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

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

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Abstract

We demonstrate that security returns consistently respond to headline-CPI shocks during the CPI month but react more to core-CPI news on announcement days. This pattern is evident in nominal bonds, commodities, and cross-sectional stocks. Firms with negative core betas show higher growth potential and longer cash flow duration. Consistently, with rising inflation, these firms see worse sales growth, cash flow, and lower IBES long-term growth forecasts. We show that a long-short portfolio based on core-focused announcement-day inflation beta predicts upcoming inflation shocks, including CPI innovations and economists' forecasting errors, and is not absorbed by information from the Treasury and commodity markets. This core-focused inflation portfolio is an unparalleled predictor for core inflation, particularly during the inflation spikes of 2021 and 1973, and in periods of high inflation risk and accommodating monetary policies.

Keywords: Inflation, Cross-section, Stock returns, Core-CPI, Announcements
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*Hong (yrhong@saif.sjtu.edu.cn) and Tian (swtian.18@saif.sjtu.edu.cn) are from the Shanghai Advanced Institute of Finance at Shanghai Jiao Tong University. Jun (junliu@ucsd.edu) is from the Rady School of Management at University of California San Diego. Pan (junpan@saif.sjtu.edu.cn) is from the Shanghai Advanced Institute of Finance at Shanghai Jiao Tong University and CAFR. We benefited from discussions with Daniel Andrei, Geert Bekaert, Hui Chen, Anna Cieslak, Adlai Fisher, Qiushi Huang, Francis A. Longstaff, Alexi Savov, Fabricius Somogyi, Jonathan Wright. We thank seminar and conference participants at EFA 2024, CICF 2023, ABFER 2023, BWFG Annual Conference 2023, Tilburg Finance Summit 2023, NBER SI 2023, 2023 Symposium on Recent Developments in Time Series Econometrics and Applied Macroeconomics, School of Management at Fudan University, SAIF at Shanghai Jiao Tong University, MIT Finance PhD Workshop, Xi'an Jiaotong-Liverpool University, Peking University, FISF at Fudan University, PBCSF Tsinghua, UC Irvine University, Chinese Academy of Sciences, University of Oxford, Imperial College Business School, Renmin University of China, and Tongji University.

1 Introduction

Understanding the relationship between stock returns and inflation has long been a topic of interest in financial economics. The seminal works by Fama and Schwert (1977) and Bodie (1976) show that the stock market is a poor hedge against inflation, with the relationship between stock returns and inflation being particularly unstable and even changing sign in the post-2000 period (Bekaert and Wang (2010), Campbell et al. (2017)). 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 leverage the announcement-day sensitivity of stock returns to core-inflation components to measure their inflation betas. We demonstrate that the relative pricing between stocks with high and low core-inflation exposures provides unique information about inflation expectations and can predict realized inflation going forward.

Our focus on inflation forecasting arises from the recent failures of traditional methods during the 2021 inflation episode. Core CPI surged to a 40-year high of 6.6% year-over-year in September 2021. While Ang et al. (2007) show that among all the inflation forecasters, survey-based forecasters tend to outperform others. During critical months in 2021, economists consistently underestimated the rapid month-over-month increases in core CPI: by 10 basis points in March, 60 basis points in April, 20 basis points in May, and 50 basis points in June. The most striking miss occurred in April 2021, where the highest Bloomberg survey projection was 50 basis points, far below the actual 90 basis points. Amid the heated debate on the transitory vs permanent nature of the surging inflation, the Fed also chose the wrong side. Throughout 2021 and into March 2022, the Federal Reserve maintained a zero interest-rate policy and continued $120 billion monthly bond purchases, pivoting not until March 2022 and tightening aggressively since June 2022.

The collective failure of economists and policymakers during recent inflation episodes motivates us to examine the informativeness of financial assets, particularly cross-sectional stocks, in forecasting inflation. Under rational expectations, if asset returns react to changes in expected inflation, then asset prices can be utilized to predict changes in the inflation

[1]Notable exceptions include Chen et al. (1986) and Boons et al. (2020) on inflation risk premium, Campbell and Vuolteenaho (2004) on cross-firm inflation exposure, and Chordia and Shivakumar (2005) on money illusion.

rate. If inflation exposures are persistent and vary across firms – where inflation is more detrimental to stocks with negative inflation betas compared to those with positive betas – an increase in the pricing spread between stocks with high and low inflation betas, ceteris paribus, would signal a rise in the inflation rate. This cross-sectional approach allows us to move away from the weak and unstable relation between aggregate market and inflation and focus specifically on the inflation expectations embedded in the stocks.[2]

As investor compositions vary across asset classes, the price discovery in cross-sectional stocks may offer additional insights compared to other asset markets. Specifically, in contrast to the Treasury bond market – whose yield curves have been widely used to forecast inflation – the information contained in cross-sectional stocks can provide unique value. This is particularly relevant when U.S. Treasury bond pricing is influenced by factors unrelated to inflation risk, such as illiquidity or risk aversion. For instance, illiquidity in the market for Treasury Inflation-Protected Securities (TIPS) can introduce noise into breakeven inflation forecasts. Additionally, government interventions in the Treasury market, such as quantitative easing (QE), can distort bond pricing, thereby masking true inflation expectations.

Announcement-Day vs. Full-Month Inflation Beta – Price discovery with respect to inflation occurs not only during the month when inflation is realized but also on CPI announcement days when unexpected inflation news is released. Traditionally, the literature estimates securities' inflation exposures by examining the sensitivity of monthly security returns to contemporaneous month CPI innovations (e.g., Chen et al. (1986); Boons et al. (2020)), often neglecting the impact of announcement days. There is a lag of over a month between the Bureau of Labor Statistics (BLS) collecting price data and the CPI announcement. 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.

This hypothesis is confirmed by analyzing the announcement-day and full-month inflation betas for a wide range of assets, including equity (VWRETD), treasury (2-year and 10-year U.S. Treasury yields, TIPS-UST return), corporate bonds, and commodities (GSCI). We

[2]This informational channel is similar to the seminal work by Roll (1984), which examines the market's information processing ability by relating orange-juice futures price changes to subsequent errors in temperature forecasts issued by the National Weather Service for the central Florida region where most juice oranges are grown.

find that both inflation betas effectively capture securities' inflation exposures, but their information content varies. Specifically, on CPI announcement days, asset returns primarily react to core-CPI innovations; an unexpected increase in core CPI leads to a decrease in equity and bond returns and an increase in commodity returns, while energy-CPI innovations have no significant impact. Conversely, during the contemporaneous month when investors experience inflation, asset returns are most sensitive to the energy component in the headline CPI, but less so to the core component.

Thus, the full-month approach better captures sensitivity to headline CPI, particularly the energy component, while the announcement-day approach better captures sensitivity to core CPI, particularly the goods and services component. The intuitive pairing of announcement-day beta for core CPI and full-month beta for headline CPI stems from the nature of their components. Headline-CPI elements, such as energy, are continuously monitored via commodity markets, providing real-time data throughout the month. In contrast, core-CPI components like goods and services are less visible and thus tend to create more surprises on announcement days.

When extending this analysis to cross-sectional stocks, we observe a similar pattern. There are significant variations in firms' exposure to inflation, and this cross-firm characteristic is persistent. Firms that have historically responded negatively to core-CPI innovations on announcement days continue to do so in the future. This persistence is also observed in the full-month headline beta, primarily driven by the energy component. Our findings are consistent with those of Fang et al. (2021), who show that the full-month beta is more negative and significant for core CPI than for headline CPI. However, while their focus is on aggregate asset classes, our objective is to differentiate securities based on their relative inflation exposures. Consequently, our results demonstrate that full-month beta effectively captures headline-CPI exposure, whereas announcement-day beta better reflects core-CPI exposure.

Examining the determinants of a firm's inflation beta, we uncover that firms with more positive core betas tend to have lower growth potential, higher dividend payouts, and higher cash flows, indicating a concentration of immediate cash flows and a shorter cash flow duration. Conversely, firms with more negative core betas exhibit longer cash flow durations and higher growth potential, similar to longer-maturity bonds that suffer more from rising core

inflation. Despite the significant relationship between cash flow duration and core beta, the explanatory power is limited, suggesting other factors at play.

Inflation Forecasting – Given the persistent variations in inflation exposures across firms, if rational expectations hold and stock returns react to changes in expected inflation, the relative pricing between stocks with high and low inflation betas can effectively aggregate investors' expectations of future inflation. To test this, we sort stocks by their pre-ranking inflation betas into quintile portfolios and form the monthly rebalanced top-minus-bottom inflation portfolios. The core-focused inflation portfolio (IP^{Core}) is constructed using announcement-based and core-focused beta, while the headline-focused inflation portfolio (IP^{Head}) uses full-month and headline-focused beta. Our hypothesis posits that, when informed by higher inflation expectations, investors would underprice stocks in the bottom portfolio (more negative inflation betas) more severely than those in the top portfolio (more positive inflation betas), resulting in positive inflation portfolio returns. Thus, a higher-than-usual inflation portfolio return thus reflects heightened inflation expectations and can help predict the inflation yet to be realized. Moreover, as inflation price discovery relies on sophisticated investors incorporating inflation expectations, we expect stronger price discovery among firms with better information environments.

Our empirical findings support the active price discovery of inflation news. The 30-day return of IP^{Core}, observed at the end of month t, significantly and positively predicts both the core- and headline-inflation innovations of month $t+1$ (announced in the mid of month $t+2$). Specifically, a one standard deviation increase in IP^{Core} predicts a 2.7 bps (t-stat=3.40) increase in core-CPI innovations and a 7.5 bps increase (t-stat=6.83) in headline-CPI innovations. Given the standard deviations of core- and headline-CPI innovations are 15.6 bps and 26 bps respectively, such a magnitude of predictability is not trivial. While the headline-focused inflation portfolio, IP^{Head}, can also predict headline inflation with similar magnitude, it is less effective in predicting core-CPI movements. Furthermore, by examining the information environment using firm size, analyst coverage, and institutional ownership, we find that the predictability of IP^{Core} is stronger among larger firms, those with greater analyst coverage, and higher institutional ownership.[3]

[3]To isolate the effects of analyst coverage and institutional ownership from firm size, we use residuals obtained by orthogonalizing these variables with respect to firm size (Hong et al. (2000)).

When comparing our equity-based inflation forecasts against two market-based forecasts known to contain inflation expectations—the Goldman Sachs Commodity Index (GSCI) and the breakeven-inflation portfolio of TIPS-UST (which buys the inflation-neutral TIPS and sells the inflation-negative nominal U.S. Treasury bonds) – we find that although the commodity-based GSCI is the most informative for forecasting headline inflation, IP^{Core} adds additional value. Moreover, 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.

Leading up to each pre-scheduled CPI announcement, economists routinely make their inflation forecasts, with the Bloomberg survey of economists being a widely followed inflation source. Between the time when our inflation forecast is observed (end of month t) and the announcement of the month-$t+1$ CPI (usually in the mid of month $t+2$), over a month elapses. It is therefore interesting to study whether economists update their inflation expectations using market-based information, particularly that embedded in cross-sectional stocks, or to what extent market-based forecasts can predict the announcement-day errors made by economists.

We find that our core-focused inflation portfolio can also predict the announcement-day errors made by economists (survey-based forecasting errors) above and beyond other market-based predictors. A one standard deviation increase in IP^{Core} predicts an increase of 2 bps (t-stat=2.70) and 3.6 bps (t-stat=4.06), respectively, in the core and headline CPI not expected by economists. As the respective CPI forecasting errors have standard deviations of 11 bps and 13 bps, the information from cross-sectional stocks can help improve the economists' forecast. However, despite being available over a month in advance, this information does not fully integrate into economists' forecasts.

Time-Varying Forecastability – Inflation is difficult to predict due to its time-varying nature. Often dormant for long periods, it can surge rapidly, as exemplified by the inflation spike in 2021. Active price discovery regarding inflation risk becomes crucial when inflation re-emerges as a significant risk factor in capital markets. Therefore, it is essential to examine the efficacy of inflation portfolios during periods when inflation is most pertinent to the economy.

In 2021, core CPI increased by 90 bps in just one month (April 2021) for the first time since 1982. Prior to this surge, IP^{Core} signaled a 3.59-sigma alert. During the 24 months from October 2020 to the peak of core CPI in September 2022, the predictability of IP^{Core} increases tremendously, achieving an R-squared of 18.5% and an economic magnitude of 8.4 bps (t-stat=2.35), compared to the whole sample magnitude of 2.7 bps. When using the market-based predictors, including IP^{Core}, TIPS-UST, and GSCI, jointly to forecast core CPI during this period, IP^{Core} emerges as the only significant predictor, dominating the others both economically and statistically. This increased predictive power for core CPI amid debates on the transitory versus permanent nature of rising inflation suggests active price discovery in cross-sectional stocks regarding crucial inflation information.

Drawing a parallel to 2021, the 1973 inflation episode is often referenced to understand recent runaway inflation. Tracking the performance of IP^{Core} in the 24 months leading up to the core-CPI peak in February 1975 (March 1973 to February 1975)), we find a similar pattern: IP^{Core} significantly predicts core-CPI innovations with a much improved R-squared of 32.8% and an economic magnitude of 18.2 bps (t-stat=3.50). As in the 2021 episode, this enhanced predictability is primarily captured by IP^{Core}, rather than IP^{Head}, UST, or GSCI.

The cases from 1973 and 2021 suggest that the effectiveness of inflation forecasting varies over time. Among all forms of inflation forecasts, IP^{Core} offers the most timely information, but the predictive power also varies over time. We further investigate this by examining the informativeness of IP^{Core} under conditions of inflation uncertainty and noise from the Treasury market. Using the absolute value of last-month CPI innovations and the magnitude of economists' disagreement as proxies for inflation uncertainty, we demonstrate that IP^{Core} 's predictability strengthens with higher disagreement and uncertainty.

Additionally, we explore how monetary policies affect the time-varying informativeness of inflation forecasters. Monetary policies influence Treasury prices through interest rate adjustments or quantitative easing (QE). We find that IP^{Core}'s predictive power and economic significance are notably larger when the Fed Fund Rate lags behind the rate recommended by the Taylor rule and during periods of QE. These results suggest that a strong signal from cross-sectional stocks does not necessarily lead to sustained core-inflation increases, as seen in 2021 and 1973. When the Fed is ahead of the curve, inflation can be effectively contained, resulting in muted predictability. Conversely, when the Fed is behind the curve or follows an

accommodative monetary policy, allowing inflation to remain unchecked, the predictability of IP^{Core} can be stronger.

The inflation forecasting ability of IP^{Core} is robust both in-sample and out-of-sample. When benchmarked against the ARMA (1,1) time-series model, IP^{Core} enhances the forecasting accuracy of month $t+1$ core-CPI growth by approximately 4-8%, a performance unmatched by any other predictors in our analysis. For headline CPI, the improvement ranges from 6-13%. In contrast, the out-of-sample enhancements provided by GSCI and TIPS-UST for predicting core inflation are significantly weaker, at about 1-2%. Furthermore, the robustness of IP^{Core} extends to various alternative measures of CPI-announcement day surprises, such as survey-based surprises, changes in inflation swap rates, and changes in nominal yields. When these measures are used to estimate stocks' announcement-day betas, the forecasting ability of the announcement-day based inflation portfolio remains intact. The results hold true even when forecasting quarterly CPI, using rolling five-year periods to estimate beta, excluding the industry component, or forecasting inflation-linked asset returns like inflation swap rates and changes in nominal yields.

The Cash Flow Channel – A simple valuation model of Gordon Growth Formula suggests that inflation can affect firm values either through the discount rate channel or the cash flow channel. To empirically investigate the mechanism behind the relative pricing of stocks with high and low inflation exposures, we first examine the impact of inflation on firm fundamentals conditional on inflation expectation. Our analysis reveals that, in response to heightened inflation expectations, as reflected by an increase in IP^{Core}, firms with more positive β^{Core} tend to have relatively better sales growth, cash flow, and higher IBES long-term growth forecast of EPS. For example, a 10% increase in IP^{Core} at the end of quarter Q predicts 6.6% standard deviation decrease in cash flow in quarter $Q+1$ for the firms with the most negative β^{Core} compared to those with the most positive β^{Core}. This evidence underscores the significant impact of inflation expectations on firm cash flows. Specifically, shocks in inflation expectations affect the valuation of individual firms through their cash flows, which partially explains why an increase in the relative price of high core beta stocks signals upcoming inflation.

Interestingly, we find no evidence that the discount rate channel drives the forecastability. For core beta-sorted portfolios, the return dispersion of the the top and bottom quintiles

(IP^{Core}) is insignificant, suggesting that β^{Core} primarily captures information exposure rather than risk. Further analyzing the inflation risk premium conditional on the nominal-real covariance (NRC) following Boons et al. (2020), we find the effect of NRC is insignificantly negative for core beta-sorted portfolios, reinforcing the conclusion that the variation in IP^{Core} returns is not driven by the time-varying inflation risk premium.

Related Literature: Our paper is related to the literature that study the pricing impact of inflation risk at the cross-sectional stocks, including Chen, Roll, and Ross (1986) and, more recently, Boons et al. (2020). Foundational to estimating the risk premium is a stable measure of risk exposures, which is found illusive for inflation risk in the stock market. Given the weak contemporaneous correlation between stock and inflation documented by Fama and Schwert (1977), the common belief is that stock market is not a good place for inflation hedge.[4] Extrapolating from this idea, it is often believed that the equity market is not an active venue for price discovery with respect to inflation. The strong predictability documented in our paper challenges this belief. By focusing on the timing and content of price discovery, we contribute methodologically to this literature by offering two separate approaches to estimating the inflation beta. We show that the information-based beta is more suitable for core CPI, while the risk-based beta is more appropriate for headline CPI. This distinction enhances our understanding of how inflation expectations are priced into equities and provides a more nuanced view of the relationship between inflation and stock market returns.

The differential pricing impact of core versus headline inflation has been examined recently in Ajello, Benzoni, and Chyruk (2020) by focusing on the Treasury yield curves, and in Fang, Liu, and Roussanov (2021) by showing that the aggregate stock market is more negatively correlated with the core component of inflation. We contribute to the disentanglement of core from headline CPI in two ways. First, we show that for the purpose of estimating cross-sectional exposures to core CPI, our proposed information-based beta is much more effective, owing to the fact that information release with respect to core CPI is concentrated on CPI announcement days. Second, we show that price discovery with respect to core CPI

[4]Among others, Bekaert and Wang (2010) provide international evidence on the negative and unstable relationship between equity and inflation. Using industry portfolios, Ang, Brière, and Signori (2012) and Boudoukh, Richardson, and Whitelaw (1994) further show that inflation betas vary substantially across industries and over time.

does take place actively in the cross-sectional stocks. Among all market-based predictors, our information-based core-focused inflation portfolio emerges as the best predictor for core CPI, particularly during the 1973 and 2021 episodes.

Our paper also belongs to the literature on inflation forecasting. Comparing the forecastability of traditional methods, Ang, Bekaert, and Wei (2007) and Faust and Wright (2013) find the survey forecasts to perform the best, outperforming the information from the Treasury yield curve, the macro variables, and the time-series models using past inflation growths. Relative to this literature, our paper documents the unique and important role played by the cross-sectional stocks in forecasting inflation, particularly the illusive core inflation. We find the inflation forecasts from the cross-sectional stocks outperform the bond-based predictor by a wide margin and consistently forecast the forecasting errors made by economists, particularly during the 2021 inflation surge.

Conceptually, the closest paper to ours is Downing, Longstaff, and Rierson (2012), who use industry portfolios from the equity market to track inflation growth over the subsequent month, and Titman and Warga (1989), who study the predictability of aggregate stock market returns on inflation. Our focus and implementation, however, differ significantly from theirs. Instead of tracking inflation growths, our focus is on predicting the unexpected component (i.e., innovations) of inflation growth. Instead of using industry or market portfolios, we construct our inflation portfolios from the ground up using individual stocks. Finally, new to the literature are our predictive results for the core-CPI innovations and the significantly stronger predictability of our core-focused inflation portfolio during the 1973 and 2021 episodes.

The rest of our paper is organized as follows. Section 2 describes our data. Section 3 documents the announcement-day and contemporaneous-month inflation exposures. Section 4 explores the predictability of market-based inflation forecasters. Finally, Section 5 discusses the cash flow channels and Section 6 concludes.

2 Data

We obtain monthly data on Consumer Price Index (CPI), including Headline, Core, and Energy CPI from the U.S. Bureau of Labor Statistics (BLS).[5] The CPI announcement dates are also collected from 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: $\pi_t = log(P_t/P_{t-1})$, 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, 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 inflation growth for month $t+1$ ($\widehat{\pi_{t+1}}$). CPI innovation for month $t+1$ is calculated as the actual inflation growth minus the forecasted growth: CPI-Innov$_{t+1} = \pi_{t+1} - \widehat{\pi_{t+1}}$. We require at least ten years of observations. Since data on core CPI starts after 1957, the sample on CPI innovations starts from 1967.

Appendix Table C1 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 15.6 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 forecast by Bloomberg economists, to captures surprises in CPI announcements. The headline foresting 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.

[5]The BLS CPI data series are as follow: Headline (CPIAUCSL), Core (CPILFESL), and Energy (CPIENGSL).

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 (see 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 two-year and ten-year U.S. Treasury yields from the Federal Reserve Bank of St. Louis. As Treasury Inflation-Protected Securities (TIPS) provides 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 is included as a control variable. To capture corporate bond and commodity market performance, we use the Bloomberg U.S. Corporate Bond Index return and the Goldman Sachs Commodity Index return (GSCI), respectively.[6]

3 Inflation Beta: 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 announcement days (e.g., Chen et al. (1986), Boons et al. (2020), Fang et al. (2021)). In this section, we analyze assets' inflation exposures to various components of inflation on the CPI announcement days, contrasting them with their contemporaneous-month inflation exposures.

[6]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.

3.1 Assets' Inflation Exposure

We begin by estimating the inflation exposures of various assets, including equity (VWRETD), treasury (2-year and 10-year U.S. Treasury yields, TIPS-UST return), corporate bonds, and commodities (GSCI) market returns. To construct the announcement-day inflation beta, we regress assets' excess returns on CPI innovations released on the announcement days. Given that different CPI components (e.g., core vs. non-core) may affect asset prices at different times and with varying intensities, we estimate assets' sensitivities to core-, headline-, and energy-CPI innovations separately using the following regression specification:

$$R_{K,A_t} = \alpha + \beta_K^{\text{Ann}} \text{CPI-Innov}_{A_t} + + \varepsilon_{K,A_t}, \tag{2}$$

where A_t denotes the CPI announcement day, and R_{K,A_t} denotes the return of asset K on the announcement day A_t. CPI-Innov_{A_t} refers to the CPI innovation released on the announcement day A_t. β_K^{Ann} then captures asset K's announcement-day inflation beta.

The full-month inflation beta is constructed by measuring the sensitivity of asset 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):

$$R_{K,t} = \alpha + \beta_K^{\text{Full}} \text{CPI-Innov}_t + \varepsilon_{K,t}, \tag{3}$$

where t denotes the calendar month, and $R_{K,t}$ denotes asset K's return (or change in yields) in month t.

Table 1 presents the β_K^{Ann} and β_K^{Full} estimates, separately constructed using core-, headline-, and energy-CPI innovations. To ensure comparability across asset classes, all variables, both dependent and independent, are standardized with means of zero and standard deviations of one during beta estimation. Focusing on announcement days, core-inflation innovations notably and adversely impact equity and bond prices, while positively affecting commodities, contrasting with the effects of headline and energy components. For instance, a one standard deviation increase in core-CPI innovation on the announcement day yields a 12.2% (t-stat=2.40) standard deviation increase in 10-year Treasury yield, while the same one standard deviation increase in energy-CPI innovation can only result in an insignificant

4.1% (t-stat=0.90) increase in yield. These estimates underscore the importance of core innovations in driving announcement-day asset returns.

In contrast, the full-month inflation beta follows a different pattern. We observe that asset returns in the contemporaneous month of CPI are more sensitive to the headline-CPI innovations, primarily driven by the energy component, but less so to core-CPI innovations. For instance, a one standard deviation increase in headline innovation results in a 19.5% (t-stat=4.08) standard deviation increase in 10-year yield during the CPI month, compared to only 10.4% (t-stat=1.72) for the same increase in core-CPI innovation. This aligns with the notion that non-core inflation components (such as energy and food) can be readily observed and hedged using commodity instruments when investors experience inflation throughout the month. Conversely, core components (like goods and services) are harder to observe and present larger surprises on CPI announcement days.

3.2 Cross-Sectional Stocks' Inflation Exposure

Next, we delve into the stock market to explore if the observed contrast between full-month and announcement-day betas, seen in aggregate asset classes, persists for individual stocks. Specifically, we aim to determine if cross-sectional stocks demonstrate diverse sensitivities to core inflation on announcement days and if this exposure remains consistent over time.

We measure individual stocks' inflation exposure following the methodology in Boons et al. (2020). Specifically, each month after the CPI announcement (when month-t CPI innovation becomes public), we construct the announcement-day and full-month inflation exposures of firm i using a WLS regression with exponential weights over an expanding window that includes all historical observations. We require a stock to have at least 24 out of the last 60 months of returns available. Firm i's announcement-day inflation beta ($\beta^{\text{Ann}}_{i,A_t}$) is given by:

$$
\begin{aligned}
(\widehat{\alpha_{i,A_t}}, \widehat{\beta^{\text{Ann}}_{i,A_t}}) = \arg \min_{\alpha_{i,A_t}, \beta^{\text{Ann}}_{i,A_t}} \sum_{\tau_A=1}^{t} K(\tau_A)(R_{i,\tau_A} - \alpha_{i,A_t} - \beta^{\text{Ann}}_{i,A_t}\text{CPI-Innov}_{\tau_A})^2, \\
\text{with } K(\tau_A) = \frac{\exp(-|t-\tau_A|/h)}{\sum_{\tau_A=1}^{t-1}\exp(-|t-\tau_A|/h)},
\end{aligned}
\tag{4}
$$

where R_{i,A_t} denotes firm i's return (minus the risk free rate) on the announcement day A_t. Using $h = \log(2)/60$ means the half-life of the weights $K(\tau_A)$ converges to 60 months for large t. The choice of a 60-month half life is consistent with the standard five-year rolling window used in empirical asset pricing tests.[7]

Similarly, the full-month inflation beta ($\beta_{i,t}^{\text{Full}}$) is estimated by:

$$(\widehat{\alpha_{i,t}}, \widehat{\beta_{i,t}^{\text{Full}}}) = \arg \min_{\alpha_{i,t}, \beta_{i,t}^{\text{Full}}} \sum_{\tau=1}^{t} K(\tau)(R_{i,\tau} - \alpha_{i,t} - \beta_{i,t}^{\text{Full}} \text{CPI-Innov}_\tau)^2, \\ \text{with } K(\tau) = \frac{\exp(-|t-\tau|/h)}{\sum_{\tau=1}^{t-1} \exp(-|t-\tau|/h)}, \tag{5}$$

where $R_{i,t}$ denotes firm i's return (minus the risk free rate) in month t. Following Elton et al. (1978), Cosemans et al. (2016), and Boons et al. (2020), we further transform the estimated $\beta_{i,A_t}^{\text{Ann}}$ and $\beta_{i,t}^{\text{Ann}}$ using a Vasicek (1973) adjustment:

$$\widehat{\beta_{i,t}^{v}} = \widehat{\beta_{i,t}} + \frac{\text{var}_{TS}(\widehat{\beta_{i,t}})}{\text{var}_{TS}(\widehat{\beta_{i,t}}) + \text{var}_{CS}(\widehat{\beta_{i,t}})} \times (\text{mean}_{CS}(\widehat{\beta_{i,t}}) - \widehat{\beta_{i,t}}), \tag{6}$$

where each $\widehat{\beta_{i,t}^{v}}$ represents a weighted average of the stock's beta derived from time-series data ($\widehat{\beta_{i,t}}$) and the cross-sectional beta average ($\text{mean}_{CS}(\widehat{\beta_{i,t}})$).

Appendix B provides a detailed illustration of the timeline in the beta estimation. On announcement day A_t (released in month M_{t+1} about the inflation of month M_t), for β^{Ann}, we use the daily stock returns and inflation innovations from announcement A_1 to announcement A_t for estimation. For β^{Full}, we use the monthly stock returns and inflation innovations from month M_1 to month M_t for estimation. Since data on CPI innovations starts from 1967, with five-year estimation periods, the individual stocks' CPI beta information begins from 1972.

For each CPI announcement, 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

[7]Appendix Table C3 reports the main results using a five-year rolling window to estimate inflation beta.

inflation beta quintiles.[8] 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, when the next-announcement CPI innovation is ready to update the estimates of individual stocks' CPI betas.

Table 2 reports the post-ranking announcement-day and full-month inflation betas for cross-sectional stocks, with the two size groups collapsed together. 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 the announcement days than headline and energy components. A one standard deviation increase in core-CPI innovation negatively affects the return of bottom quintile core beta-sorted stocks by -11.8% (t-stat=3.17) standard deviation on the CPI announcement days. In contrast, the same increase in headline- and energy-CPI innovations results in only 1.8% (t-stat=0.26) and 5% (t-stat=0.68) standard deviation impacts, respectively. 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.

As our focus is on the cross-sectional dispersion in individual stocks' inflation exposure, Panel B of Table 2 further reports the beta estimates while controlling for the aggregate stock market return. By removing the negative inflation exposure at the market level, the inflation estimates become generally less negative. However, significant dispersion in cross-sectional stocks' post-ranking core-inflation exposures on announcement days remains. 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 core innovation leads to a 10.2% (t-stat=2.38) standard deviation increase in the core beta-sorted inflation portfolio, while the dispersions in inflation exposures are absent for headline and energy beta-sorted portfolios on CPI announcement days.[9]

[8]In our main analysis of inflation forecasting, we use the equal-weighted large stock portfolio, as the small stocks could be illiquid.

[9]One caveat is that since both the dependent and independent variables are standardized in the beta estimation, the beta estimate in the row "Quintile 5-1" does not equal the difference between Quintile 5 and Quintile 1.

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 -1.3% to the highest value of 5.6% for the quintile portfolios sorted based on stocks' pre-ranking full-month headline betas. The core-, headline, and energy-inflation exposures for the top-minus-bottom portfolios sorted based on the corresponding pre-ranking betas are 2.7% (t-stat=0.45), 16.3% (t-stat=2.89), and 15.5% (t-stat=2.47), respectively. Overall, the cross-sectional stocks' inflation exposure exhibits a consistent pattern as observed for the asset classes: Stocks show differential and persistent inflation exposure, with announcement-day returns most sensitive to core-inflation news and contemporaneous month returns most sensitive to headline-inflation news. 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.[10]

As a graphical illustration, Appendix Figure C2 plots the inflation betas for the aggregate stock market (upper graph), and the β^{Core} and β^{Head} sorted inflation portfolios (lower graph). These betas are estimated using a rolling five-year window. Consistent with existing literature, the sensitivity of market returns to headline inflation shifts from negative to positive in the early 2000s (Bekaert and Wang (2010), Campbell et al. (2017), Boons et al. (2020)), while the sensitivity to core-CPI innovations remains, on average, more negative (Fang et al. (2021)). Turning to the inflation betas of cross-sectional stocks formed inflation portfolios, on average, the five-year rolling inflation betas lie above zero, consistent with the significant post-ranking estimates in Table 2. Moreover, the core beta and headline beta have distinct patterns. A one standard deviation increase in core-CPI innovation leads to over a 20% standard deviation increase in the β^{Core} sorted inflation portfolio during significant inflation episodes like the 1980s, 1990s, early 2008, and 2021. In contrast, the impact of headline-inflation innovations on the β^{Head} sorted inflation portfolio during those periods is less pronounced. Overall, the evidence suggests that inflation betas constructed using CPI announcement days contain unique information about individual securities' core-inflation

[10]Consistent with the ordering of post-ranking inflation beta, Appendix Figure C1 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 being remaining in the same quintile is 84% and 83% after 6 months.

exposure and are different from the full-month identified headline-inflation exposure.

3.3 Determinants of Inflation Beta

Section 3.2 reveals that inflation betas derived from CPI announcement days offer unique insights into individual securities' core-inflation exposure, contrasting with those obtained from full-month headline betas. Next, we explore the determinants of a firm's inflation beta to better understand why different firms react differently to inflation news.

To understand the cross-sectional variations in firms' inflation exposures, we regress quintile ranks of firms' core (headline) beta at the end of quarter Q against quarter $Q-1$ firm characteristics. These characteristics include firm size (Log(Size)), quarterly asset growth, last 12-month stock return (Momentum), market-to-book ratio (ME/BE), dividend payout ratio, cash flow, and the cash flow duration from Weber (2018).[11] Columns (1) to (4) of Table 3 report the estimates with only time fixed effects. The findings indicate that firms with more positive core betas tend to have lower growth potential (ME/BE), higher dividend payouts, and higher cash flows, which points to a concentration of immediate cash flows realized in the near term but lower long-term cash flows, leading to a shorter cash flow duration. Conversely, firms with more negative core betas exhibit cash flow distributions resembling those of longer-maturity bonds, with higher growth potential and longer cash flow duration. Similar to how longer-duration bonds experience larger price drops when interest rates rise, firms with longer cash flow duration suffer more from increases in core inflation.

Despite the significant relationship between cash flow duration and firm core beta, the explanatory power is weak, with an R^2 of 0.3%. This suggests that factors beyond static cash flow distributions drive cross-sectional variations in core beta. Furthermore, the relationship between cash flow duration and core beta remains robust when industry (Fama-French 48 industries) fixed effects and firm fixed effects are included in columns (5) and (6), respectively. Notably, industry variations explain only 3.2% of the cross-sectional variations, whereas including firm fixed effects increases the R^2 to 49%. This implies that inflation beta is more of a firm-specific property rather than an industry-specific one.

Finally, columns (7) to (12) report the determinants regression for headline beta, where a

[11] Detailed descriptions of variables are provided in Appendix .

similar but weaker pattern emerges. Firms with more negative headline betas also have longer cash flow duration, but weaker relation 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 has stronger temporal fluctuations and a less persistent impact on firm cash flows compared to the core component. In sum, the determinants of inflation betas, particularly the roles of cash flow duration and growth potential, reveals that inflation sensitivity is more of a firm-specific attribute rather than industry-specific.

4 Empirical Results: Inflation Forecasting

Given the persistent variations in inflation exposures across firms, if rational expectations hold and stock returns react to changes in expected inflation, the relative pricing between stocks with high and low inflation betas can effectively aggregate investors' expectations of future inflation. In this section, we investigate whether the return difference between high and low inflation beta stocks can timely reflect inflation expectations and help predict future inflation. By eliminating the noisy aggregate component (Fama and Schwert (1977)), the cross section of stock returns may offer a more stable and accurate forecast of inflation.

4.1 Predicting Inflation Innovations

To examine cross-sectional stocks' inflation forecasting ability, we use the monthly rebalanced top-minus-bottom quintile inflation portfolios constructed in Section 3.2. 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 by the full-month headline beta β^{Head}. As shown in Section 3.2, stocks in the bottom-ranked portfolio, whose inflation betas are ranked the lowest, suffer most severely when inflation increases. Therefore, in expectations of heightened inflation, investors would underprice stocks in the bottom portfolio more severely than those in the top portfolio, resulting in a positive return of the inflation portfolios. In other words, a higher-than-usual inflation portfolio return could be an early alarm sent from the equity market about upcoming inflation surge.

4.1.1 Event Study around Extreme CPI Months

To explore whether inflation portfolios provide insight into inflation expectations, we begin by tracking their performance around extreme CPI events. 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[12]. We categorize all CPI events into quintiles based on headline- and core-CPI innovations. 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 1, 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}). Conversely, the headline-focused inflation portfolio better identifies unexpected decreases in headline inflation, as shown by its stronger downward drift before the bottom-quintile CPI innovations. The lower graph, conditional on core-CPI innovations, shows similar evidence: an increase in IP^{Core} leads to higher-than-expected core-CPI innovations, and a decrease in IP^{Head} leads to lower-than-expected core-CPI innovations.

To pinpoint when the equity market starts incorporating next-month inflation expectations, Table 4 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-

[12]We contrast the forecastability of big stocks with small stocks in Section 4.3

CPI innovations, initiating 30 days before the CPI month. This trend persists across the stock market, Treasury market, and commodity market. For instance, within the [-30,-20] window, a one standard deviation increase in the 10-day return of IP^{Core} predicts a 1.95 bps (t-stat=2.55) and 4.13 bps (t-stat=2.84) 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 shifts sign for the [-40,-30] window preceding it. This pattern holds true for inflation portfolios, TIPS-UST, and GSCI, indicating active inflation news price discovery across assets 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.

4.1.2 Unique Predictability of Core-Focused Inflation Portfolio

Building on the event window analysis in Section 4.1.1, 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 IP^{Core}, comparing it with the headline-inflation portfolio and market-based signals from bond and commodity markets. Specifically, as shown in Appendix B, 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:

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

where Core-Innov_{t+1} denotes month-$t+1$ core-CPI innovations, and X_t includes the 30-day return of TIP-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 5 shows the predictive power of IP^{Core} on inflation changes. A one standard deviation increase in the 30-day core beta inflation portfolio (IP^{Core}) observed at the end of month t predicts a 2.7 basis points (bps) increase (t-stat=3.4) in core-CPI innovations and a 7.5 bps increase (t-stat=6.83) in headline-CPI innovations for month $t+1$. Given the sample

standard deviations of core- and headline-CPI innovations are 16 bps and 26 bps, respectively, the economic significance of IP^{Core} is non-trivial. This evidence confirms our finding in Section 4.1.1 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^{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.[13] Including GSCI with IP^{Core} boosts the predictability on headline inflation from an R^2 of 8.1% to 23.6%, while adding TIPS-UST enhances the R^2 to 18.9%. In both cases, the coefficient estimate on IP^{Core} remains robust both economically and statistically.

While TIPS-UST and GSCI can predict headline-CPI innovations, their ability to forecast core-CPI innovations is limited. According to the estimate in column (4), a one standard deviation increase in IP^{Core} predicts a 2.5 bps increase in core-CPI innovations (t-stat=2.56), whereas TIPS-UST and GSCI predict increases of 0.64 bps (t-stat=0.64) and 1.15 bps (t-stat=1.43), 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 still adds significant value in forecasting core-CPI innovations.

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 7.9 bps (t-stat=5.75) increase in headline-CPI innovations, close to the 7.5 bps (t-stat=6.83) 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 0.4 bps (t-stat=0.65), 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

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

policy, the unique predictability from cross-sectional stocks is crucial.[14]

Figure 2 provides a graphical illustration of the rolling 12-month average return of the core-focused inflation portfolio observed at the end of month t, plotted against the rolling 12-month (YoY) core-CPI and headline-CPI growths ending in month $t+1$. Core- and headline-CPI growths are shown by blue and yellow bars on the left axis, while the red solid line represents IP^{Core}, normalized over the entire sample and plotted on the right axis. The figure shows a strong comovement between our core-focused inflation portfolio and CPI growth.

Importantly, IP^{Core} effectively captures significant inflationary episodes, such as those in 1973–82, 1988-1991, 2008, and 2021-2022. For instance, as inflation peaked in Feburary 2022, IP^{Core} returns began rising significantly in August 2021, providing an early inflation warning. During the same period, IP^{Head} was less effective in capturing the inflation surge. Similarly, IP^{Core} successfully predicted the inflation surge in 1973-1974 and the decline during Paul Volcker's disinflation efforts in the early 1980s. The lower graph replicates this analysis for bond- and commodity-based inflation indicators, showing consistent patterns. This indicates that the variations in IP^{Core} are not due to pure noise. Notably, compared to TIPS-UST and GSCI, our core-focused portfolio was less affected by the 2007-2009 recession and provided a stronger signal of the 2021-2022 inflation surge.

4.2 Predicting Economists' Forecasting Errors

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 scenario presents an intriguing question: Do market participants update their inflation expectations based on market-based information, particularly that embedded in cross-sectional stock data? Alternatively, if market participants do not fully incorporate the information from IP^{Core}, to what extent can the inflation portfolio predict the announcement-day forecasting errors made by market participants?

[14]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 4.4.

To capture market participants' expectations for month-$t+1$ inflation growth, we utilize Bloomberg Economists' survey forecasts for headline- and core-CPI month-over-month growth.[15] 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 6 shows that although economists are generally responsive to market-based inflation signals observed at the end of month-t, they do not sufficiently update their beliefs regarding IP^{Core}. Consequently, IP^{Core} can significantly predict announcement-day forecasting errors with considerable magnitude. Specifically, we employ 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), we find that although economists respond to the core-focused inflation portfolio, their reactions are predominantly to its overlapping commodity component. A one standard deviation increase in the GSCI return predicts an upward adjustment of 1.3 (t-stat=2.75) and 10.7 bps (t-stat=4.72) in the economists' forecast of core and headline inflation, respectively. However, 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 panels 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 bps (t-stat=2.70) and 3.6 bps (t-stat=4.06) 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

[15]Bloomberg Individual Economist Estimates are derived from a diverse group of forecasters, including traders, portfolio managers, think tanks, and academics.

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.

4.3 Conditional on Firm Information Environment

Our hypothesis on inflation forecasting assumes that stock prices are efficient and incorporate rational expectations of inflation, thereby predicting innovations in realized inflation. However, not all firms are the same. If investors have limited capacity to analyze the impact of inflation on firm fundamentals, inflation expectations may not be promptly reflected in stock prices. In such cases, the predictability of inflation should be stronger among firms with a more opaque information environment. We use analyst coverage as a proxy for firms' information environment, as analysts specialize in gathering and processing information about firm fundamentals and are likely to understand the impact of inflation.

Additionally, we examine the informativeness of stock prices across our sample with different degrees of arbitrage costs. Pricing efficiency relies on sophisticated investors, such as arbitrageurs, who incorporate information in a timely manner and bring stock prices to their full-information 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. Since analyst coverage and institutional ownership are strongly correlated with firm size, we orthogonalize institutional ownership and analyst coverage with respect to firm size and use the residual values for sorting (Hong et al. (2000)).

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)[16]. We then sort stocks within each category by their β^{Core} into quintiles. Table 7 reports the predictability of the top-minus-bottom quintile inflation portfolio for each group on month-$t+1$ inflation innovations. While IP^{Core} (X$\leq$Median), representing stocks with below-average information environments, are sometimes significant, their pre-

[16]The two size groups are defined by the median cutoff of NYSE market capitalization. Stocks with size $>$ Median are the large stocks we focus on in the paper.

dictive power is fully absorbed by IP^{Core} (X>Median) when considered together in columns (3), (6), and (9). This evidence supports active price discovery of inflation news among cross-sectional stocks, and the effect is most pronounced among larger firms with higher institutional ownership and analyst coverage.

4.4 Time-Varying Forecastability

Inflation's role in the economy and its impact on asset prices vary over time. When inflation is low, it minimally affects firms' fundamentals, resulting in weak information from inflation portfolios. Conversely, when inflation emerges as a significant risk factor in the capital market, the price discovery of inflation-related news among assets intensifies. This section discusses the role of core-focused inflation portfolios during critical inflation episodes and conducts a comprehensive analysis on their time-varying forecastability, considering inflation uncertainty and noise from the Treasury market.

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 underestimated the severity of inflation, missing the rapid rise of core CPI by significant margins. 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.

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, together with the month-$t+1$ 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

3.59 times of its sample standard deviation. Meanwhile, IP^{Core} comoves 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 25 bps (t-stat=2.35) increase in core-CPI innovations for month $t+1$, with an R-squared of 18.5%. 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 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. Table 8 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.[17] Importantly, the coefficient estimates of IP^{Core} on core-CPI innovation and core forecasting error are more than three times larger than the full-sample estimates, highlighting the importance of 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 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.

[17]The coefficient estimates in Figure 4 and Table 8 differ because the independent variables are in units of return in Figure 4 and are standardized in Table 8.

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 accuracy in forecasting inflation during the 1973 episode. For our analysis, we define the 1973 episode by including the 24 months leading up to and including the inflation peak in February 1975 (i.e., from March 1973 to February 1975). 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 70 bps (t-stat=3.50) in month-$t+1$ core-CPI innovations, with a much improved R-squared of 33%. This enhanced predictability on core-CPI innovations is uniquely captured by our core-focused inflation portfolio, mirroring the results observed in the 2021 episode. Columns (5) and (6) of Table 8 report the predictability of bond and commodity-based forecasters with IP^{Core} for next-month core-CPI innovation. 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. Among all these forecasters, only IP^{Core} significantly and positively predicts upcoming core-CPI innovations, underscoring its robustness as a predictive tool during the Great Inflation period.

The Episode of 2008: The episode of 2008 serves as another instance where our core-focused inflation portfolio effectively provided an early warning of inflation. However, unlike the episodes of 1973 and 2021, the inflation that peaked in mid-2008 quickly subsided due to the onset of the Great Recession. In July 2008, the consumer price index rose by 0.7%, almost double the 0.4% increase anticipated by Bloomberg economists, pushing the annual inflation rate from 4.8% to 5.4%, the sharpest year-on-year increase since January 1991. This inflation surge was primarily driven by skyrocketing oil prices. The price of a barrel of WTI crude oil increased from \$67 in July 2007 to \$134 in July 2008, a two-sigma increase based on its historical standard deviation.

Accompanying the rapid oil price shock that peaked in July 2008, IP^{Core} provided unusually high signals prior to July 2008. As shown in the upper graph of Figure 2, at the end of June 2008, IP^{Core} surged to its 3.52-sigma level. However, this signal was short-lived. By August 2008, IP^{Core} had plummeted to -1.15-sigma and continued to decline following the Lehman Brothers collapse in September 2008. Similar patterns were observed in commodity- and bond-based forecasters. The GSCI, which closely tracks oil price movements, jumped to 1.32-sigma in June 2008 before crashing to -1.81-sigma in August 2008. TIPS-UST ex-

hibited a comparable trend, albeit with a smaller magnitude. The sharp reversal in IP^{Core}, as well as in other market-based forecasters, reflects a drastic reset in inflation expectations informed by the impending financial crisis. This evidence suggests that early warnings of surging inflation may fail to materialize when followed immediately by a severe recession.

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

We use two proxies of inflation disagreement to capture the time-varying importance of inflation news: (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;[18] Panel B of Table 8 reports the predictability of IP^{Core} on core-CPI innovations and forecasting errors for subsamples defined using the median cutoffs of the two proxies.

We find that the forecasting power IP^{Core} is much stronger when the last-month |CPI Innovation| is above the median cutoff and when the CPI disagreement is above average. For example, a one standard deviation increase in IP^{Core} predicts 4.2 bps (t-stat=3.67) and 2.8 bps (t-stat=2.51) 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 an insignificant 0.7 bps and 1.1 bps, respectively.[19] Overall, the evidence suggests that IP^{Core} can provide valuable information about future inflation expectations when the market most needs it.

Next, we further explore how monetary policies impact the time-varying informativeness of inflation forecasters. Monetary policies influence Treasury prices through interest rate

[18]Different from the monthly Bloomberg Economists' Survey Forecasts that starts in 1997, SPF offers quarterly forecasts but with the benefit that it can be traced back to the third quarter of 1981.

[19]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.

adjustments or quantitative easing, thereby affecting the informativeness of asset returns. The Taylor rule (Taylor (1993)) provides a useful framework for describing activist monetary policy. 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 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 Fed 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 formally 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 Fed Fund rate recommended by the Taylor rule and the actual Fed Fund Rate. The recommended Fed Fund 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).[20] Panel B of Table 8 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 Fund Rate is above the 67% percentile cutoff. A one standard deviation increase in IP^{Core} predicts a 3.3 bps (t-stat=2.54) increase in core-CPI innovations with an R-squared of 5%, when Fed is behind the curve. While for the rest of the periods, the predictability of IP^{Core} is 2.2 bps (t-stat=2.78) with an R-squared of 1.5%.

Since the great financial crisis in 2008, with an effective zero-interest rate policy, the Fed started pursuing the unconventional monetary policy of purchasing large quantities of long-term securities, including Treasuries, Agency bonds, Mortgage Backed Securities, and more recently corporate bonds (quantitative easing, or "QE"). On the one hand, Fed injects

[20]We set the target core-inflation rate to be 2%, as suggested by former Fed vice chair Richard H. Clarida (Clarida (2021)).

liquidity into the market via the purchasing of long-term assets. On the other hand, the pricing of nominal bonds and real bonds could be directly affected due to such government interventions (e.g., Krishnamurthy and Vissing-Jorgensen (2011), Todorov (2020), Bond and Goldstein (2015)). Therefore, it is worthwhile to examine the forecastability of inflation indicators conditional on QE implementation.

Dividing the sample into "QE" and "Non-QE" periods in Panel B of Table 8, we find that IP^{Core} performs significantly better during "QE" periods, when "noise" in the Treasury market is greater.[21] In particular, a one standard deviation increase in IP^{Core} predicts a next-month increase of 6 bps (t-stat=2.52) in core-CPI innovations with an R^2 of 17%. The corresponding estimate for "Non-QE" periods is only 1.2 bps (t-stat=1.70). In untabulated results, we find that the predictability of TIPS-UST in forecasting core-CPI innovations is rather weak. Thus, consistent with findings related to the Fed being behind the curve, the QE evidence suggests that while monetary policy interventions could impact the informativeness of the bond market, the price discovery of equities regarding inflation expectations is stronger during these periods.

4.5 Out-of-Sample Forecastability

Section 4.1 presents in-sample evidence that the core-focused inflation portfolio has strong predictive power for future inflation. To better reflect real-time information available to forecasters, we follow the methodologies of Ang, Bekaert, and Wei (2007) and Faust and Wright (2013), examining the out-of-sample forecasting power of IP^{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 the concern of overfitting.

At the end of each month t, we estimate the forecasting model $CPIG_{k+1} = a + \sum b * X_k + \epsilon_{k+1}$ using only publicly available information up to month t (i.e., $K < t-1$). Here, X_k represents the forecasting signal observed at the end of month k, and CPIG_{k+1} represents the inflation growth for month $k+1$. 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

[21] QE includes the periods from November 2008 to March 2010, November 2010 to June 2011, September 2012 to October 2014, and March 2020 to March 2022.

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 forecast 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 IP^{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 9 shows the relative RMSE for various forecasting models. IP^{Core} improves the forecasting accuracy of month-$t+1$ core and headline CPI by 4.3% (p-value=0.07) and 6.3% (p-value=0.00) respectively, relative to the ARMA(1,1) model. Among all forecasters from the treasury, equity, and commodity markets, IP^{Core} has the highest incremental forecasting power for core CPI and ranks third for headline CPI, after GSCI and IP^{Head}. Consistent with the in-sample evidence, GSCI has the highest forecasting power for headline CPI, with an RMSE improvement of 13.6%. Interestingly, TIPS-UST, designed to track inflation expectations, only improves forecasting accuracy by 4%.

In addition to these market-based indicators, we include economists' inflation forecasts from the Survey of Professional Forecasters (SPF) database. Ang, Bekaert, and Wei (2007) and Faust and Wright (2013) have shown that subjective survey forecasts outperform those from Phillips curve or term structure models. 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.[22] Table 9 indicates that economists' preliminary forecasts at month t can only improve the time-series model by only 1.4%. Motivated by the Phillips curve economic model (e.g., Stock and Watson (1999)), we also include real GDP growth as a proxy for economic activity in the forecasting model. Consistent with Ang, Bekaert, and Wei (2007), real activity measures do not add positive value. Finally, we find limited out-of-sample evidence that aggregate stock market and nominal bond yields can forecast upcoming inflation growth.

Finally, Panel B of Table 9 reports the out-of-sample performance of IP^{Core} for subsamples

[22]We do not use Bloomberg Economist Forecasts here because they are updated until the last minute before the announcement.

when inflation is particularly significant to the economy. Consistent with Section 4.4, the forecasting power of IP^{Core} is stronger during periods when inflation plays a critical role. The out-of-sample predictability for core and headline CPI improves by 8.2% and 11.3%, 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 range from 4.7% to 6.4% for core CPI and from 6.6% to 13.2% for headline CPI. Overall, IP^{Core} provides unique information about inflation both in-sample and out-of-sample, particularly during heightened inflation periods.

4.6 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 their inflation component. This potential predictability builds on the assumption 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 on inflation-linked assets could help investors hedge against or speculate on inflation risk.

Table 10 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 start of month $t+1$ 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 an 18 bps (t-stat=2.72) 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 12.3 bps for the one-year yield to the lowest of 5 bps for the 30-year yield. These yield changes align roughly with the monthly predictability of around 2.5 bps in forecasting CPI innovations. Overall, it suggests that IP^{Core} can capture information not yet incorporated by inflation-linked assets. A strategy formed based on the IP^{Core} signal observed at the end of month t can predict inflation-linked asset returns going forward.

4.7 Robustness Tests and Other Discussions

Predictability on CPI Growth: In our primary analysis, we focus on predicting one-month ahead CPI innovation. Our findings remain robust when using IP^{Core} to predict CPI growth and when extending to longer horizons. Appendix Table C2 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 5, a one standard deviation increase in IP^{Core} predicts a 2.2 bps increase (t-stat=3.1) in next-month core-CPI growth and a 6.2 bps increase (t-stat=6.0) in headline-CPI growth. For quarterly (three-month) CPI growth, a one standard deviation increase in IP^{Core} predicts a 7.8 bps increase (t-stat=4.22) in core-CPI growth and a 15.6 bps increase (t-stat=4.83) in headline-CPI growth over the next three months.

Beta Constructed Using Rolling Five-Year Window: In our baseline specification, following the methodology in Boons et al. (2020), we estimate individual stocks' inflation beta using all historical observations with WLS and Vasicek adjustment. Appendix Table C3 further presents results based on inflation betas constructed using a simple five-year rolling window approach (Fama and French (1993)). Panel A reports post-ranking announcement-day and full-month inflation betas for cross-sectional stocks. Consistent with Table 2, there is a significant beta difference between the top and bottom quintiles for core CPI during 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 10.7% (t-stat=2.49), and the full-month headline-CPI exposure of the inflation portfolio is 17.3% (t-stat=2.96). Panel B reports the inflation predictability of IP^{Core} constructed based on the rolling five-year window estimated β^{Core}. IP^{Core} observed at the end of month t

significantly predicts month t+1 CPI innovations and economists' forecasting errors for both core CPI and headline CPI, with similar magnitudes as in our baseline specification.

Beta Constructed Using Ann-Day Surprise: When estimating the announcement-day core-focused inflation betas, we use the sensitivity of asset returns to core-CPI innovations. However, it is possible that a large portion of news in the CPI innovations has already been incorporated into asset prices well before the announcement. Given that asset prices should be most responsive to the surprise component in the CPI announcement, we use alternative measures to capture the announcement content and to measure the announcement-day inflation beta. The alternative surprise measures include economists' forecasting errors of core CPI, announcement-day 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}).

Panel A reports the post-ranking announcement-day inflation betas for the quintile portfolios sorted based on the corresponding pre-ranking announcement-day betas constructed using the specific surprise measures. The results show that the announcement-day inflation betas exhibit significant and persistent sensitivity to inflation surprises under all five models. Panel B further reports the predictability of inflation portfolios constructed based on the corresponding inflation betas in Panel A (IP^{Surp}, $\text{IP}^{\text{ISWAP2YR}}$, $\text{IP}^{\text{ISWAP5YR}}$, $\text{IP}^{\text{UST2YR}}$ and $\text{IP}^{\text{UST5YR}}$) on upcoming CPI innovations. All five inflation portfolios can significantly predict core-CPI innovations and headline-CPI innovations at month-$t+1$.

Industry vs. Stock: In our study, we uncover substantial cross-firm variations in inflation betas, demonstrating that stock-based inflation portfolios hold valuable insights for forecasting future inflation expectations. Yet, a critical question remains: are these variations primarily driven by differences between industries or within them?

To address this, we turn to Appendix Table C5, where we construct industry-specific CPI betas similarly to individual stock CPI betas. This is estimated by regressing returns of the Fama and French 48 Industry portfolios on standardized CPI innovations using the "CAPM Model". Panel A presents the average industry betas over time for the top 10 and bottom 10 industries most and least sensitive to announcement-day core-CPI innovations and full-month headline-CPI innovations. Consistent with the findings of Boudoukh, Richardson, and Whitelaw (1994) and Ang, Brière, and Signori (2012), we observe significant variations in

inflation exposures across different industries. Specifically, industries such as oil, mining, and metals emerge as effective inflation hedgers, exhibiting positive full-month headline betas. This aligns with the general understanding that oil and gas stocks benefit from commodity price increases. Conversely, cyclical industries like soda, restaurants, hotels, and banking are more adversely affected by unexpected inflation shocks, a finding that resonates with the results of Boudoukh, Richardson, and Whitelaw (1994) and Boons et al. (2020).

The literature has less frequently documented the distribution of announcement-day core-based inflation betas. Panel A's core beta rankings reveal that β^{Core} captures distinct information compared to β^{Head}. For instance, the agriculture industry appears in the top 10 for β^{Head} with a positive headline beta of 0.59 per month but falls into the bottom 10 for β^{Core} with a negative core beta of -0.01 per announcement day. This contradictory behavior makes intuitive sense: while rising goods and services prices increase operational costs for agricultural firms, price hikes in food products benefit them. Comparing industries most impacted by unexpected headline- and core-CPI changes, consumer goods and services sectors—such as communication, recreation, and entertainment—feature more prominently in the core-CPI list.

Given these significant cross-industry variations in inflation exposures, 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 C5 examines the forecastability of industry-constructed inflation portfolios. The 30-day cumulative returns for these portfolios, denoted as $\text{IP}_{\text{Ind}}^{\text{Core}}$ and $\text{IP}_{\text{Ind}}^{\text{Head}}$, involve taking long positions in top-quintile CPI beta industries and short positions in bottom-quintile CPI beta industries. $\text{IP}_{\text{Ind}}^{\text{Core}}$ exhibits weak predictability for core-CPI innovations, with an R-square of just 0.3%. When we use both $\text{IP}_{\text{Ind}}^{\text{Core}}$ and IP^{Core} to predict core-CPI innovations, the information content of industry portfolios is absorbed by stock-based portfolios. Similarly, while industry-based inflation portfolios can significantly predict headline-CPI innovations, their economic and statistical significance pales in comparison to stock-based inflation portfolios. In summary, our evidence suggests that the inflation exposure of stocks is not merely a byproduct of their industry affiliation, but rather reflects deeper, more nuanced factors.

5 Mechanism: The Cash Flow Channel

5.1 Inflation and Firm Future Cash Flows

Based on simple valuation models like the Gordon Growth Formula, inflation can impact firm valuation through two primary channels: cash flow and discount rate.[23] On one hand, cross-firm variations in inflation betas could be driven by changes in the growth rate of cash flows. If a firm has the capability to pass on higher costs to consumers through price increases, its cash flows might remain resilient despite inflationary pressures. However, if consumers' purchasing power diminishes significantly, leading to a reduction in demand, the firm may struggle to maintain its cash flow growth. Thus, the ultimate impact of inflation on a firm's cash flows is contingent upon a complex interplay of factors along the entire supplier-customer chain, resulting in different outcomes for different firms.

On the other hand, cross-firm variations in inflation exposures could also be driven by changes in the discount rate. Higher inflation typically prompts central banks to raise interest rates in an effort to control inflationary pressures. Additionally, higher inflation can heighten the default risk for firms, particularly those with significant debt burdens, as their cost of borrowing rises. Consequently, investors may demand higher returns for holding stocks, especially those with negative core betas, which are more sensitive to economic downturns.

To unravel the mechanism behind the relative price movements of stocks with varying inflation exposures, we first examine the impact of rising inflation on firms' fundamentals. An increase in IP^{Core} signals heightened inflation expectations, which should adversely affect firms with more negative β^{Core} compared to those with more positive β^{Core}. If the price effects are primarily driven by the cash flow channel, we anticipate that firms with higher β^{Core} will experience relatively more positive cash flows in response to increased inflation expectations. Conversely, if the discount rate channel is the dominant factor, we would expect firms with higher β^{Core} to face lower required rates of return in the context of elevated inflation expectations.

Table 11 reports the relation between firm quarter-Q β^{Core} and the firm fundamentals, captured by sales growth and cash flow of quarter $Q+1$. We also include change of IBES long-

[23] In the Gordon Growth Formula, $P = \frac{D_0(1+g)}{r-g}$, a change in inflation expectations could affect both the discount rate r and the dividend growth rate of g.

term growth forecast of EPS, and quarterly return at quarter $Q+1$. The variable of interest is the interaction between the quintile rank of β^{Core} 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} firms compared to the more negative ones. We control for other firm characteristics including size, asset growth, momentum, market-to-book, dividend payout, and the lagged values of the dependent variables in all specifications.

Across models with and without firm fixed effects, we find that inflation adversely affects sales growth, cash flow and IBES long-term growth forecast more for firms with negative inflation betas. 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 around a 6% of standard deviation decrease in sales growth when the quintile ranks of β^{Core} move from the top to the bottom quintile. After taking into account operational costs, we observe a larger economic impact of IP^{Core} on cash flows: A 10% increase in IP^{Core} at the end of quarter Q predicts 6.6% standard deviation decrease in cash flow in quarter $Q+1$[24]. In column (5) and (6), we see that IBES forecasters also increase their long-term growth forecast of EPS for firms with positive inflation betas during periods of heightened inflation. In the last two columns, the coefficients of the interaction term are insignificant, indicating that inflation does not impact firm future returns, which partially rules out the discount rate channel.

Figure 5 offers a more intuitive graphical illustration of our findings. At the beginning of each quarter Q, we sort all stocks into quintile groups based on their core beta (β^{Core}) and compute the equal-weighted average quarter-Q 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 Q. This graph reveals a comovement between IP^{Core} and the cash flow difference, 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 core betas (i.e., those

[24]In untabulated results, we examine the predictability of IP^{Core} on COGS and SG&A, finding some evidence that inflation leads to increased operating costs. The coefficients of the interaction term are insignificantly negative for COGS and significantly negative for SG&A.

less damaged by inflation) 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 their normal levels. Overall, these visualizations highlight the significant impact of inflation expectations on firm cash flows, particularly for firms with differing core betas.

5.2 Inflation Risk Premium

Next, we examine the discount rate channel – whether the variation in IP^{Core} returns is driven by a time-varying inflation risk premium. Table 12 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.[25]

As shown in Panel A, over the full sample, there is no monotonic pattern of average returns for the core beta-sorted portfolios. The return dispersion of the top and bottom portfolios (IP^{Core}) is 1.4% (t-stat=1.21). The subsample analysis yields similar results: both pre-2002 and post-2002 subsamples show a positive but insignificant performance difference between the top and bottom portfolios. In Panel B, we find a different pattern for headline beta-sorted portfolios. Consistent with Boons et al. (2020)'s findings, annualized average returns decrease from 10.1% for the bottom quintile to 7.7% for the top quintile, resulting in a significant negative performance difference of -2.4% (t=-1.69) for annualized return and -3.1% (t=-2.12) for CAPM alpha. The inflation risk premium is larger in the pre-2002 subsample and becomes insignificant in the post-2002 subsample. In sum, differing from the risk-based inflation beta of β^{Head}, firms with more negative β^{Core} do not have higher returns unconditionally, indicating that β^{Core} mostly captures the information exposure rather than risk.

To further explore whether the insignificant return dispersion is driven by time-varying risk 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 (compounded over horizons K of one, three, and 12 months) on NRC

[25]We split the sample following Boons et al. (2020), as they document that the time-varying relation between inflation and consumption growth changed sign from negative to positive around 2002.

using the following regression specification:

$$R_{t+1:t+K} = \alpha + \beta^{\text{NRC}}\text{NRC}_t + \varepsilon_{t+1:t+K}, \tag{8}$$

For each return horizon, Appendix Table C6 presents the estimated intercept and β^{NRC}. 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. Firstly looking at the headline beta-sorted portfolios in Panel B, we find similar results to Boons et al. (2020). The effect of NRC on the inflation risk premium is positive, strengthening at longer horizons, indicating that the inflation risk premium of IP^{Head} is strongly time-varying with the nominal-real covariance. However, as shown in Panel A, for core beta-sorted portfolios, the effect of NRC is insignificantly negative, indicating that firms with more negative β^{Core} do not have higher returns conditional on NRC.

6 Conclusions

Motivated by the 2021 inflation surge and the collective failure of the policy makers and economists in forecasting its severity, we explore the inflation expectations in cross-sectional stocks and examine their forecastability for inflation innovations. Key to our predictability is our focus on the relative pricing between stocks with high- and low-inflation exposures, which allows us to shift away from the overall equity-market trends and zero in on the inflation expectations. To differentiate the cross-sectional inflation exposures, we make the important observation that cross-sectional stock returns exhibit persistent sensitivity to headline-inflation shocks during the calendar month of CPI, and to core-inflation news on CPI announcement days. Examining the relative pricing between stocks with high and low inflation exposures, captured either by the headline- or core-focused inflation betas, we find that active price discovery on inflation does take place in cross-sectional stocks.

Above and beyond the existing forecasting methods, our stock-based inflation portfolios contain fresh and non-redundant information, and the core-focused inflation portfolio emerges as a unique and unparalleled predictor for core-CPI innovations. Its predictability is especially important during the run-away inflation episodes of 2021 and 1973, when

the predictive R-squared for month-over-month core-CPI innovations increases to 18.5% and 32.8%, respectively. Given the weak contemporaneous correlation between stock and inflation documented by Fama and Schwert (1977), the common belief is that stock market is not an active place for price discovery with respect to inflation. The strong predictability documented in our paper proves this to be wrong. Moreover, relative to the Treasury bond market, whose yield curves have been used widely to forecast inflation, our results show that the information contained in the cross-sectional stocks can add value, especially when the pricing of U.S. Treasury bonds is influenced by factors unrelated to inflation risk.

Focusing on the economists' forecasting error, we find that economists do not incorporate the information contained in inflation portfolio and their room for improvement is especially large during the 2021 episode. Moreover, on policy makers, we find stronger predictability of our IP^{Core} under Fed's QE and when the Fed is behind-the-curve in fighting inflation. As both the policy makers and the economists form their forecasts by incorporating all of the information available to them, their collective failure in capturing the severity of the 2021 inflation surge reflects the limitation of the existing inflation forecasts and calls for forecasting methods from more diverse sources. By focusing on the inflation expectations embedded in the cross-sectional stocks, this is exactly what our paper can offer. Going forward, the inflation forecasting approach developed in this paper can potentially help enrich the information set of the policy makers as well as economists in their decision making.

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Figure 1. 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.

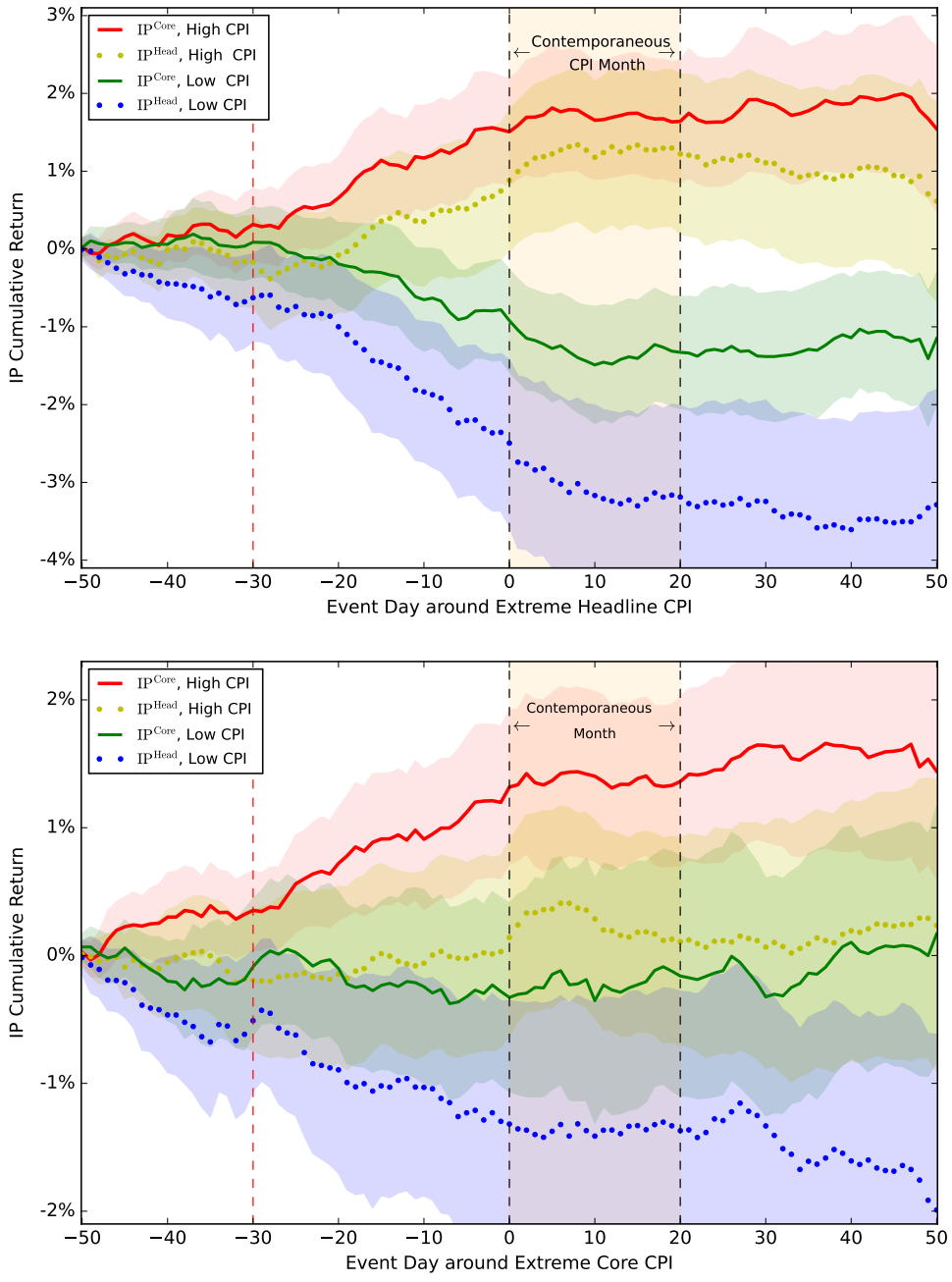


Figure 2. Inflation Portfolios and CPI Growth

The graphs show the relationship between market-based inflation forecasters and year-over-year (YoY) CPI growth. The blue and yellow bars (left axis) denote the YoY core-CPI and headline-CPI growths, respectively. The upper graph plots the standardized rolling 12-month IP^{Core} and IP^{Head} returns on the right axis. The lower graph plots the standardized rolling 12-month GSCI and TIPS-UST returns on the right axis. The grey areas denote the NBER recession periods.

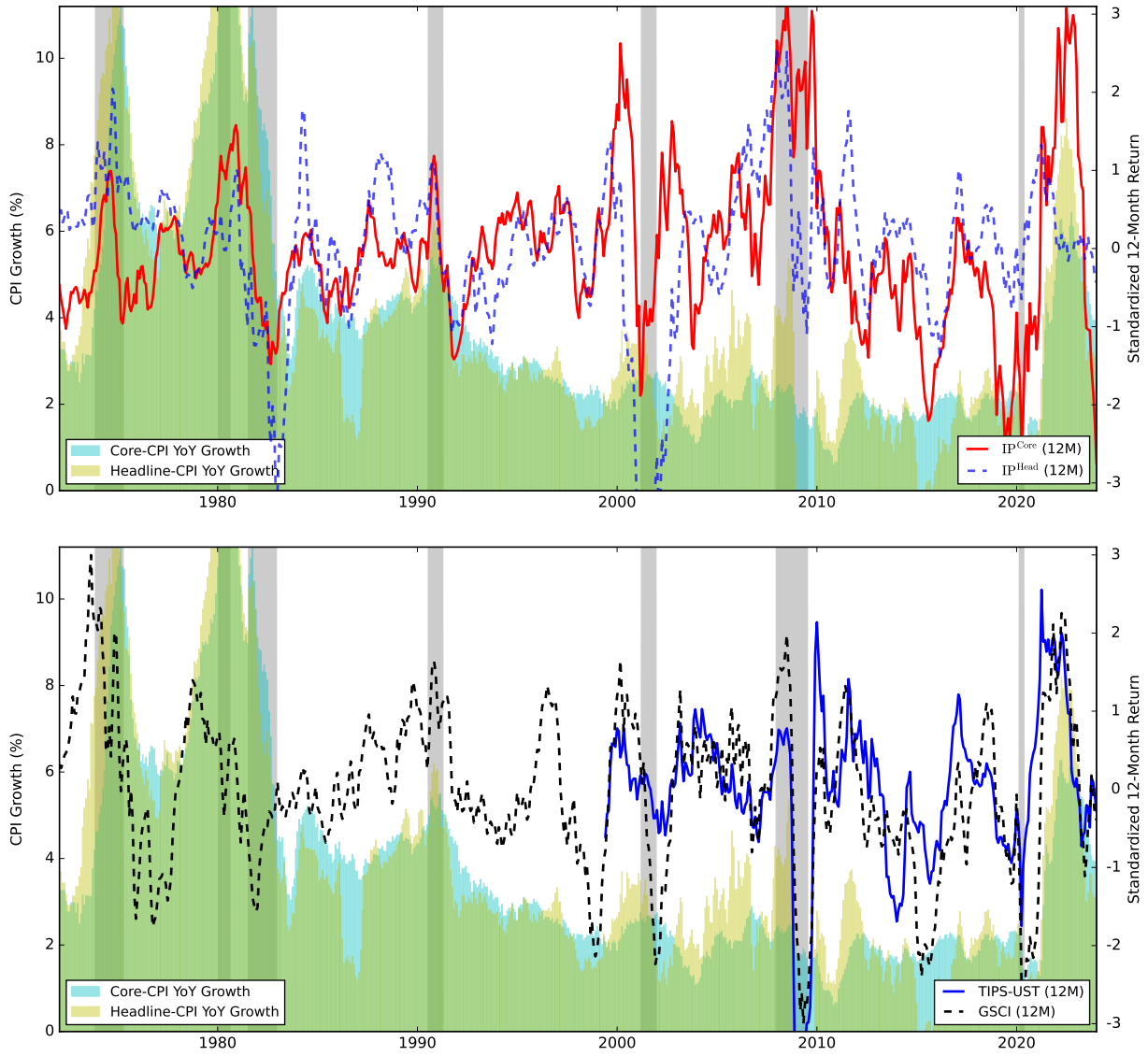


Figure 3. Economists' Forecasts and IP^{Core} Forecasts in the 2021 Episode

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) 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.

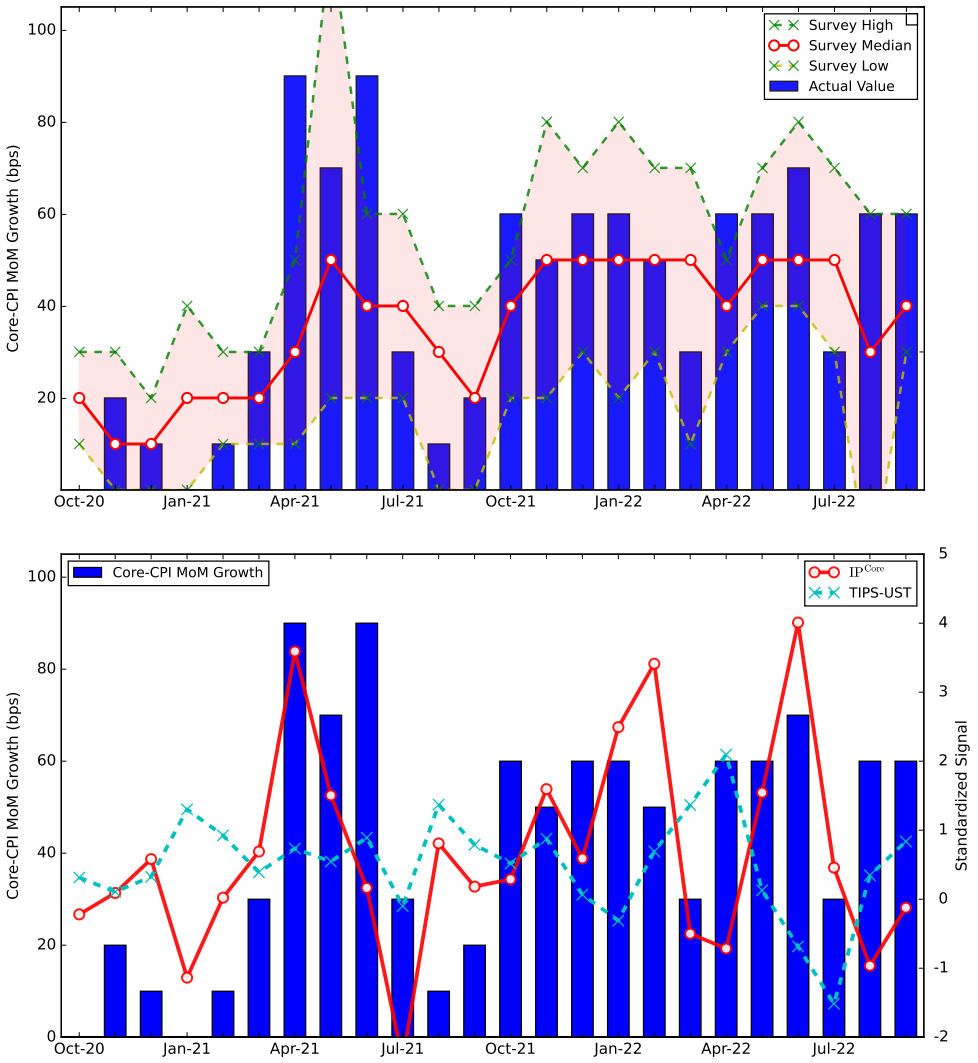


Figure 4. Predictability During Heightened Inflation Periods

The upper graphs plot the predictability of IP^{Core} and TIPS-UST on core-CPI innovations for the 24 months on and before the 2021 inflation episode peak, i.e., from October 2020 to September 2022. The lower graphs plot the corresponding relationships for the 24 months on and before the 1973 episode inflation peak from March 1973 to February 1975. Since TIPS was unavailable in the 1970s, we use the change in the 10-Year US Treasury yield as a substitute.

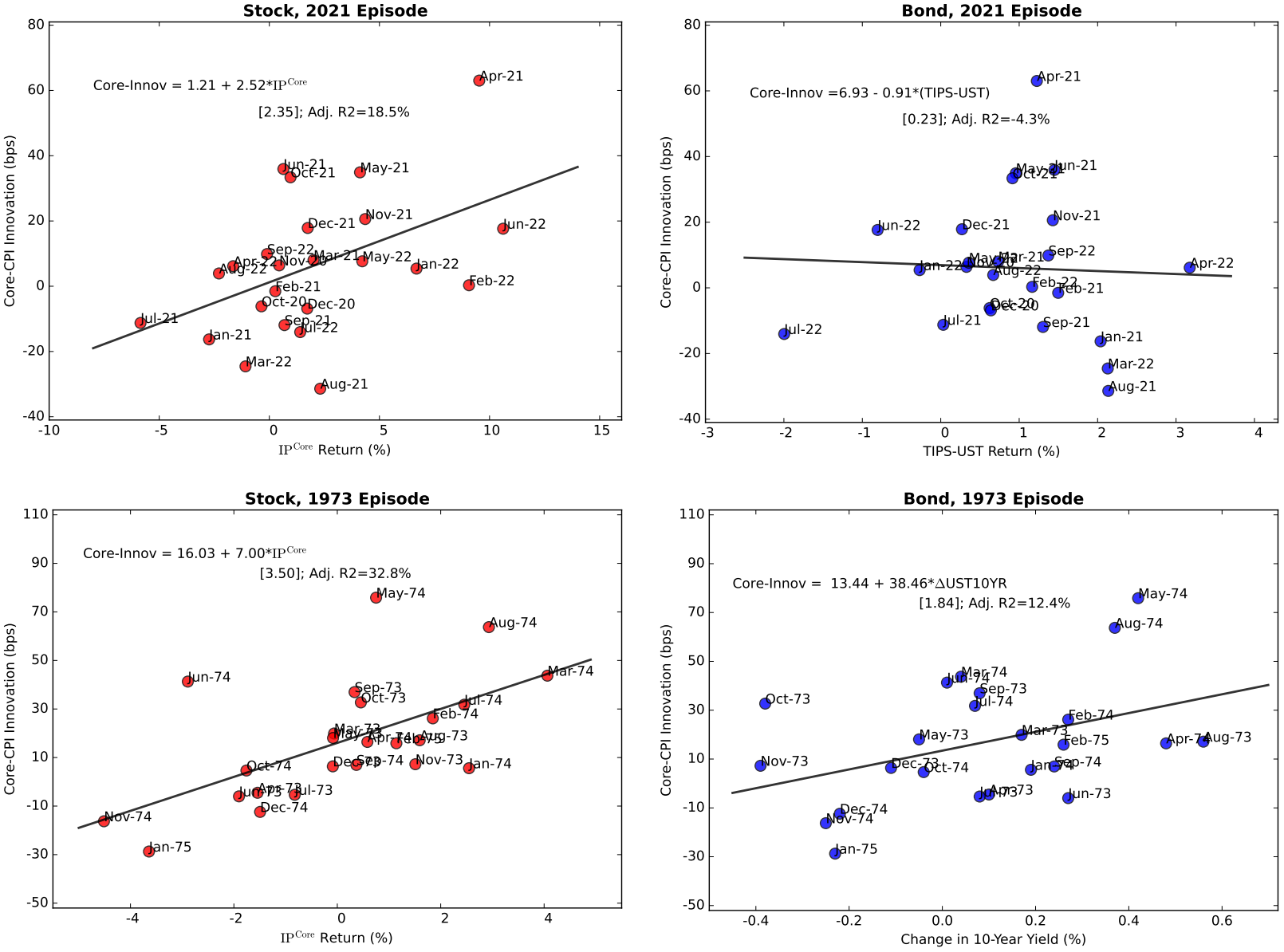


Figure 5. Core Beta and Firm Future Cash Flows

This figure reports the quarterly cash flow for inflation beta sorted portfolios. At the end of each quarter Q-1, we sort all the stocks into quintile groups based on their core beta (β^{Core}), and compute the average quarter-Q 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, together with the IP^{Core} return in quarter Q. 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, together with the IP^{Core} return in quarter Q. The shaded areas indicate the 95% confidence interval.

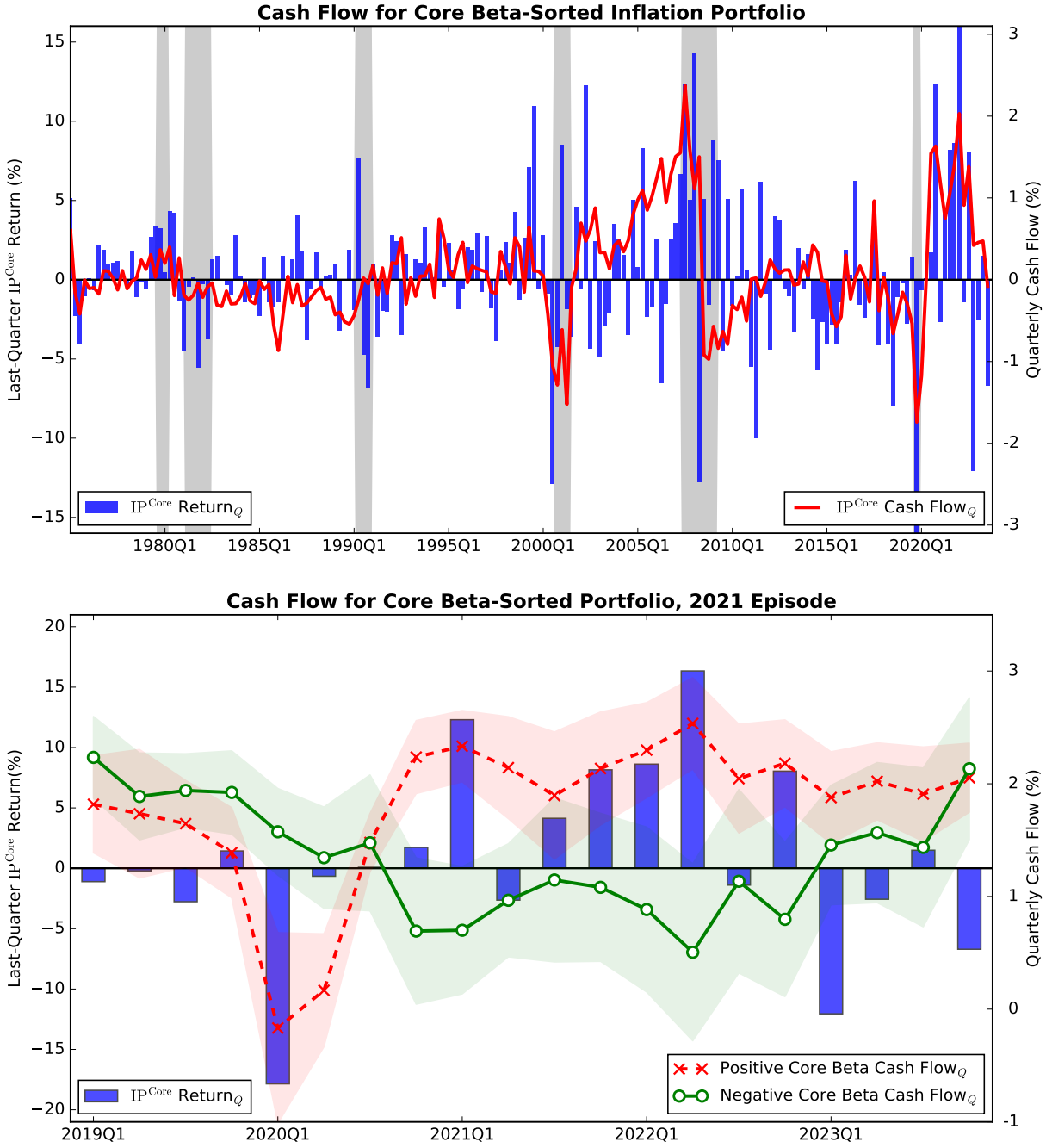


Table 1. Assets' Inflation Beta: Ann-Day vs. Full-Month

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 exposures for different assets, including aggregate stock market return (VWRETD), change in 2-Year US Treasury yield (ΔUST2YR), change in 10-Year US Treasury yield (ΔUST10YR), Bloomberg U.S. Corporate Bond Index return, the difference between Bloomberg U.S. Treasury Inflation Notes Index return and Bloomberg U.S. Treasury Index return (TIPS-UST), and Goldman Sachs Commodity Index return (GSCI). 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*
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)
ΔUST2YR	0.120	0.037	0.019	0.120	0.140	0.068
	(2.14)	(0.83)	(0.51)	(1.67)	(3.44)	(2.11)
ΔUST10YR	0.122	0.061	0.041	0.104	0.195	0.146
	(2.40)	(1.09)	(0.90)	(1.72)	(4.08)	(3.58)
Corporate Bond	−0.217	−0.081	−0.051	−0.132	−0.110	−0.068
	(−4.54)	(−1.36)	(−0.98)	(−2.12)	(−2.02)	(−1.42)
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)

Table 2. Cross-Sectional Stock Inflation Beta: Ann-Day vs. Full-Month

For each stock on every CPI announcement day, we estimate the pre-ranking announcement-day betas by regressing the excess returns of stocks on the announcement-day inflation innovations. Pre-ranking full-month betas are computed by regressing the monthly excess returns of stocks on contemporaneous-month inflation innovations. The "Raw Model" and "CAPM Model" present the estimates when CPI betas are calculated 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 depict the post-ranking core, headline, and energy betas for inflation beta sorted portfolios under the "Raw Model" and "CAPM Model", respectively. For ease of comparison, all variables are standardized with means of zero and standard deviations of one. The sample period spans from January 1972 to December 2023. Standard errors are adjusted for heteroskedasticity, and the t-stats are presented in parentheses.

Panel A. Post-Ranking Inflation Beta, Raw Model

	Announcement-Day (β^{Ann})			Full-Month (β^{Full})		
	Core	*Headline*	*Energy*	*Core*	*Headline*	*Energy*
Quintile 1	−0.118	0.018	0.050	−0.109	−0.065	0.041
	(−3.17)	(0.26)	(0.68)	(−2.61)	(−1.03)	(0.66)
Quintile 2	−0.099	0.029	0.054	−0.115	−0.059	0.044
	(−2.50)	(0.34)	(0.63)	(−2.61)	(−0.99)	(0.80)
Quintile 3	−0.095	0.020	0.058	−0.115	−0.046	0.049
	(−2.27)	(0.22)	(0.62)	(−2.58)	(−0.82)	(0.88)
Quintile 4	−0.074	0.004	0.042	−0.122	−0.034	0.052
	(−1.70)	(0.04)	(0.44)	(−2.64)	(−0.65)	(0.99)
Quintile 5	−0.093	0.005	0.023	−0.110	0.009	0.095
	(−2.09)	(0.05)	(0.24)	(−2.42)	(0.16)	(1.65)
Quintile 5-1	0.084	−0.035	−0.055	0.023	0.131	0.113
	(2.01)	(−0.32)	(−0.45)	(0.43)	(2.10)	(1.59)

Panel B. Post-Ranking Inflation Beta, CAPM Model

	Announcement-Day (β^{Ann})			Full-Month (β^{Full})		
	Core	*Headline*	*Energy*	*Core*	*Headline*	*Energy*
Quintile 1	−0.020	−0.005	−0.006	−0.018	−0.013	−0.012
	(−1.20)	(−0.28)	(−0.31)	(−0.85)	(−0.61)	(−0.51)
Quintile 2	0.005	0.021	−0.001	−0.024	−0.011	−0.004
	(0.29)	(1.10)	(−0.09)	(−1.39)	(−0.67)	(−0.21)
Quintile 3	0.012	0.009	0.014	−0.028	0.006	−0.001
	(0.62)	(0.46)	(0.62)	(−1.71)	(0.39)	(−0.06)
Quintile 4	0.027	0.018	−0.003	−0.022	0.014	0.011
	(1.31)	(0.84)	(−0.18)	(−1.27)	(0.77)	(0.56)
Quintile 5	0.021	0.009	−0.014	−0.009	0.056	0.058
	(1.08)	(0.36)	(−0.69)	(−0.47)	(2.65)	(2.37)
Quintile 5-1	0.102	0.044	−0.028	0.027	0.163	0.155
	(2.38)	(0.55)	(−0.37)	(0.45)	(2.89)	(2.47)

Table 3. Determinants of Inflation Beta

This table examines the determinants of cross-sectional stocks' inflation beta. The dependent variables are the quintile rank of core beta (β^{Core}) and the quintile rank of headline beta (β^{Head}). Independent variables include last quarter firm size (Log(Size)), asset growth, last 12-month average stock return (Momentum), market-to-book ratio (ME/BE), dividend payout, cash flow, and the cash flow duration from Weber (2018). All independent variables are standardized with means of zero and standard deviations of one for ease of interpretation. Time, industry, and firm fixed-effects are included as shown. Standard errors are double clustered by quarter and firm, and the t-stats are presented in parentheses.

	Quintile Rank of Core Beta (β^{Core})						Quintile Rank of Headline Beta (β^{Head})					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Size)	0.027	0.015	0.013	0.019	0.011	−0.030	0.000	0.019	0.019	0.027	0.011	0.109
	(1.00)	(0.52)	(0.48)	(0.69)	(0.38)	(−0.65)	(−0.01)	(0.66)	(0.64)	(0.92)	(0.43)	(2.46)
Asset Growth	−0.007	−0.002	−0.003	0.001	0.002	0.003	0.002	0.000	−0.001	0.007	0.003	−0.006
	(−1.30)	(−0.42)	(−0.60)	(0.24)	(0.36)	(0.82)	(0.40)	(−0.00)	(−0.10)	(1.26)	(0.69)	(−1.55)
Momentum	0.021	0.021	0.016	0.015	0.019	0.008	0.019	0.010	0.008	0.005	−0.005	−0.039
	(1.51)	(1.56)	(1.22)	(1.08)	(1.46)	(0.77)	(0.74)	(0.36)	(0.28)	(0.18)	(−0.23)	(−2.35)
ME/BE	−0.073	−0.053	−0.069	−0.046	−0.013	0.016	−0.018	−0.038	−0.046	−0.007	0.031	0.035
	(−3.66)	(−2.53)	(−3.43)	(−2.27)	(−0.68)	(0.83)	(−0.99)	(−1.94)	(−2.34)	(−0.37)	(1.53)	(1.81)
Dividend Payout		0.032	0.037	0.035	0.022	0.014		0.001	0.004	0.001	−0.025	−0.001
		(2.78)	(3.17)	(2.98)	(1.96)	(1.68)		(0.08)	(0.24)	(0.07)	(−1.82)	(−0.18)
Cash Flow			0.056	0.069	0.036	0.011			0.030	0.051	−0.005	0.003
			(2.63)	(3.31)	(1.93)	(1.03)			(1.32)	(2.61)	(−0.29)	(0.27)
CF Duration				−0.069	−0.075	−0.083				−0.111	−0.124	−0.092
				(−2.97)	(−3.24)	(−3.51)				(−4.13)	(−4.95)	(−4.03)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	Y	N	N	N	N	N	Y	N
Firm FE	N	N	N	N	N	Y	N	N	N	N	N	Y
Observations	166,891	154,076	153,992	152,105	149,918	151,829	166,891	154,076	153,992	152,105	149,918	151,829
Adj. R2	0.1%	0.1%	0.2%	0.3%	3.2%	48.8%	−0.1%	0.0%	0.0%	0.3%	6.5%	50.2%

Table 4. 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				Headline-CPI Innovation			
	X=IP^{Core}	X=IP^{Head}	X=GSCI	X=TIPS-UST	X=IP^{Core}	X=IP^{Head}	X=GSCI	X=TIPS-UST
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X[-10,-1]	0.979	1.418	1.038	−0.233	3.297	4.254	8.407	7.707
	(1.58)	(1.83)	(1.41)	(−0.34)	(2.40)	(3.64)	(6.20)	(3.21)
X[-20,-11]	1.853	1.183	1.436	2.285	5.687	5.633	9.027	7.766
	(2.48)	(1.91)	(1.88)	(1.88)	(4.44)	(4.76)	(6.82)	(3.43)
X[-30,-21]	1.951	0.518	1.426	1.118	4.131	3.107	3.107	1.319
	(2.55)	(0.70)	(1.86)	(1.89)	(2.84)	(1.72)	(2.78)	(0.71)
X[-40,-31]	−0.16	0.137	0.34	0.812	0.323	0.345	−0.992	−3.168
	(−0.24)	(0.21)	(0.54)	(1.37)	(0.26)	(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. R2	2.6%	1.0%	1.8%	4.4%	7.9%	9.2%	24.2%	14.4%

Table 5. The Unique Predictability of Core Beta-Sorted Portfolio

This table reports the predictability of asset returns, observed at the end of month t, on month-t+1 CPI innovation. The dependent variables are core-CPI innovations and headline-CPI innovations (in bps). IP^{Core} is 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^{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 return and TIPS-UST return 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						Headline-CPI Innovation					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
IP^{Core}	2.669	2.152	2.678	2.499			7.466	4.131	8.078	4.617		
	(3.40)	(2.90)	(2.85)	(2.56)			(6.83)	(3.15)	(4.66)	(2.06)		
IP^{Head}					1.882	0.403					7.937	5.350
					(2.86)	(0.65)					(5.75)	(3.15)
GSCI		1.670		0.637		1.458		10.782		12.272		12.268
		(2.13)		(0.64)		(1.34)		(6.63)		(5.74)		(6.24)
TIPS-UST			1.457	1.149		1.025			8.561	2.62		1.945
			(1.88)	(1.43)		(1.35)			(2.64)	(0.81)		(0.64)
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)	(−1.34)	(−0.01)	(−0.01)	(−1.31)	(−1.41)	(−0.01)	(−1.42)
Observations	624	624	308	308	624	308	624	624	308	308	624	308
Adj. R2	2.8%	3.7%	8.0%	7.9%	1.3%	3.6%	8.1%	23.6%	18.9%	30.3%	9.2%	31.0%

Table 6. Do Economists Update Inflation Expectations Using Market-Based Information?

This table presents the predictability of asset returns concerning economists' estimates of inflation growth and their estimation error. Change in forecast (in bps) is calculated as the Bloomberg economists' forecasting value of month-$t+1$ CPI growth minus the value predicted under the ARMA(1,1) model. Forecasting error (in bps) is calculated as the actual month-$t+1$ CPI growth minus the forecasting value by Bloomberg economists. The independent variables include IP^{Core}, IP^{Head}, GSCI, and TIPS-UST, all constructed at the end of month t. The independent variables are standardized with 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						Forecasting Error					
IP^{Core}	1.182	0.722	1.060	0.725			2.009	1.976	1.855	2.006		
	(2.28)	(1.78)	(2.40)	(1.78)			(2.70)	(2.33)	(2.51)	(2.38)		
IP^{Head}					0.974	0.452					0.225	−0.189
					(2.95)	(1.33)					(0.38)	(−0.28)
GSCI		1.268		1.198		1.324		0.091		−0.543		0.281
		(2.75)		(2.60)		(2.49)		(0.12)		(−0.59)		(0.33)
TIPS-UST			0.713	0.129		0.061			0.901	1.166		1.12
			(1.85)	(0.40)		(0.18)			(1.56)	(1.57)		(1.64)
Intercept	−0.550	−0.552	−0.548	−0.552	−0.549	−0.551	−0.232	−0.233	−0.23	−0.228	−0.228	−0.225
	(−1.81)	(−1.86)	(−1.82)	(−1.86)	(−1.79)	(−1.84)	(−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. R2	4.4%	8.9%	5.8%	8.6%	2.9%	7.6%	3.1%	2.8%	3.4%	3.3%	−0.3%	0.3%

Panel B. Predicting Economist Forecasts of Headline-CPI Growth

	Change in Forecast						Forecasting Error					
IP^{Core}	7.024	3.117	5.889	3.175			3.588	2.388	3.403	2.368		
	(4.11)	(1.38)	(3.31)	(1.40)			(4.06)	(2.36)	(3.71)	(2.36)		
IP^{Head}					8.268	4.248					3.240	2.008
					(4.07)	(2.40)					(4.24)	(2.50)
GSCI		10.734		9.622		9.431		3.298		3.670		3.911
		(4.72)		(4.75)		(5.19)		(3.55)		(4.04)		(4.83)
TIPS-UST			6.710	2.052		1.533			1.091	−0.686		−0.961
			(2.70)	(0.81)		(0.64)			(0.99)	(−0.60)		(−0.88)
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
	(−1.66)	(−1.81)	(−1.72)	(−1.81)	(−1.68)	(−1.83)	(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. R2	7.3%	22.6%	13.8%	22.8%	10.3%	23.9%	7.3%	12.6%	7.7%	12.5%	5.9%	11.7%

Table 7. Firm Information Environment and Inflation Forecastability

This table reports the predictability of IP^{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 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. IP^{Core} returns are standardized with means of zero and standard deviations 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)
IP^{Core} (X > Median)	2.669		2.655	2.384		2.383	2.335		1.867
	(3.40)		(3.06)	(2.84)		(2.60)	(2.82)		(2.30)
IP^{Core} (X ≤ Median)		1.465	0.026		1.298	0.001		1.974	0.670
		(1.87)	(0.03)		(1.50)	(0.00)		(2.39)	(0.89)
Observations	624	624	624	523	523	523	575	575	575
Adj. R2	2.8%	0.7%	2.6%	2.6%	0.6%	2.4%	2.4%	1.7%	2.4%

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)
IP^{Core} (X > Median)	7.466		7.714	5.693		5.515	4.796		3.375
	(6.83)		(5.92)	(4.07)		(3.34)	(4.00)		(2.20)
IP^{Core} (X ≤ Median)		3.725	−0.457		3.327	0.326		4.391	2.033
		(3.00)	(−0.37)		(2.47)	(0.23)		(3.26)	(1.17)
Observations	624	624	624	523	523	523	575	575	575
Adj. R2	8.1%	1.9%	8.0%	4.8%	1.5%	4.6%	3.4%	2.9%	3.6%

Table 8. 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 before the peak of core CPI in February 1975 (i.e., from March 1973 to February 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 Fund rate and the actual fed fund rate is higher than the 67% percentile cutoff, and "Other" refers to the rest. The Fed Fund Rate implied by the Taylor rule is estimated as 2.5%+1.5*(Core-CPI YoY Growth-2%)+0.5*OutPut Gap. "QE" captures the periods of Quantitative Easing. Independent variables are standardized with means of zero and standard deviations of one. 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		Forecasting Error		Core Innovation	
	(1)	(2)	(3)	(4)	(5)	(6)
IP^{Core}	8.438	9.686	6.428	8.359	18.164	15.730
	(2.35)	(2.51)	(1.72)	(2.33)	(3.50)	(2.93)
GSCI		−5.184		−7.224		−1.715
		(−1.06)		(−1.53)		(−0.52)
TIPS-UST (ΔUST10YR)		6.361		10.067		9.639
		(0.83)		(1.40)		(1.11)
Observations	24	24	24	24	24	24
Adj. R2	18.5%	15.7%	8.8%	11.3%	32.8%	31.7%

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

	Y=Core Innovation	Y=Forecasting Error	Y=Core Innovation	Y=Forecasting Error
	High Uncertainty		Low Uncertainty	
IP^{Core}	4.199	2.804	0.736	1.115
	(3.67)	(2.51)	(0.94)	(1.46)
Adj.R2	6.7%	5.2%	−0.1%	0.6%
	High Disagreement		Low Disagreement	
IP^{Core}	2.737	2.411	1.128	1.107
	(2.41)	(2.32)	(1.61)	(1.30)
Adj.R2	4.2%	3.9%	0.9%	0.5%
	Behind the Curve		Other	
IP^{Core}	3.335	2.703	2.185	1.500
	(2.54)	(3.10)	(2.78)	(1.34)
Adj.R2	4.9%	4.7%	1.5%	1.5%
	QE		Non-QE	
IP^{Core}	6.038	4.251	1.190	0.669
	(2.52)	(2.75)	(1.70)	(0.93)
Adj.R2	16.9%	10.8%	1.3%	0.0%

Table 9. Out-of-Sample Forecastability

Panel A reports the out-of-sample incremental inflation forecasting power for inflation portfolios and other inflation forecasters. The forecasting period is from May 2003 to December 2023. At each month t, we estimate the forecasting model, $CPIG_{k+1} = a + \sum b * X_k + \epsilon_k$, using only information on and before month t. We then use the estimated coefficients to forecast month-t+1 inflation growth. We include forecasting signals of IP^{Core}, IP^{Head}, GSCI, TIPS-UST, the latest SPF survey forecasted inflation growth (Survey), real GDP growth, VWRETD, ΔUST1YR, ΔUST2YR, and ΔUST10YR. "Relative RMSE" reports the ratio of the root mean squared forecasting error estimated using the corresponding forecast 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), when the alternative is 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 8, including the 2021 episode, high uncertainty, high disagreement, behind the curve, and QE periods.

Panel A. Relative RMSE for the Whole Sample

	Core-CPI		Headline-CPI	
Forecasting Model	Relative RMSE	p-value	Relative RMSE	p-value
IP^{Core}	95.71%	0.07	93.67%	0.00
IP^{Head}	100.41%	0.66	93.58%	0.00
GSCI	97.53%	0.13	86.36%	0.00
TIPS-UST	99.21%	0.26	95.93%	0.19
Survey	102.24%	0.83	98.62%	0.25
Real GDP Growth	101.34%	0.79	100.65%	0.97
VWRETD	100.91%	0.99	99.45%	0.23
ΔUST1YR	99.37%	0.34	99.58%	0.23
ΔUST2YR	99.49%	0.39	99.16%	0.08
ΔUST10YR	99.31%	0.35	99.44%	0.22
IP^{Core}+GSCI+TIPS-UST	96.70%	0.07	87.83%	0.01

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

	Core-CPI		Headline-CPI	
Subsample	Relative RMSE	p-value	Relative RMSE	p-value
2021 Episode	91.79%	0.05	88.67%	0.06
High Uncertainty	93.57%	0.05	93.45%	0.01
High Disagreement	95.32%	0.09	93.06%	0.00
Behind the Curve	94.76%	0.08	92.34%	0.02
QE	93.58%	0.06	86.81%	0.03

Table 10. Forecasting Inflation Swaps and Nominal Yields

This table 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). Changes in swap rates and nominal yields are calculated from the start of month $t+1$ to the announcement day of month $t+1$ CPI. IP^{Core} is standardized with 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}	0.181	0.114	0.086	0.057	0.044	0.033	0.030	0.022
	(2.72)	(2.34)	(2.25)	(1.95)	(1.75)	(1.89)	(1.75)	(1.37)
Observations	234	233	233	233	233	234	233	233
Adj. R2	6.6%	4.7%	4.5%	3.3%	2.8%	2.3%	2.3%	1.1%

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}	0.123	0.109	0.102	0.081	0.069	0.059	0.065	0.050
	(3.99)	(3.79)	(3.93)	(3.43)	(3.24)	(3.04)	(3.27)	(2.81)
Observations	624	571	624	624	624	624	542	563
Adj. R2	2.7%	2.5%	2.7%	2.0%	1.6%	1.4%	1.9%	1.2%

Table 11. Core Beta and Firm Future Cash Flows

This table presents the predictive regressions of firm next-quarter fundamentals conditional on firms' core betas. The dependent variables are quarter-Q 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} with IP^{Core} return, the quintile rank of core beta ($\beta^{\text{Core}}_{\text{Rank}}$), Log(Size), asset growth, Momentum, ME/BE, and dividend payout, all observed at the end of quarter $Q-1$. To control for the persistence in firm fundamentals, we also include the quarter $Q-1$ value of the dependent variable as controls. 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 as shown. Standard errors are double clustered by quarter and firm, and the t-stats are presented in parentheses.

	Sales Growth		Cash Flow		IBES LTG		Return	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\beta^{\text{Core}}_{\text{Rank}} \times \text{IP}^{\text{Core}}$	0.148	0.152	0.166	0.130	0.175	0.173	−0.023	0.019
	(2.69)	(2.76)	(3.53)	(2.91)	(2.28)	(2.25)	(−0.18)	(0.17)
$\beta^{\text{Core}}_{\text{Rank}}$	0.001	0.004	0.004	0.001	−0.003	0.001	0.003	0.003
	(0.28)	(1.37)	(1.59)	(0.25)	(−1.16)	(0.35)	(0.77)	(0.67)
Log(Size)	−0.037	−0.104	0.012	0.088	−0.002	−0.024	−0.128	−0.473
	(−7.53)	(−9.40)	(1.79)	(7.09)	(−0.61)	(−3.27)	(−11.36)	(−17.21)
Asset Growth	0.184	0.182	0.006	0.014	−0.001	0.003	0.003	0.001
	(15.61)	(14.97)	(1.27)	(3.75)	(−0.51)	(1.11)	(0.66)	(0.45)
Momentum	0.082	0.083	0.051	0.083	0.068	0.075	0.021	0.011
	(12.73)	(13.72)	(8.28)	(12.75)	(12.09)	(12.99)	(0.91)	(0.54)
ME/BE	0.063	0.061	0.133	0.143	−0.012	−0.009	0.004	−0.023
	(9.60)	(8.18)	(13.58)	(16.15)	(−3.52)	(−1.94)	(0.45)	(−2.42)
Dividend payout	−0.005	0.009	−0.004	−0.031	0.021	0.021	−0.019	−0.023
	(−1.18)	(1.99)	(−1.15)	(−8.59)	(7.97)	(5.39)	(−3.84)	(−5.06)
Lag(Y)	−0.321	−0.347	0.585	0.277	−0.071	−0.085	−0.011	−0.016
	(−20.28)	(−21.90)	(35.25)	(17.34)	(−5.34)	(−6.31)	(−0.67)	(−1.07)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y	N	Y
Observations	150,861	150,560	151,204	150,904	124,437	124,176	153,140	152,854
Adj. R2	13.0%	14.6%	38.5%	48.0%	3.7%	4.1%	26.5%	29.2%

Table 12. Inflation Beta Sorted Portfolios and Inflation Risk Premium

The table presents the performance of quintile portfolios sorted based on core beta (β^{Core}, Panel A) and headline beta (β^{Head}, Panel B) respectively. It includes annualized returns 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	
	Avg.Ret.	α_{CAPM}	*Avg.Ret.*	α_{CAPM}	*Avg.Ret.*	α_{CAPM}
Quintile 1	8.43	0.55	6.76	1.03	10.91	−0.19
	(3.20)	(0.66)	(1.95)	(1.01)	(2.69)	(−0.13)
Quintile 2	9.31	2.48	7.54	2.59	11.93	2.29
	(4.10)	(3.69)	(2.50)	(2.71)	(3.48)	(2.62)
Quintile 3	9.13	2.31	7.79	3.02	11.10	0.93
	(4.01)	(3.19)	(2.65)	(2.91)	(3.09)	(1.10)
Quintile 4	8.98	1.88	7.58	2.66	11.05	0.33
	(3.78)	(2.46)	(2.52)	(2.70)	(2.87)	(0.28)
Quintile 5	9.78	1.37	8.03	2.05	12.38	0.11
	(3.45)	(1.41)	(2.21)	(1.84)	(2.72)	(0.06)
Quintile 5-1	1.35	0.82	1.27	1.02	1.47	0.29
(IP^{Core})	(1.21)	(0.72)	(1.14)	(0.93)	(0.66)	(0.12)

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

	Whole sample		Pre-2002		Post-2002	
	Avg.Ret.	α_{CAPM}	*Avg.Ret.*	α_{CAPM}	*Avg.Ret.*	α_{CAPM}
Quintile 1	10.06	2.33	9.56	3.85	10.80	0.21
	(3.85)	(2.49)	(2.72)	(3.03)	(2.80)	(0.16)
Quintile 2	9.66	2.76	8.38	3.41	11.56	1.72
	(4.18)	(3.66)	(2.73)	(3.07)	(3.31)	(1.97)
Quintile 3	9.11	2.29	7.65	2.88	11.26	1.12
	(4.01)	(3.30)	(2.61)	(2.90)	(3.14)	(1.32)
Quintile 4	9.18	2.07	6.89	1.96	12.56	1.85
	(3.92)	(3.27)	(2.32)	(2.37)	(3.30)	(2.00)
Quintile 5	7.70	−0.79	5.32	−0.62	11.22	−1.43
	(2.67)	(−0.74)	(1.44)	(−0.45)	(2.41)	(−0.82)
Quintile 5-1	−2.36	−3.12	−4.24	−4.47	0.42	−1.64
(IP^{Head})	(−1.69)	(−2.12)	(−2.29)	(−2.31)	(0.20)	(−0.75)

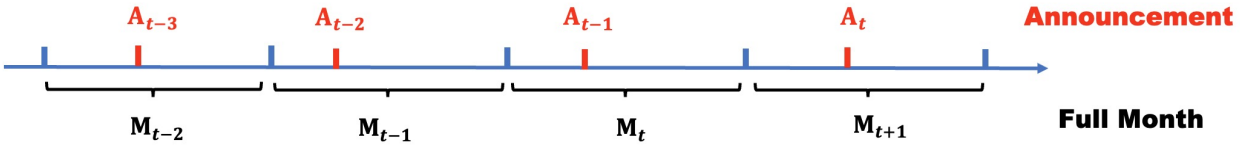
Appendix A. Variable Definition

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	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^{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^{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 Fund rate (2.5%+1.5*(Core-CPI YoY Growth-2%)+0.5*OutPut Gap) and the actual fed fund 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
Log(Size)	The natural logarithm of a firm's market capitalization
Asset Growth	Growth rate of total asset: $AT_t/AT_{t-1} - 1$
Momentum	Last 12-month average return
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	Constructed following Weber (2018)
Sales Growth	Change of gross sales divided by total asset: $(Sales_t - Sales_{t-1})/AT_{t-1}$
Cash Flow	Income before extraordinary items plus depreciation and amortization, divided by total asset (Hennessy et al. (2007)): $\sum(IB_t, DP_t)/AT_t$

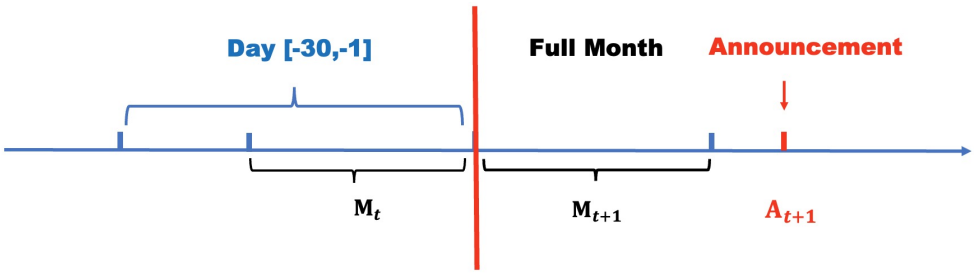
Appendix B. Illustration of the Time Line

Beta Estimation– To capture the inflation exposure of individual stocks as well as for 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 exposures for firm i using a WLS regression with exponential weights over an expanding window that uses all historical observations. 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_1 to A_t under the equation (5). A_1 is the first CPI announcement day that a stock is included in the sample.

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_1 to M_t. For example, if we are estimating inflation beta on May 12, 2022, which is the CPI announcement day for April 2022, we use the monthly returns and monthly CPI innovations from the first month a stock is included in the sample up 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 12, 2022.

Figure C1. 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 still stay in the top (bottom) quintile group for the 24 months after the portfolio formation month t.

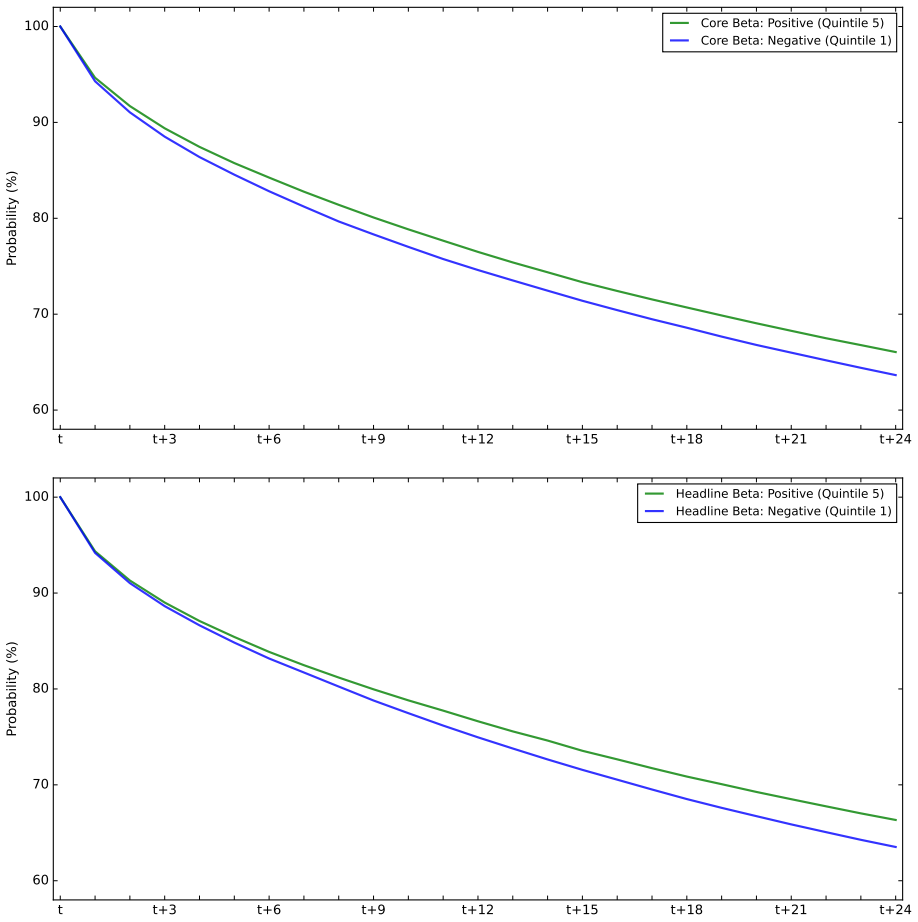


Figure C2. Time-Series Fluctuations in Inflation Beta

The upper graph plots the inflation betas (β^{Core} and β^{Head}) for the aggregate stock market (VWRETD), estimated using a rolling five-year window. The lower graph plots the rolling five-year estimated core beta for the IP^{Core} portfolio and the headline beta for the IP^{Head} portfolio. For ease of comparison across portfolios and over time, inflation betas are estimated using standardized returns and inflation innovations. The blue and yellow bars (left axis) denote the YoY core-CPI and headline-CPI growths, respectively. The grey areas denote the NBER recession periods.

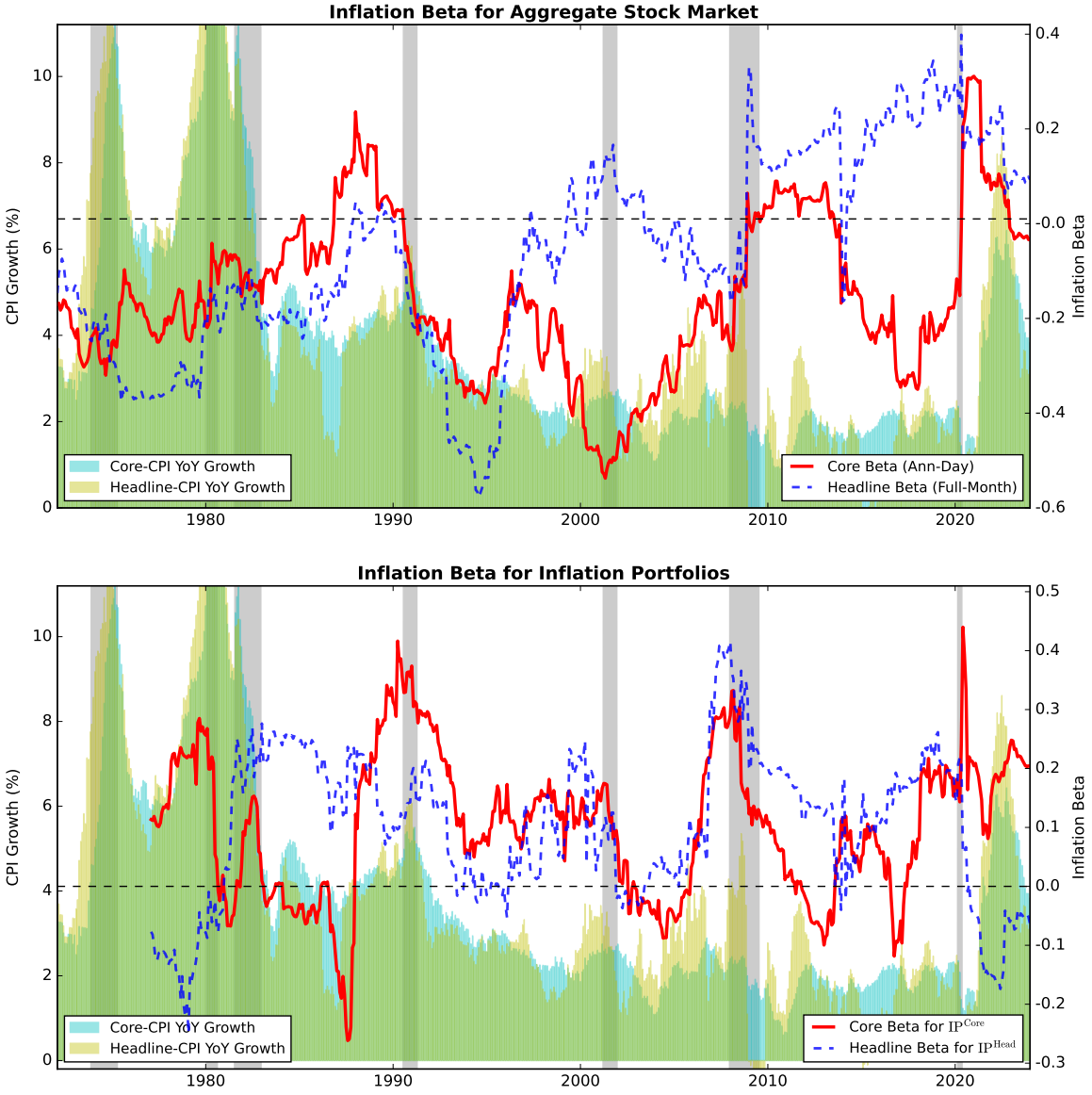


Table C1. Summary Statistics

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-Error$_{t+1}$ and Core-Error$_{t+1}$, 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 return of the β^{Core} and β^{Head} sorted stock portfolios observed at the end of month t. We also include statistics for asset returns, including aggregate stock market return (VWRETD), change in two-year and ten-year US Treasury yields (ΔUST2YR and ΔUST10YR), Goldman Sachs Commodity Index return (GSCI), and the difference between Bloomberg TIPS index return and US Treasury index return (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-Error$_{t+1}$ (bps.)	308	0.10	0.00	−10.00	10.00	13.00
Core-Error$_{t+1}$ (bps.)	307	−0.23	0.00	−10.00	10.00	10.92
IP$^{\text{Core}}$ (%)	624	0.21	0.05	−1.23	1.48	2.60
IP$^{\text{Head}}$ (%)	624	−0.26	−0.21	−1.73	1.58	3.41
VWRETD (%)	624	1.23	1.70	−1.42	4.43	5.21
ΔUST2YR (%)	571	−0.01	−0.01	−0.25	0.18	0.53
ΔUST10YR (%)	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 C2. The Unique Predictability of Core Beta-Sorted Portfolio on CPI Growth

This table reports the predictability of asset returns observed at the end of month t on month-$t+1$ CPI growth and next 3-month CPI growth (in bps). The independent variables are IP^{Core}, IP^{Head}, GSCI, and TIPS-UST returns. All 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}	2.231	1.765	2.660	2.658			6.199	3.615	7.528	3.692		
	(3.10)	(2.41)	(3.15)	(2.91)			(6.00)	(3.18)	(5.23)	(2.25)		
IP^{Head}					1.142	0.357					5.968	3.040
					(1.70)	(0.56)					(4.67)	(2.28)
GSCI		1.511		0.008		0.897		9.123		15.001		15.356
		(1.93)		(0.01)		(0.91)		(5.69)		(8.17)		(8.77)
TIPS-UST			1.358	1.354		1.232			8.909	3.418		2.976
			(2.04)	(1.93)		(1.71)			(3.08)	(1.23)		(1.12)
Lag (Y)	0.747	0.744	0.575	0.575	0.747	0.579	0.613	0.542	0.317	0.161	0.609	0.165
	(16.62)	(16.69)	(11.25)	(11.02)	(16.50)	(9.99)	(13.28)	(11.56)	(4.93)	(2.51)	(13.45)	(2.49)
Observations	624	624	308	308	624	308	624	624	308	308	624	308
Adj. R2	56.7%	57.0%	39.4%	39.2%	56.2%	35.9%	43.2%	49.4%	36.3%	50.0%	42.9%	49.5%

Panel B. Predicting Next 3-Month CPI Growth

	Core-CPI Growth						Headline-CPI Growth					
IP^{Core}	7.845	6.521	7.888	7.359			15.551	10.070	15.329	9.433		
	(4.22)	(3.41)	(3.83)	(3.25)			(4.83)	(2.84)	(4.34)	(2.50)		
IP^{Head}					3.250	0.775					16.332	6.681
					(1.90)	(0.55)					(4.03)	(1.38)
GSCI		4.295		1.874		4.401		17.953		20.623		21.877
		(2.33)		(0.77)		(1.75)		(5.23)		(4.44)		(4.76)
TIPS-UST			4.104	3.201		2.841			21.964	12.902		11.808
			(2.92)	(1.98)		(1.51)			(4.06)	(2.46)		(2.43)
Lag (Y)	0.802	0.799	0.490	0.487	0.800	0.487	0.615	0.582	0.129	0.079	0.615	0.087
	(19.35)	(19.26)	(6.52)	(6.41)	(18.85)	(5.98)	(14.79)	(13.30)	(1.96)	(1.15)	(14.37)	(1.23)
Observations	622	622	306	306	622	306	622	622	306	306	622	306
Adj. R2	65.3%	65.6%	32.0%	31.9%	64.2%	27.8%	41.2%	45.1%	21.0%	26.5%	41.6%	25.6%

Table C3. Inflation Beta Constructed Using Rolling Five-Year Window

Panel A reports cross-sectional stocks' post-ranking inflation betas when the pre-ranking inflation betas are estimated using a rolling five-year window under the CAPM model in Table 2. Panel B reports the inflation predictability of IP^{Core} constructed based on the rolling five-year window estimated β^{Core} 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*
Quintile 1	−0.02	−0.01	−0.012	−0.015	−0.002	−0.008
	(−1.14)	(−0.52)	(−0.64)	(−0.70)	(−0.12)	(−0.35)
Quintile 2	0.008	0.013	0.001	−0.018	−0.009	−0.007
	(0.44)	(0.62)	(0.06)	(−1.04)	(−0.55)	(−0.38)
Quintile 3	0.018	0.012	0.01	−0.033	−0.01	0.003
	(0.92)	(0.59)	(0.45)	(−2.09)	(−0.63)	(0.21)
Quintile 4	0.020	0.025	0.009	−0.026	0.007	0.016
	(1.01)	(1.11)	(0.44)	(−1.56)	(0.44)	(0.90)
Quintile 5	0.020	0.012	−0.018	−0.009	0.061	0.048∗
	(1.01)	(0.50)	(−1.05)	(−0.47)	(2.73)	(1.91)
Quintile 5-1	0.107	0.068	−0.025	0.019	0.173	0.137
	(2.49)	(0.98)	(−0.39)	(0.35)	(2.96)	(2.23)

Panel B. Predicting Month t+1 Inflation

	Core-CPI				Headline-CPI			
	Innovation		Forecasting Error		Innovation		Forecasting Error	
IP^{Core}	2.235	2.394	2.300	2.308	7.901	5.556	3.786	2.597
	(2.98)	(2.47)	(3.10)	(2.70)	(6.54)	(2.97)	(4.22)	(2.57)
GSCI		0.715		−0.626		12.003		3.625
		(0.71)		(−0.67)		(5.95)		(3.98)
TIPS-UST		1.014		1.055		2.348		−0.82
		(1.30)		(1.44)		(0.74)		(−0.73)
Intercept	−0.072	−0.835	−0.23	−0.225	−0.012	−1.942	0.097	0.097
	(−0.12)	(−1.37)	(−0.38)	(−0.37)	(−0.01)	(−1.42)	(0.14)	(0.14)
Observations	624	308	307	307	624	308	308	308
Adj. R-squared	1.9%	7.5%	4.1%	4.2%	9.1%	31.3%	8.2%	13.1%

Table C4. 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

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Quintile 5-1
β^{Surp}	−0.070	−0.036∗	−0.005	0.012	0.02	0.209
t-stat	(−2.81)	(−1.81)	(−0.22)	(0.47)	(0.73)	(2.64)
β^{ISWAP2YR}	−0.108	−0.036	−0.004	−0.005	0.063	0.465
t-stat	(−2.56)	(−1.22)	(−0.16)	(−0.18)	(1.80)	(3.57)
β^{ISWAP5YR}	−0.101	−0.043	−0.018	0.023	0.061	0.401
t-stat	(−2.60)	(−1.52)	(−0.67)	(0.81)	(1.76)	(3.58)
β^{UST2YR}	−0.032	0.001	0.018	0.03	0.054	0.248
t-stat	(−0.95)	(0.04)	(0.77)	(1.34)	(2.05)	(2.63)
β^{UST5YR}	−0.014	0.004	0.011	0.026	0.038	0.142
t-stat	(−0.52)	(0.15)	(0.40)	(1.23)	(1.58)	(2.06)

Panel B. Predicting Month t+1 CPI Innovation

	Core-CPI Innovation					Headline-CPI Innovation				
IP^{Surp}	2.022					8.234				
	(2.35)					(4.43)				
$\text{IP}^{\text{ISWAP2YR}}$		3.822					8.805			
		(2.10)					(3.41)			
$\text{IP}^{\text{ISWAP5YR}}$			3.085					10.895		
			(1.85)					(4.58)		
$\text{IP}^{\text{UST2YR}}$				1.545					2.640	
				(2.66)					(2.54)	
$\text{IP}^{\text{UST5YR}}$					1.511					1.711
					(2.58)					(1.76)
Observations	264	173	173	511	624	264	173	173	511	624
Adj. R2	2.9%	4.6%	2.9%	1.3%	0.8%	7.3%	7.7%	12.4%	0.9%	0.3%

Table C5. 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 as 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. IP^{Core}_{Ind} and IP^{Head}_{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. IP^{Core} and IP^{Head} are the 30-day cumulative returns for the stock-constructed inflation portfolios as in Table 5. 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	0.255	Candy & Soda	-0.063	Oil & Natural Gas	1.116	Candy & Soda	-0.280
2	Ship Building	0.188	Communication	-0.054	Mining	0.902	Tobacco Products	-0.280
3	Coal	0.183	Beer & Liquor	-0.043	Precious Metals	0.652	Restaurants & Hotels	-0.224
4	Oil & Natural Gas	0.160	Recreation	-0.029	Coal	0.651	Construction	-0.172
5	Mining	0.113	Entertainment	-0.024	Agriculture	0.593	Banking	-0.158
6	Defense	0.064	Business Services	-0.019	Steel Works	0.411	Insurance	-0.154
7	Business Supplies	0.063	Computers	-0.016	Ship building	0.330	Apparel	-0.151
8	Machinery	0.060	Electronic Equipment	-0.016	Machinery	0.306	Transportation	-0.138
9	Shipping Containers	0.059	Insurance	-0.013	Fabricated Products	0.300	Automobiles & Trucks	-0.117
10	Automobiles	0.057	Agriculture	-0.010	Chemicals	0.249	Rubber & Plastic	-0.108

Panel B. Predictability of Industry vs. Stock Portfolios

	Core-CPI Innovation						Headline-CPI Innovation					
IP^{Core}_{Ind}	1.009		−0.151				5.621		2.992			
	(1.69)		(−0.26)				(4.32)		(2.11)			
IP^{Core}		2.669	2.733					7.466	6.197			
		(3.40)	(3.23)					(6.83)	(5.05)			
IP^{Head}_{Ind}				1.505		0.543				5.82		1.43
				(2.69)		(0.79)				(4.53)		(1.13)
IP^{Head}					1.882	1.544					7.937	7.046
					(2.86)	(1.86)					(5.75)	(4.73)
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. R2	0.3%	2.8%	2.6%	0.8%	1.3%	1.2%	4.5%	8.1%	9.1%	4.9%	9.2%	9.2%

Table C6. 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}
Quintile 1	12.731	−1.577	12.914	−1.401	13.412	−1.603
	(4.65)	(−0.61)	(5.37)	(−0.58)	(5.86)	(−0.67)
Quintile 2	13.610	−1.689	13.736	−1.686	14.216	−2.013
	(5.85)	(−0.72)	(6.78)	(−0.78)	(7.51)	(−1.02)
Quintile 3	13.425	−1.943	13.532	−1.986	13.984	−2.374
	(5.80)	(−0.81)	(6.78)	(−0.92)	(7.69)	(−1.27)
Quintile 4	13.274	−2.554	13.373	−2.622	13.814	−3.104
	(5.51)	(−1.01)	(6.46)	(−1.15)	(7.39)	(−1.60)
Quintile 5	14.082	−2.256	14.186	−2.201	14.586	−2.513
	(4.88)	(−0.78)	(5.70)	(−0.84)	(6.53)	(−1.15)
Quintile 5-1	1.35	−0.68	1.358	−0.86	1.484	−0.886
(IP^{Core})	(1.20)	(−0.62)	(1.31)	(−0.85)	(1.31)	(−0.77)

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

	K=1		K=3		K=12	
	Intercept	β^{NRC}	Intercept	β^{NRC}	Intercept	β^{NRC}
Quintile 1	14.356	−3.142	14.578	−3.174	15.072	−3.653
	(5.28)	(−1.17)	(6.14)	(−1.27)	(7.00)	(−1.69)
Quintile 2	13.960	−2.435	14.089	−2.522	14.658	−2.981
	(5.89)	(−1.02)	(6.90)	(−1.17)	(7.65)	(−1.53)
Quintile 3	13.404	−2.163	13.514	−2.197	14.042	−2.608
	(5.79)	(−0.90)	(6.72)	(−1.00)	(7.39)	(−1.30)
Quintile 4	13.479	−1.314	13.614	−1.286	14.084	−1.53
	(5.63)	(−0.54)	(6.53)	(−0.57)	(7.34)	(−0.76)
Quintile 5	11.999	−1.038	12.074	−0.802	12.384	−1.03
	(4.07)	(−0.35)	(4.76)	(−0.30)	(5.25)	(−0.44)
Quintile 5-1	−2.357	2.104	−2.250	2.054	−2.079	2.161
(IP^{Head})	(−1.58)	(1.40)	(−1.69)	(1.51)	(−1.50)	(1.68)