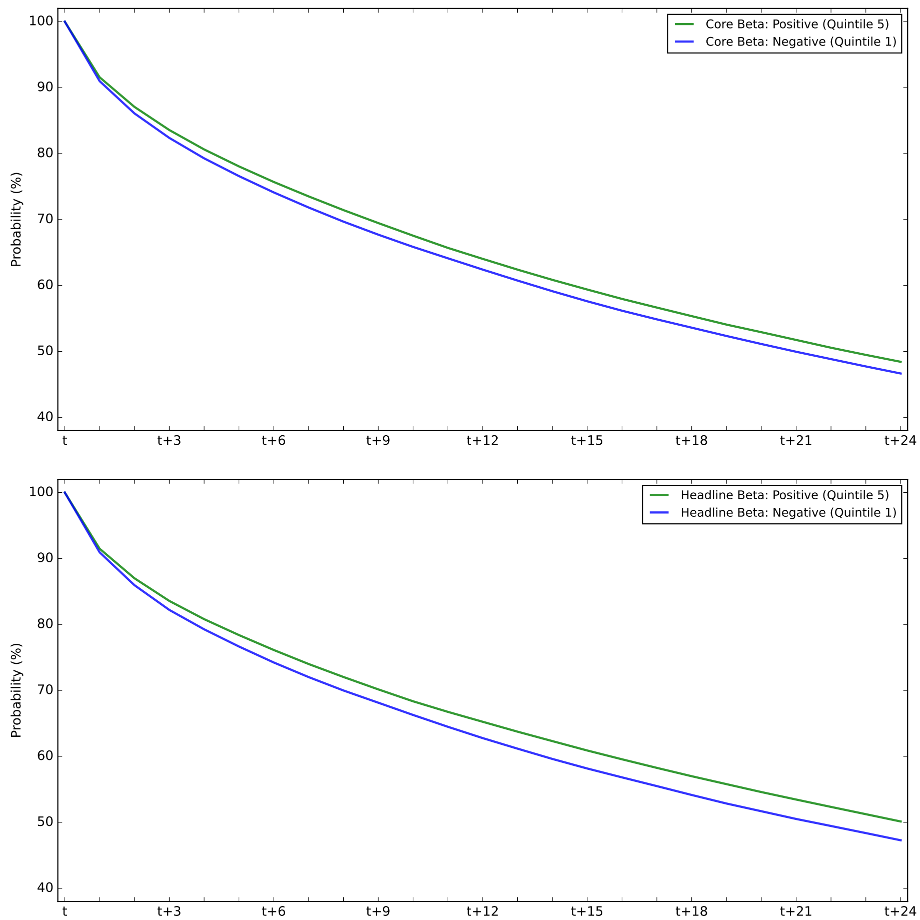
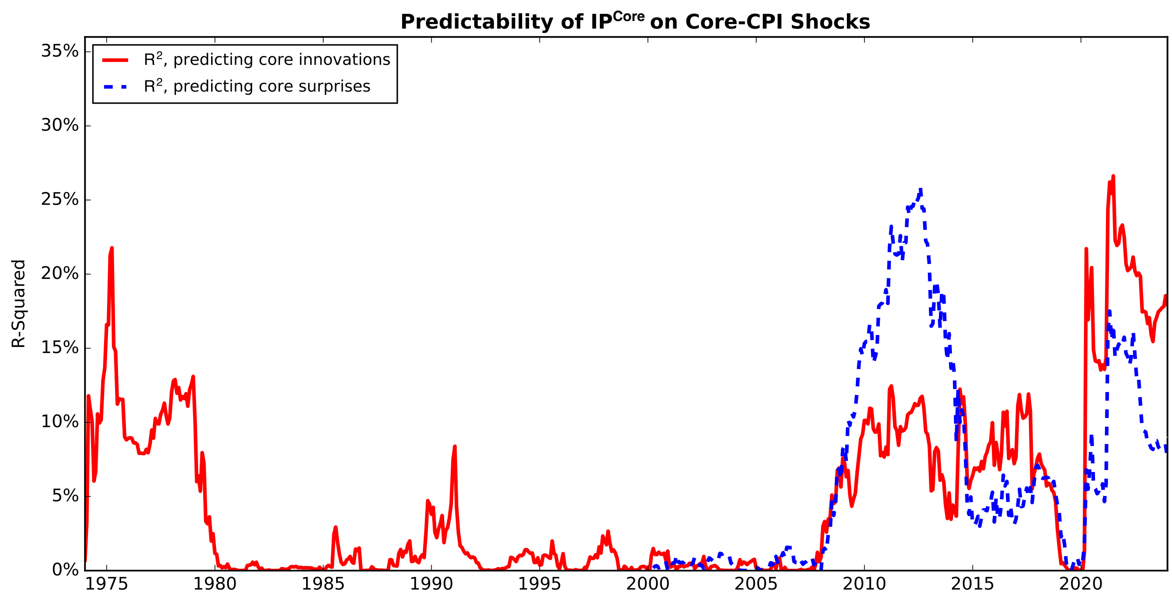


Figure IA2. Predicting CPI Shocks using $\mathrm{IP}^{\mathrm{Core}}$, R-Squared

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: $\text{CPI Shock}_{t+1} = \alpha + \gamma^{\mathrm{IP}} \times \mathrm{IP}_t^{\mathrm{Core}} + \varepsilon_{t+1}$, using observations from $t-59$ to t. We require at least 24 months of data for 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.



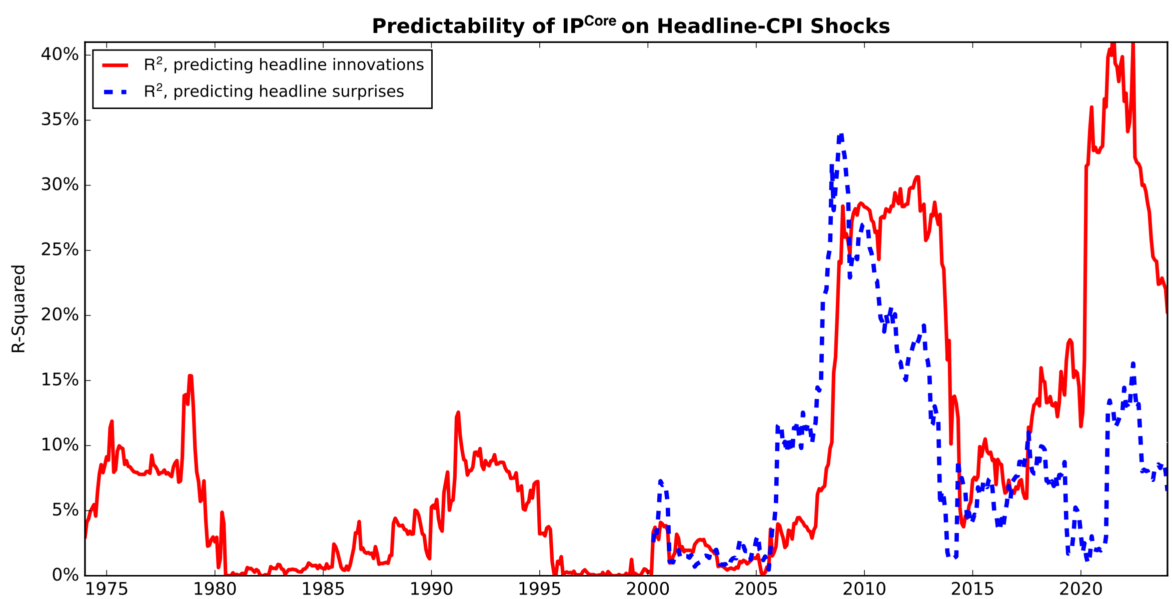


Table IA1. Summary Statistics

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. IP$^{\text{Core}}$ and IP$^{\text{Head}}$ 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 ($\Delta y^{2\text{YR}}$ and $\Delta y^{10\text{YR}}$), 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$^{\text{Core}}$ (%)	624	0.19	0.12	−1.06	1.42	2.56
IP$^{\text{Head}}$ (%)	624	−0.24	−0.25	−1.72	1.52	3.22
VWRETD (%)	624	1.23	1.70	−1.42	4.43	5.21
$\Delta y^{2\text{YR}}$ (%)	571	−0.01	−0.01	−0.25	0.18	0.53
$\Delta y^{10\text{YR}}$ (%)	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 reports the post-ranking inflation betas for stock portfolios formed when pre-ranking betas are constructed by regressing announcement-day stock excess returns on announcement-day 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}) under the "CAPM Model". Panel B examines the predictability of 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, observed at the end of month t, on core-CPI innovations and headline-CPI innovations at month-$t+1$. 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 Boons et al. (2020). Firm i's announcement-day inflation beta ($\beta^{\text{Ann}}_{i,A_t}$) is given by: $\min_{\alpha_{i,A_t},\beta^{\text{Ann}}_{i,A_t}} \sum_{\tau=1}^{t} w(\tau)(R_{i,A_\tau} - \alpha_{i,A_t} - \beta^{\text{Ann}}_{i,A_t}\text{CPI-Innov}_{A_\tau})^2,$, 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: $\widehat{\beta^v_{i,t}} = \widehat{\beta_{i,t}} + \frac{\text{var}_{TS}(\widehat{\beta_{i,t}})}{\text{var}_{TS}(\widehat{\beta_{i,t}})+\text{var}_{CS}(\widehat{\beta_{i,t}})} \times (\text{mean}_{CS}(\widehat{\beta_{i,t}}) - \widehat{\beta_{i,t}})$, where each $\widehat{\beta^v_{i,t}}$ 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%