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

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First Draft: November 18, 2022. This Draft: September 13, 2024

Abstract

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

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1 Introduction

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

Our focus on the cross-section aspect of the stock market is motivated by the 2021 inflation surge, which was missed by the policy makers, as well as the economists contributing to the survey-based inflation forecasts.[2] As both the policy makers and economists form their expectations by incorporating the information available to them at the time, their collective failure in 2021 calls for alternative instruments, potentially from financial assets, to enrich the existing forecasting approach. Relative to the Treasury bond market, whose yield curves have been widely used to forecast inflation, the information contained in cross-sectional stocks can add value, especially when the pricing of U.S. Treasury bonds is influenced by factors unrelated to inflation risk.[3] Relative to the commodity market, which typically contains rich information about energy prices, cross-sectional stocks can offer additional information with respect to core inflation, both in terms of exposure and forecasting.

Relative to the aggregate stock market, our focus on the relative pricing between stocks with high and low inflation exposure allows us to shift away from the overall equity-market trends and zero in on the inflation expectations contained in the cross-section. To the extent that stock-level inflation exposures are persistent over time and vary across firms,

[1]Focusing on the aggregate, Fama and Schwert (1977), Bekaert and Wang (2010), and Fang et al. (2021) show that the stock market is a poor hedge against inflation. In the cross-section, Chen et al. (1986) and Boons et al. (2020) examine the pricing of inflation risk.

[2]During the most consequential months in 2021, the median estimate of the Bloomberg surveys of economists missed the rapid ascend of the core CPI, month-over-month, by 0.1% in March, 0.6% in April, 0.2% in May, and 0.5% in June. The case for April 2021 is the most egregious, when the highest projection of the Bloomberg surveys was only 0.5%, missing the actual announcement of 0.9% by a wide margin.

[3]For example, the illiquidity of the market for TIPS can add noise to the breakeven inflation forecasts, and Fed interventions (e.g., QE) can distort bond pricing and thereby mask inflation expectations.

this cross-sectional approach allows us to harness the active price discovery that takes place in the equity market with respect to future inflation.[4] This informational channel is akin to the seminal paper of Roll (1984), which examines the market's information processing ability by relating orange-juice futures price changes with subsequent errors in temperature forecasts issued by the National Weather Service for the central Florida region where most juice oranges are grown.

Cross-Sectional Inflation Exposure – To estimate the extent to which inflation expectations affect the pricing of a stock, we use the pre-ranking inflation beta, estimated by regressing stock returns on inflation innovations using past observations over a rolling window. Following the standard approach of Chen et al. (1986) and Boons et al. (2020), we estimate the full-month inflation beta, β^{Full}, by regressing monthly stock returns on the contemporaneous-month inflation innovations. Since price discovery with respect to inflation occurs not only during the contemporaneous month when inflation is realized but also on CPI announcement days when inflation news is released, we further introduce an information-based inflation beta that has not been previously studied in the literature. Specifically, our announcement-day inflation beta, β^{Ann}, measures the sensitivity of announcement-day stock returns to inflation innovations. For the purpose of identifying inflation-sensitive stocks, the risk-based measure β^{Full} gauges their contemporaneous inflation exposure during the entire month, while the information-based measure β^{Ann} focuses on their price reactions on the announcement day.

Both measures are found to be effective in differentiating cross-sectional inflation exposure, but their information content varies. The full-month inflation beta β^{Full} can capture the relative exposures to headline CPI, particularly the energy component, while the announcement-day beta β^{Ann} is more effective for core CPI, particularly goods and services. An unexpected increase in core CPI shocks leads to a decrease in CPI-announcement day returns more for firms with a more negative pre-ranking β^{Ann}. Conversely, headline CPI shocks more negatively impact the firms with a more negative pre-ranking β^{Full} during the contemporaneous month. In other word, there are substantial cross-sectional differences in

[4]For example, consider two firms whose cash flow exposures to inflation shocks are positive and negative, respectively. In anticipation of a positive inflation shock, the market prices of these two stocks would diverge if this information with respect to future inflation is priced into the respective stock prices.

firms' exposures to headline and core inflation, and these differences persist over time.[5]

Estimating β^{Full} and β^{Ann} for both the Treasury bond and the commodity market, we find the same pattern – inflation-sensitive securities comove with headline CPI during the contemporaneous month and respond to core CPI on announcement days. This pairing of β^{Full} for headline and β^{Ann} for core makes intuitive sense as components of the headline CPI such as energy can be observed continuously and contemporaneously by the market participants throughout the CPI month, while components of the core CPI (e.g., goods and services) are not easily observed during the CPI month and constitute a bigger surprise on the CPI announcement days. For this reason, we apply the full-month approach to headline CPI and the announcement-day approach to core CPI, referring them as β^{Head} and β^{Core}, respectively.

We further link firms' inflation betas to their cash flows and observe a clear alignment between return-based inflation exposure and cash flow-based inflation exposure. Firms with more positive β^{Core} experience an increase in their quarterly cash flows as inflation rises. Moreover, in terms of cash flow distributions, firms with more negative β^{Core} have higher growth potential, lower dividend payouts, and lower immediate cash flows, indicating a concentration of cash flows at the long end and a higher cash flow duration, akin to longer-maturity bonds that are more adversely affected by rising core inflation.

Inflation Forecasting with IP Portfolios – Sorting stocks by their pre-ranking beta into quintile portfolios, we form the monthly rebalanced top-minus-bottom inflation portfolios – the core-focused portfolio (IP$^{\text{Core}}$) is constructed using the announcement-based and core-focused β^{Core}, while the headline-focused inflation portfolio is constructed by the risk-based and headline-focused β^{Head}. The aggregate stock market in general has a negative though unstable inflation beta, suffering in performance amid positive inflation shocks. Relative to the aggregate market, stocks in the bottom-ranked portfolio, whose inflation betas are ranked the lowest, suffer even more severely when inflation increases. The long-short portfolio thus helps to cancel out any aggregate noise or common factors that affect all stocks universally. Our hypothesis is that, when informed by higher inflation expectations, investors would

[5] Consistent with Fang, Liu, and Roussanov (2021), we find that the post-ranking β^{Full}, estimated from 1972 to 2022, is more negative and significant for core CPI than headline CPI. Unlike their focus on the aggregate stock market, however, our objective is to differentiate stocks by their relative inflation exposure. For this, our results show that β^{Full} works for headline CPI and β^{Ann} is more effective for core CPI.

underprice stocks in the bottom portfolio more severely than those in the top portfolio, resulting in positive IP returns. A higher than usual IP return is therefore a reflection of heightened inflation expectations and can help predict the inflation yet to be realized.

Our empirical findings support the active price discovery of inflation news among cross-sectional stocks. 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 $t + 1$, which are realized in month $t + 1$ and announced in the middle 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 that 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 cannot predict core-CPI movements. Thus, although consistent with the existing literature (Boons et al. (2020)), IP^{head} better captures the inflation risk premium. However, in terms of inflation forecasting, IP^{Core}, constructed based on the announcement-day beta, is more effective.

The equity-based IP^{Core} is further tested 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 (UST) bonds. While financial markets in general and the commodity index in particular can predict the innovations in headline inflation well, their forecastability of core inflation is very much limited. When used jointly to predict core CPI, IP^{Core} is the only forecaster that significantly predicts core-CPI movements, while the other market-based predictors are insignificant. 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 (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 surprise) 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 surprise. As the respective CPI surprises have standard deviations of 11 bps and 13 bps, the information from cross-sectional stocks can help improve 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 because of its time-varying nature. Dormant for extended periods of time, inflation has the tendency to surge rapidly and the 2021 experience is one perfect example. In September 2021, core CPI surged to 6.6% year-over-year, a level not seen in 40 years. However, both policymakers and economists underestimated the severity of inflation during this period. Amid the heated debate on the transitory versus permanent nature of surging inflation, the Fed seemed to have misjudged the situation. Throughout 2021 and into March 2022, the Fed maintained a zero interest-rate policy and continued $120 billion in monthly bond purchases, pivoting only in March 2022 and tightening aggressively since June 2022. Economists also consistently underestimated the rapid month-over-month core CPI increases, notably by 60 bps in April and 50 bps in June 2021.

Remarkably, prior to the inflation surge, IP^{Core} had already 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.

As a parallel to 2021, the 1973 experience has frequently been brought back from history to shed light on the recent runaway inflation. Tracking the performance of IP^{Core} in the 24 months leading up to the core-CPI peak in 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). Moreover, similar to the case of 2021-22, this enhanced predictability is captured exclusively by our core-focused inflation portfolio, and not by the Treasury or commodity markets.

The cases from 1973 and 2021 suggest that the effectiveness of inflation forecasting varies over time. Our IP^{Core} offers the most timely and valuable information when inflation emerges as an important risk factor in the capital markets. Exploring this idea further, we sort CPI month by the absolute value of CPI innovations and find the predictability of IP^{Core} to be significantly stronger when inflation risk is more volatile. Using the magnitude of economists' disagreement as another proxy for time-varying inflation volatility, we observe a similar pattern.

Studying the time-varying predictability, we further focus on the unique role played by monetary policies in fighting inflation. Measuring the extent to which the Fed is behind-the-curve by the distance between the Fed Fund Rate and the rate recommended by the Taylor rule, we find that, when the Fed is behind the curve, the predictive power and economic significance of IP^{Core} are significantly larger. These findings suggest that a higher-than-usual signal from the cross-sectional stocks does not automatically lead to sustained increases in core inflation, as observed in 2021 and 1973. To the extent that the Fed is ahead of the curve, inflation can be effectively contained, resulting in much muted predictability. Conversely, when the Fed is behind the curve, 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.[6] In contrast, the out-of-sample enhancements provided by GSCI and TIPS-UST for predicting core inflation are significantly

[6] For predicting headline CPI out-of-sample, the improvement measured by relative RMSE ranges from 6-11%.

weaker, less than 3%. Furthermore, the robustness of IP^{Core}, both in terms of inflation beta construction and inflation forecasting, extends to various alternative measures of inflation shocks, such as survey-based surprises, changes in inflation swap rates, and changes in nominal yields. The results hold true when forecasting quarterly CPI, using rolling five-year periods to estimate beta, and excluding the industry component.

Mechanism – Inflation can affect firm values either through the discount rate channel or the cash flow channel. To empirically investigate the mechanism behind the return difference between stocks with high and low inflation exposure, we first examine the impact of inflation on firm cash flows. 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 forecasts. For example, a 10% increase in IP^{Core} at the end of quarter t predicts an 8.3% standard deviation decrease in cash flow in quarter $t+1$ for firms in the bottom (most negative) β^{Core} quintile compared to those in the top quintile. This evidence underscores the significant impact of inflation shocks on firm cash flows, which in turn explains why an increase in IP^{Core} signals upcoming positive inflation shocks.

Interestingly, we find no evidence that the discount rate channel drives the forecastability. For core beta-sorted portfolios, the return dispersion between the top and bottom quintiles (IP^{Core}) is insignificant. Further analyzing the inflation risk premium conditional on the nominal-real covariance (NRC) following the methodologies of Boons et al. (2020), we find that NRC cannot explain the variations in IP^{Core}, though consistent with Boons et al. (2020), IP^{Head} significantly loads on NRC.

To further pin down the information channel, we examine the predictability of IP^{Core} conditional on firm information environment. Our hypothesis relies on sophisticated investors incorporating inflation expectations into the cross-sectional pricing of stocks. If investors have limited capacity or face constraints to arbitrage, inflation expectations may not be promptly reflected in stock prices. Therefore, we anticipate stronger price discovery among firms with better information environments. Consistently, we find that the predictability of IP^{Core} is stronger among larger firms, those with greater analyst coverage, and higher institutional ownership, proxies for a better information environment.[7]

Related Literature: Our paper is related to the literature that uses the cross-sectional stocks to price the inflation risk premium, 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.[8] 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.

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 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

[7] 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)).

[8] 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.

(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, especially when inflation merges as a significant risk factor in the economy.

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 exposure. Section 4 explores the predictability of market-based inflation forecasters. Finally, Section 5 discusses the cash flow channels and Section 7 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).[9] 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.

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

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: $\text{CPI-Innov}_{t+1} = \pi_{t+1} - \widehat{\pi_{t+1}}$. 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 capture 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.

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 2-year and 10-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 commodity market performance, we use the Goldman Sachs Commodity Index return (GSCI).[10]

3 Measuring Inflation Exposure

In this section, we investigate the variation in inflation exposure across different securities, with a particular focus on the differences between the announcement-day approach and the full-month approach.

3.1 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)). 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.

To illustrate the differing information content captured by the full-month and announcement-day approaches, we first examine the inflation exposure of inflation-sensitive assets, as reflected in the Treasury and commodity markets. The announcement-day inflation beta is constructed by regressing assets' announcement-day excess returns on CPI innovations released on the announcement days. Given that different CPI components (e.g., core vs.

[10]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.

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 assets' monthly excess returns to contemporaneous-month CPI innovations, following the methodology in Chen, Roll, and Ross (1986), Boons et al. (2020), and Fang, Liu, and Roussanov (2021):

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

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, for a wide range of assets, including equity (VWRETD), Treasury (2-year and 10-year U.S. Treasury yields, TIPS-UST return), and commodities (GSCI). 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 have a significantly negative impact on equity and bond returns and a positive impact on commodities, whereas the effects of headline and energy components on asset prices are negligible. 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 the 10-year Treasury yield, while the same one standard deviation increase in energy-CPI innovation results in an insignificant estimate of 4.1% (t-stat=0.90). These estimates underscore the importance of core innovations in driving announcement-day asset returns.

In contrast, the full-month inflation beta shows a different pattern. Asset returns during the CPI month are more sensitive to headline-CPI innovations, mainly driven by the energy component, and less sensitive to core-CPI innovations. For instance, a one standard deviation increase in headline innovation leads to a 19.5% (t-stat=4.08) standard deviation increase in the 10-year Treasury yield during the CPI month, compared to only 10.4% (t-stat=1.72) for the same increase in core-CPI innovation. This supports the idea that non-core inflation components (like energy and food) are more observable and can be hedged using commodity instruments as investors experience inflation throughout the month. In contrast, core components (such as goods and services) are harder to observe and tend to cause larger surprises on CPI announcement days.

3.2 Cross-Sectional Stocks' Inflation Exposure

Next, we estimate individual stocks' inflation exposure to see if there are cross-firm differences in headline and core inflation exposure, and if these exposures are persistent over time. We estimate individual stocks' pre-ranking inflation beta using a rolling window, 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 exposure 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:

$$\min_{\alpha_{i,t},\beta^{\text{Ann}}_{i,t}} \sum_{\tau=1}^{t} w(\tau)(R_{i,A_\tau} - \alpha_{i,t} - \beta^{\text{Ann}}_{i,t}\text{CPI-Innov}_{A_\tau})^2, \tag{4}$$

where R_{i,A_τ} denotes firm i's return (minus the risk free rate) on the announcement day A_τ. The weight is given by $w(\tau) = \frac{\exp(-|t-\tau|/h)}{\sum_{\tau=1}^{t-1}\exp(-|t-\tau|/h)}$. Using $h = \log(2)/60$ means the half-life of the weights $w(\tau)$ converges to 60 months for large t. The choice of a 60-month half life is consistent with the standard five-year rolling window used in empirical asset pricing tests.[11]

[11] Appendix Table C6 reports the main results using a five-year rolling window to estimate inflation beta.

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

$$\min_{\alpha_{i,t},\beta_{i,t}^{\text{Full}}} \sum_{\tau=1}^{t} w(\tau)(R_{i,\tau} - \alpha_{i,t} - \beta_{i,t}^{\text{Full}}\text{CPI-Innov}_{\tau})^2, \tag{5}$$

where $R_{i,\tau}$ denotes firm i's return (minus the risk free rate) in month τ.[12]

Appendix B provides a detailed illustration of the timeline for beta estimation. On announcement day A_t, which is released in month M_{t+1} about the inflation of month M_t, we estimate β^{Ann} using announcement-day observations from announcement A_1 to announcement A_t. For β^{Full}, we use the monthly stock returns and inflation innovations from month M_1 to month M_t. 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 inflation beta quintiles.[13] 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' inflation exposure.

Table 2 reports the post-ranking announcement-day and full-month inflation betas for cross-sectional stocks, with the two size groups combined. We find that cross-sectional stocks' core-inflation betas are significantly more negative than their headline betas, consistent with Fang, Liu, and Roussanov (2021). Additionally, core CPI has a much larger impact on stock returns on announcement days compared to headline and energy components. A one

[12]Following Elton et al. (1978), Cosemans et al. (2016), and Boons et al. (2020), we further transform the estimated $\beta_{i,t}^{\text{Ann}}$ and $\beta_{i,t}^{\text{Full}}$ 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 ($\text{mean}_{CS}(\widehat{\beta_{i,t}})$).

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

standard deviation increase in core-CPI innovation negatively affects the bottom quintile of core beta-sorted stocks by -14.2 bps (t-stat=3.17) on the CPI announcement days. In contrast, the same increase in headline- and energy-CPI innovations has a positive and trivial impact of 2 bps (t-stat=0.26) and 5.2 bps (t-stat=0.68), respectively.

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, we can still observe significant dispersion in cross-sectional stocks' post-ranking core-beta when estimated using announcement days. The row labeled "Quintile 5-1" refers to an inflation portfolio constructed with a long position in the top quintile (most positive inflation beta stocks) and a short position in the bottom quintile (most negative inflation beta stocks). A one standard deviation increase in announcement-day core innovation leads to a 4.7 bps (t-stat=2.38) return increase in the core beta-sorted portfolio, while such dispersion is absent for headline and energy beta-sorted portfolios on CPI announcement days. This suggests significant cross-sectional variations in firms' core-inflation exposure, with firms showing strong sensitivity to core-CPI innovations on past announcement days continuing to respond significantly to core innovations in future announcements.

The full-month inflation betas, on the other hand, exhibit significant and persistent sensitivity to headline inflation, particularly the energy component, but not to the core component. In the version controlling for market returns, the post-ranking headline beta increases monotonically from the lowest value of -7.4 bps to the highest value of 35.9 bps for the quintile portfolios sorted based on stocks' pre-ranking full-month headline betas. The core-, headline-, and energy-inflation exposure for the top-minus-bottom portfolios sorted based on the corresponding pre-ranking betas are 5.4 (t-stat=0.45), 43.4 (t-stat=2.89), and 44.4 (t-stat=2.47), respectively, suggesting a stronger response of monthly returns to the energy component but not the core component.

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.[14]

3.3 Determinants of Inflation Beta

To better understand the cross-firm variations in inflation exposure, we next examine the determinants of a firm's inflation exposure. Specifically, how are firms' inflation betas, estimated using returns, related to their cash flow inflation betas? Furthermore, how does the cash flow distribution differ between firms with high and low inflation exposure?

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

This suggests that return-based and cash flow-based betas align well with each other. In response to positive inflation shocks, firms with more negative β^{Core} experience more significant deterioration in their quarterly cash flows. However, the two measures also have unique differences: return-based cash flow betas have the advantage of being a comprehensive measure and should better reflect the timely impact of inflation shocks on all future cash flows.

Further examining the role of other firm characteristics, we include firm market-to-book ratio (ME/BE), cash flow, dividend payout ratio, and the cash flow duration from Weber (2018) to capture the distribution of cash flows[15]. Table 3 suggests that firms with more

[14]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 remaining in the same quintile is 84% and 83% after 6 months.

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

positive β^{Core} tend to have lower growth potential, 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 β^{Core} and cash flow characteristics, the explanatory power is weak, with an R^2 of 1.6%. This suggests that, beyond the static linear relationship with cash flow characteristics, other factors might also be driving variations in core beta. Notably, when including industry fixed effects, the R^2 increases only to 4.6%, implying 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 β^{Head}, where a similar but weaker pattern emerges. Firms with more negative headline betas also exhibit longer cash flow durations, but show weaker relationships with dividend payout, growth potential, and cash flows. The weaker relationship with cash flows may be attributed to the energy component in headline inflation, which experiences stronger temporal fluctuations and has a less persistent impact on firm cash flows compared to the core component.

4 Inflation Forecasting

In this section, we provide evidence that the relative pricing between stocks with high and low inflation exposure contains fresh and non-redundant predictive information about future inflation shocks.

4.1 Predicting Inflation Innovations

We use monthly rebalanced top-minus-bottom quintile inflation portfolios from Section 3.2 to predict inflation shocks. The core-focused inflation portfolio (IP^{Core}) is constructed using the announcement-day core-beta β^{Core}, while the headline-focused inflation portfolio

(IP^{Head}) is constructed using the full-month headline beta β^{Head}. As shown in Section 3.2, stocks in the bottom-ranked portfolio, whose inflation betas are ranked the lowest, suffer the most when inflation increases. Therefore, in anticipation of heightened inflation, sophisticated investors would underprice stocks in the bottom portfolio more severely than those in the top portfolio, leading to a positive return for the inflation portfolios. In other words, a higher-than-usual return for the inflation portfolio could serve as an early warning from the equity market about an upcoming surge in inflation.

4.1.1 Event Study around Extreme CPI Months

We begin by tracking the performance of inflation portfolios around extreme CPI events to understand the timing of price discovery. According to Lo and MacKinlay (1990), large stocks have better liquidity and often lead small stocks in incorporating market-wide information, so we focus on inflation portfolios constructed using large stocks[16]. We categorize all CPI events into quintiles based on headline- and core-CPI innovations, with the top (bottom) quintile capturing the events with very positive (negative) surprises. We then plot the cumulative performance of inflation portfolios (IP^{Core} and IP^{Head}) from $t = -50$ trading days before the start of the CPI month to $t = 50$ days afterward in Figure 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.

[16]We contrast the forecastability of big stocks with small stocks in Section 6.1

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-CPI innovations, initiating 30 days before the CPI month. For instance, within the [-30,-20] day window, a one standard deviation increase in the 10-day return of 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 not only for the inflation portfolios, but also for TIPS-UST and GSCI, indicating active inflation news price discovery across various asset classes, around 30 days before the actual CPI month begins. Our findings align with Downing, Longstaff, and Rierson (2012), highlighting asset prices' forward-looking nature regarding future inflation expectations.

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 Treasury 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:

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

where Core-Innov$_{t+1}$ denotes month-$t+1$ core-CPI innovations, and X_t includes the 30-day return of 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$^{\text{Core}}$ on inflation innovations. A one standard deviation increase in the 30-day core beta inflation portfolio (IP$^{\text{Core}}$) observed at the end of month t predicts a 2.7 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$^{\text{Core}}$ 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$^{\text{Core}}$ remains strong even when controlling for market indicators from the Treasury and commodity markets. Given that TIPS are directly linked to headline inflation and commodities are key inputs for it (Gorton and Rouwenhorst (2006) and Downing, Longstaff, and Rierson (2012)), it is unsurprising that TIPS-UST and GSCI are strong predictors of headline-CPI innovations.[17] Including GSCI with IP$^{\text{Core}}$ 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$^{\text{Core}}$ remains robust both economically and statistically.

While TIPS-UST and GSCI can predict headline-CPI innovations, their ability to forecast core-CPI innovations is limited. According to the estimates in column (4), a one standard deviation increase in IP$^{\text{Core}}$ predicts a 2.5 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 can still add significant value, especially in terms of core-CPI shocks.

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

Finally, columns (5)-(6) and (11)-(12) analyze the headline-focused portfolio (IP^{Head}) for predicting inflation. The forecastability of IP^{Head} on headline inflation is similar to that of IP^{Core}. A one standard deviation increase in IP^{Head} predicts a 7.9 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 policy, the unique predictability from cross-sectional stocks is crucial.[18]

4.2 Do Economists Update Beliefs about Inflation?

Our IP^{Core} forecaster is constructed at the end of month t, while the inflation data for month-$t+1$ is typically announced in the second or third week of month $t+2$. This results in a lag of over one month between the signal formation and the CPI announcement. This scenario presents an intriguing question: Do economists update their inflation expectations based on market-based information, particularly that embedded in cross-sectional stock data? Alternatively, if economists do not fully incorporate the information from IP^{Core}, to what extent can the inflation portfolio predict the announcement-day forecasting errors made by economists?

To capture market economists' expectations for month-$t+1$ inflation growth, we utilize Bloomberg Economists' survey forecasts for headline- and core-CPI month-over-month growth.[19] 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.

[18]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 4.3.

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

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 panel shows that our core-focused inflation portfolio can predict announcement-day errors for both headline- and core-CPI, beyond what other market-based predictors can achieve. A one standard deviation increase in IP^{Core} predicts an increase of 2 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 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 Time-Varying Predictability

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

The Episode of 2021 – In 2021, the global economy saw a significant surge in inflation, driven by supply chain disruptions from COVID-19, increased demand from fiscal and monetary stimulus, and rising energy prices. After surpassing the 2% Fed target in April 2021, core CPI continuously increased, reaching a 40-year high of 6.6% year-over-year growth by September 2022. Despite this, the Fed maintained its zero interest-rate policy throughout 2021, only beginning to tighten in mid-2022. Economists also underestimated the severity of inflation. The upper graph of Figure 2 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 ($\mathrm{IP}^{\mathrm{Core}}$) appeared to correctly anticipate the inflation surge during this period. The lower graph of Figure 2 plots the 30-day $\mathrm{IP}^{\mathrm{Core}}$ return (red line), observed by the end of month $t-1$, together with the month-t core CPI (blue bars). We observe a tremendous increase in $\mathrm{IP}^{\mathrm{Core}}$ just before the rapid surge of core CPI in April 2021. The magnitude of $\mathrm{IP}^{\mathrm{Core}}$ observed at the end of March 2021 is 3.59 times of its sample standard deviation. Meanwhile, $\mathrm{IP}^{\mathrm{Core}}$ 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 3 further demonstrates the capability of $\mathrm{IP}^{\mathrm{Core}}$ in predicting core-CPI innovations during this crucial period. A 10% increase in the 30-day $\mathrm{IP}^{\mathrm{Core}}$ 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, $\mathrm{IP}^{\mathrm{Core}}$ 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 3 shows that TIPS-UST fails to predict core-CPI innovations and even exhibits a negative correlation. Panel A of Table 7 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.[20] Importantly, the coefficient estimates of IP^{Core} on core-CPI innovation and survey-based forecasting error are more than three times larger than the full-sample estimates, highlighting the importance of 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 end of 1973, inflation had escalated to 8.6%, significantly exceeding the average inflation rate of 2.5% observed between 1947 and 1972. This surge was driven by stimulative fiscal policies under Nixon's presidency, excessive government spending for the Vietnam War, and the Arab oil shock. Both periods experienced highly accommodative monetary policies leading up to their respective inflationary episodes. In 1973, inflation persisted at elevated levels until Paul Volcker's appointment as Chair of the Federal Reserve in 1979, when he initiated a stringent monetary tightening campaign.

Similar to the 2021 scenario, economists and policymakers in the early 1970s severely underestimated the rate of inflation. However, the core-focused inflation portfolio demonstrated exceptional power in forecasting inflation during the 1973 episode. 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 3 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 IP^{Core}, mirroring the results observed in the 2021 episode. Columns (5) and

[20]The coefficient estimates in Figure 3 and Table 7 differ because the independent variables are in units of return in Figure 3 and are standardized in Table 7.

(6) of Table 7 further report the predictability of bond and commodity-based forecasters together with $\mathrm{IP}^{\mathrm{Core}}$.[21] Among all these forecasters, $\mathrm{IP}^{\mathrm{Core}}$ is again the only significant variable that predicts core-CPI innovations during the Great Inflation episode.

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

We use two proxies to capture the time-varying nature of inflation uncertainty: (a) |CPI Innovation|, the absolute value of CPI innovation in the last month; (b) CPI disagreement, the difference between the 75th percentile and 25th percentile of quarterly CPI forecasts from the Survey of Professional Forecasters (SPF) database.[22] Panel B of Table 7 reports the predictability of $\mathrm{IP}^{\mathrm{Core}}$ on core-CPI innovations and the forecasting errors (survey-based surprises) for subsamples defined using the median cutoffs of the two proxies.

The forecasting power of $\mathrm{IP}^{\mathrm{Core}}$ is much stronger when the last-month |CPI Innovation| and the CPI disagreement are above the median cutoff. For example, a one standard deviation increase in $\mathrm{IP}^{\mathrm{Core}}$ predicts a 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.[23] Overall, the evidence suggests that $\mathrm{IP}^{\mathrm{Core}}$ can provide valuable information about future inflation expectations when the market most needs it.

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

[21] 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.

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

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

inflation preemptively, inflation can be effectively contained, reducing the predictability of market-based forecasters. For instance, during the 1989-1991 inflation period, driven by the first Gulf War and rising oil prices, annual CPI rose to 5% in May 1989 but was controlled to below 3% by October 1991. The Effective 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 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).[24] Panel B of Table 7 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 $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$ is 2.2 bps (t-stat=2.78) with an R-squared of 1.5%.

As a graphical illustration, Figure 4 plots the time-series predictive power of $\mathrm{IP}^{\mathrm{Core}}$. For each time t, we estimate equation (7) using a rolling five-year window from $t - 59$ to t and plot the coefficient estimate γ^{IP} on the left axis.[25] On the right axis, the upper and lower graphs plot the volatility of inflation shocks and the extent to which the Fed is behind the curve, respectively. We observe a strong comovment between the γ^{IP} estimate and the importance of inflation risk at the time. γ^{IP} peaks during significant core inflationary episodes in 1973–82 and 2021–2022. Zooming into these periods, the predictive power is

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

[25]Appendix Figure C2 plots the regression R-squared.

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

4.4 Out-of-Sample Forecastability

Section 4.1 to 4.3 presents in-sample evidence that the core-focused inflation portfolio has strong predictive power for future inflation shocks, particularly the core component. To better reflect real-time information available to market participants, we follow the methodologies of Ang, Bekaert, and Wei (2007) and Faust and Wright (2013), examining the out-of-sample forecasting power of 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 concerns 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 actual inflation growth minus the forecasted growth. Out-of-sample accuracy is measured by relative RMSE, which is the ratio of the root-mean-square forecasting error (RMSE) for a particular model relative to that of the benchmark model. We use an ARMA(1,1) time-series model as our benchmark. Additional forecasting signals such as 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 8 shows the relative RMSE for various forecasting models. IP^{Core} improves the forecasting accuracy of month-$t+1$ core and headline CPI by 4.2% (p-value=0.07) and 6.1% (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 fourth for headline CPI, after GSCI, TIPS-UST and IP^{Head}. Consistent with the in-sample evidence, GSCI has the highest forecasting power for headline CPI, with an RMSE improvement of 14.2%. Interestingly, while TIPS-UST, designed to track inflation expectations, improves forecasting accuracy by 7%, the improvement is not statistically significant (p-value=0.11). Besides, we find limited out-of-sample evidence that aggregate stock market and nominal bond yields can forecast upcoming inflation growth.

In addition to these market-based indicators, we include economists' inflation forecasts from the Survey of Professional Forecasters (SPF) database, and Surveys of Consumers by the University of Michigan. 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[26]. Table 8 indicates that economists' preliminary forecasts at month t can only improve the time-series model by only 1.7%. Motivated by the Phillips curve economic model (e.g., Stock and Watson (1999)), we also include real GDP growth, output gap, unemployment rate, labor income share, and CFNAI as proxies for economic activity in the forecasting model. Consistent with Ang, Bekaert, and Wei (2007), real activity measures do not add value.

Finally, Panel B of Table 8 reports the out-of-sample performance of IP^{Core} for subsamples when inflation is particularly significant to the economy. Consistent with Section 4.3, the forecasting power of IP^{Core} is stronger during periods when inflation plays a critical role. The out-of-sample predictability for core and headline CPI improves by 8.2% and 11.4%, 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 4.6% to 6.3% for core CPI and from 6.3% to 7.3% for headline CPI. Overall, IP^{Core} provides unique information about inflation both in-sample and out-of-sample, particularly during heightened inflation periods.

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

5 Mechanism

This section examines the mechanism and provides supporting evidence for the active price discovery of cash flow news.

5.1 The Cash Flow Channel

Based on simple valuation models like the Gordon Growth Formula, inflation can impact firm valuation through two primary channels: cash flow and discount rate.[27] On one hand, cross-firm variations in inflation exposure could be driven by the differential impact of inflation on firm cash flows. Upon heightened inflation, if a firm can pass on higher input costs to consumers, its cash flows might remain resilient. However, if consumers' purchasing power diminishes significantly, leading to a reduction in demand, the firm may experience deterioration in cash flows. 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 inflation exposure for different firms. On the other hand, cross-firm variations could also be driven by changes in the discount rate. Higher inflation typically prompts central banks to raise interest rates and could also heighten the default risk for firms.

To test these two channels, we first examine the impact of rising inflation expectations on firms' fundamentals. If the cash flow channel dominates, an increase in IP^{Core}, which signals heightened inflation expectations, should adversely affect firm cash flows more for firms with negative β^{Core} compared to those with more positive β^{Core}. Table 9 reports the relation between quarter-t β^{Core} and the quarter-$t+1$ firm fundamentals, captured by sales growth, cash flow, and IBES long-term growth forecast. The variable of interest is the interaction between the quintile rank of inflation beta $\beta^{\text{Core}}_{Rank}$ and IP^{Core}, as it captures the additional effect of heightened inflation expectations (an increase in IP^{Core}) on firm fundamentals for the more positive β^{Core} firms compared to the more negative ones. We control for other firm characteristics including size, lagged values of the dependent variables, asset growth, market-to-book, and dividend payout as indicated. Firm and time fixed effects are included in all specifications.

[27] 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 g.

Across all the specifications, inflation adversely affects sales growth, cash flow, and IBES long-term growth forecast more for firms with more negative β^{Core}. Focusing on sales growth in the first two columns, the coefficients of the interaction term are significantly positive. A 10% increase in IP^{Core} leads to around a 8% 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 similar magnitude of IP^{Core} on cash flows: A 10% increase in IP^{Core} at the end of quarter t predicts a 8.3% standard deviation decrease in quarter-$t+1$ cash flow.[28] A similar pattern is observed for the IBES long term growth forecast of EPS, indicating that analysts also update their beliefs about firm growth correspondingly.

Figure 5 offers a more intuitive graphical illustration. At the beginning of each quarter t, we sort all stocks into quintile groups based on their core beta (β^{Core}) and compute the equal-weighted average quarter-t cash flow for stocks in each quintile group. The upper graph plots the cash flow difference between the top and bottom quintiles, alongside the IP^{Core} return in quarter t. We observe a comovement between the return and cash flow of IP^{Core}, indicating that firms with higher β^{Core} (those less negatively impacted by inflation) tend to have relatively better cash flows during periods of rising inflation expectations. The lower graph zooms in on the cash flow distribution during the recent inflation run-up episode from 2019 Q1 to 2023 Q4. Accompanied by the warning signal sent by our IP^{Core} in the first quarter of 2021, firms with more positive β^{Core} experienced relatively more positive cash flows from 2021 Q2 to 2022 Q4. As inflation started to decline after 2022, the cash flow difference between high and low-β^{Core} firms returned to their normal levels. Overall, these visualizations highlight the significant impact of inflation expectations on firm cash flows.

5.2 Inflation Risk Premium

Inflation could affect firm valuations not only through the cash flow channel, but also potentially through the differential impact of inflation on the discount rate. If the predictability of IP^{Core} is driven by time-varying inflation risk premium, we would expect firms with higher β^{Core} to face lower required rates of return in the context of elevated inflation expectations.

[28]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.

However, we find very limited evidence. Following the same regression framework, the last two columns of Table 9 report the impact of IP^{Core} on firm returns. The coefficients of the interaction term are insignificant, indicating a lack of return dispersion between stocks with high and low β^{Core}.

Furthermore, Table 10 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.[29] As shown in Panel A, over the full sample, there is no monotonic pattern in returns for β^{Core} sorted portfolios. The return dispersion of the top and bottom portfolios (IP^{Core}) is 1.4% (t-stat=1.21). The subsample analysis yields similar results: both in the pre-2002 and post-2002 subsamples, the return difference between the top and bottom portfolios is positive and insignificant. However, for the β^{Head} sorted portfolios, as reported in Panel B, we observe a different pattern. Annualized returns for β^{Head} sorted portfolios decrease from 10.1% for the bottom quintile to 7.7% for the top quintile, resulting in a top-minus-bottom return difference of -2.4% (t=-1.69) for excess return and -3.1% (t=-2.12) for CAPM alpha. In sum, β^{Head} and β^{Core} contain uniquely different information, with β^{Head} better capturing the risk premium and β^{Core} better capturing the inflation shocks.

To further explore whether the insignificant return dispersion is driven by the 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, holding from month $t+1$ to $t+k$ (K has a value of one, three, and twelve) on month-t NRC using the following regression specification:

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

The intercept measures the unconditional inflation risk premium, and β^{NRC} measures the increase in annualized portfolio return resulting from a one standard deviation increase in NRC. Focusing on the β^{Head} sorted portfolios in Panel B of Appendix Table C2, we find consistent evidence as in Boons et al. (2020) that IP^{Head} strongly comoves with the nominal-real covariance, reflecting a compensation for inflation risk. In contrast, as shown in Panel

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

A, for β^{Core} sorted portfolios, the effect of NRC is insignificant and the sign is even negative, indicating that variations in IP^{Core} and hence the predictability of IP^{Core} on inflation shocks are not driven by the time-varying inflation risk premium.

6 Other Discussions and Robustness Tests

6.1 Firm Information Environment

Our hypothesis is based on the assumption that sophisticated market participants can understand and incorporate the impact of inflation shocks into firms' pricing. However, not all firms are alike. If investors have limited capacity, expectations about inflation may not be promptly reflected in stock prices. In such cases, the predictability of IP^{Core} should be stronger among firms with a more opaque information environment, which we capture by analyst coverage.

Additionally, we examine the informativeness of stock prices conditional on the degrees of limit to arbitrage. Pricing efficiency relies on sophisticated investors, such as arbitrageurs, to incorporate information in a timely manner and bring stock prices to their intrinsic value. Therefore, we expect that the predictability of inflation portfolios will be more pronounced among firms subject to fewer limits to arbitrage, as proxied by firm size and institutional ownership. Since analyst coverage and institutional ownership are strongly correlated with firm size, we further orthogonalize these variables with respect to firm size and use the residual values for sorting (Hong 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)[30]. We then sort stocks within each category by their β^{Core} into quintiles. Table 11 reports the informativeness of the top-minus-bottom quintile IP^{Core} portfolios constructed within each group. While IP^{Core} (X$\leq$Median), constructed based on the stocks with below-median information environments, is sometimes significant in predicting the core-CPI shocks, their predictive power is fully absorbed by IP^{Core} (X>Median) when in-

[30]The two size groups are defined by the median cutoff of NYSE market capitalization. Stocks with size > Median are the large stocks that we focus on in the baseline results.

cluded together in columns (3), (6), and (9). This evidence is consistent with our hypothesis and indicates a stronger active price discovery among larger firms with higher institutional ownership and analyst coverage.

6.2 Predicting Inflation-Linked Asset Returns

Given that $\mathrm{IP}^{\mathrm{Core}}$ effectively predicts both inflation innovations and economists' forecasting errors, it is worthwhile to examine whether $\mathrm{IP}^{\mathrm{Core}}$ can also predict interest rate changes, especially the 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 $\mathrm{IP}^{\mathrm{Core}}$ can predict the inflation component, it may also predict nominal yield changes, provided the real component does not perfectly offset the inflation change. This predictability of inflation-linked assets could help investors hedge against or speculate on inflation risk.

Table 12 reports the predictability of $\mathrm{IP}^{\mathrm{Core}}$, observed at the end of month t, on the change in inflation swap rates (Panel A) and the change in nominal yields (Panel B) from the end of month t to the announcement day when the actual inflation of month $t+1$ is publicly released. For ease of interpretation, $\mathrm{IP}^{\mathrm{Core}}$ is standardized with a mean of zero and a standard deviation of one. A one standard deviation increase in $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$ can capture information not yet incorporated by inflation-linked assets. A strategy formed based on the $\mathrm{IP}^{\mathrm{Core}}$ signal observed at the end of month t can predict inflation-linked asset returns going forward.

6.3 Industry vs. Stock-Specific Information:

In our study, we uncover substantial cross-firm variations in inflation betas. Yet, it is unclear whether such variations are primarily driven by industry-specific or firm-specific inflation exposure. To better understand the industry inflation exposure and to differentiate firms' inflation exposure from their industry counterparts, we construct inflation betas for the Fama and French 48 Industries, similarly to the way we construct individual stock inflation betas. Panel A of Appendix Table C3 presents the top 10 and bottom 10 industries that are most and least sensitive to announcement-day core-CPI innovations and full-month headline-CPI innovations, respectively. Consistent with the findings of Boudoukh, Richardson, and Whitelaw (1994) and Ang, Brière, and Signori (2012), we observe significant variations in inflation exposure 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.

The distribution of announcement-day core-based inflation betas is less documented in the literature. The core beta ranking reveals that β^{Core} captures distinct information compared to β^{Head}. For instance, the 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 exposure, we further investigate whether the predictive power of our stock-based inflation portfolios is subsumed when we control for industry-based inflation portfolios. Panel B of Table C3 examines the forecastability of industry-constructed inflation portfolios. The 30-day cumulative returns for these portfolios, denoted as $\text{IP}^{\text{Core}}_{\text{Ind}}$ and $\text{IP}^{\text{Head}}_{\text{Ind}}$, are constructed by taking long positions in top-quintile inflation beta industries and short positions in the bottom-quintile. $\text{IP}^{\text{Core}}_{\text{Ind}}$ exhibits weak predictability for core-CPI innovations, with an R-squared of just 0.3%. When we use both $\text{IP}^{\text{Core}}_{\text{Ind}}$ and IP^{Core} to predict core-CPI innovations, the information content of industry portfolios is 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 that there exists active price discovery of inflation news among cross-sectional stocks.

6.4 Alternative Measures of IP and Robustness Tests

The information content of IP^{Core} is robust across alternative construction methods, different model specifications, and when used to forecast quarterly inflation growth.

Forecasting CPI Growth – In our primary analysis, we focus on predicting one-month ahead CPI shocks. Our findings remain robust when using IP^{Core} to predict CPI growth and when extending to longer horizons. Appendix Table C4 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.

Risk Factors and Portfolio Alpha – Panel A of Appendix Table C5 presents the beta loadings of the inflation portfolios on the Fama-French five factors. In line with the results from Table 3, IP^{Core} exhibits a positive loading on HML, although the t-stat is only marginally significant. Panel B additionally reports the predictability of the Fama-French five-factor adjusted inflation portfolio alphas in response to inflation shocks. The findings are robust and exhibit similar economic magnitudes.

Rolling Five-Year Window – In our baseline specification, following the methodology in Boons et al. (2020), we estimate individual stocks' inflation betas using all historical observations with WLS and Vasicek adjustments. Appendix Table C6 further presents results based on inflation betas constructed using a simple five-year rolling window approach (Fama and French (1993)). Consistent with Table 2, there is a significant post-ranking 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 4.6 bps (t-stat=2.49), and the full-month headline-CPI exposure of the inflation portfolio is 42.3 bps (t-stat=2.96). Using the rolling five-year window estimated β^{Core} to form inflation portfolios and to predict inflation shocks yields similar results, both in terms of predicting CPI innovations and economists' forecasting errors.

Ann-Day Surprise Estimated Beta – In our baseline specification, we estimate inflation exposure by the sensitivity of asset returns to CPI innovations. However, it is possible that a large portion of the 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 and 5-year Inflation Swap Rates, and changes in 2-year and 5-year UST yields. Appendix Table C7 reports the baseline results on inflation exposure and inflation forecasting using these five alternative measures of announcement-day surprise. The post-ranking announcement-day inflation betas are significantly positive for the top-minus-bottom portfolio constructed based on the corresponding pre-ranking betas. In terms of inflation forecasting, consistent with our baseline results, all five inflation portfolios can significantly predict core-CPI innovations and headline-CPI innovations.

7 Conclusions

Motivated by the 2021 inflation surge and the collective failure of policy makers and economists in forecasting its severity, we explore the price discovery of inflation news among cross-sectional stocks. To understand the cross-firm variations in inflation exposure, 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. We show that both the headline- and core-beta effectively capture individual stocks' inflation exposure, but their content varies. The headline beta captures more of the cross-firm variations headline exposure and variations in inflation risk premium, while the announcement-based core beta can better unravel core-inflation shocks.

Examining the relative pricing between stocks with high and low inflation exposure, we find that active price discovery on inflation does take place in cross-sectional stocks. Beyond 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. Consistent with the hypothesis that inflation affects firm pricing through cash flows, we show that firms with more negative inflation betas experience a deterioration in cash flow upon receiving a positive inflation shock.

Given the weak contemporaneous correlation between stocks and inflation documented by Fama and Schwert (1977), the common belief is that the stock market is not an active place for price discovery with respect to inflation. The strong predictability documented in our paper suggests that much can be gained from the cross-section. Key to our predictability is the cross-sectional approach, in which the relative pricing between stocks with high and low inflation exposure allows us to shift away from the overall equity-market trends and zero in on inflation expectations. Relative to the Treasury and commodity markets, whose price movements have been widely used to forecast inflation, our results show that the information contained in cross-sectional stocks can add value, especially for the core component.

Focusing on economists' forecasting errors, we find that they do not incorporate the information contained in the inflation portfolio, and their room for improvement is especially large during the 2021 episode. During the critical months of the 2021 inflation run-up, economists missed the April 2021 core-CPI reading by 60 bps. However, our inflation portfolio had already signaled a 3.59-sigma alert beforehand. By incorporating the equity market information into their information set, economists could enhance the predictive R-squared by around 9% during the 2021 inflation episode. Additionally, regarding policymakers, we find stronger predictability of our inflation portfolio 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.

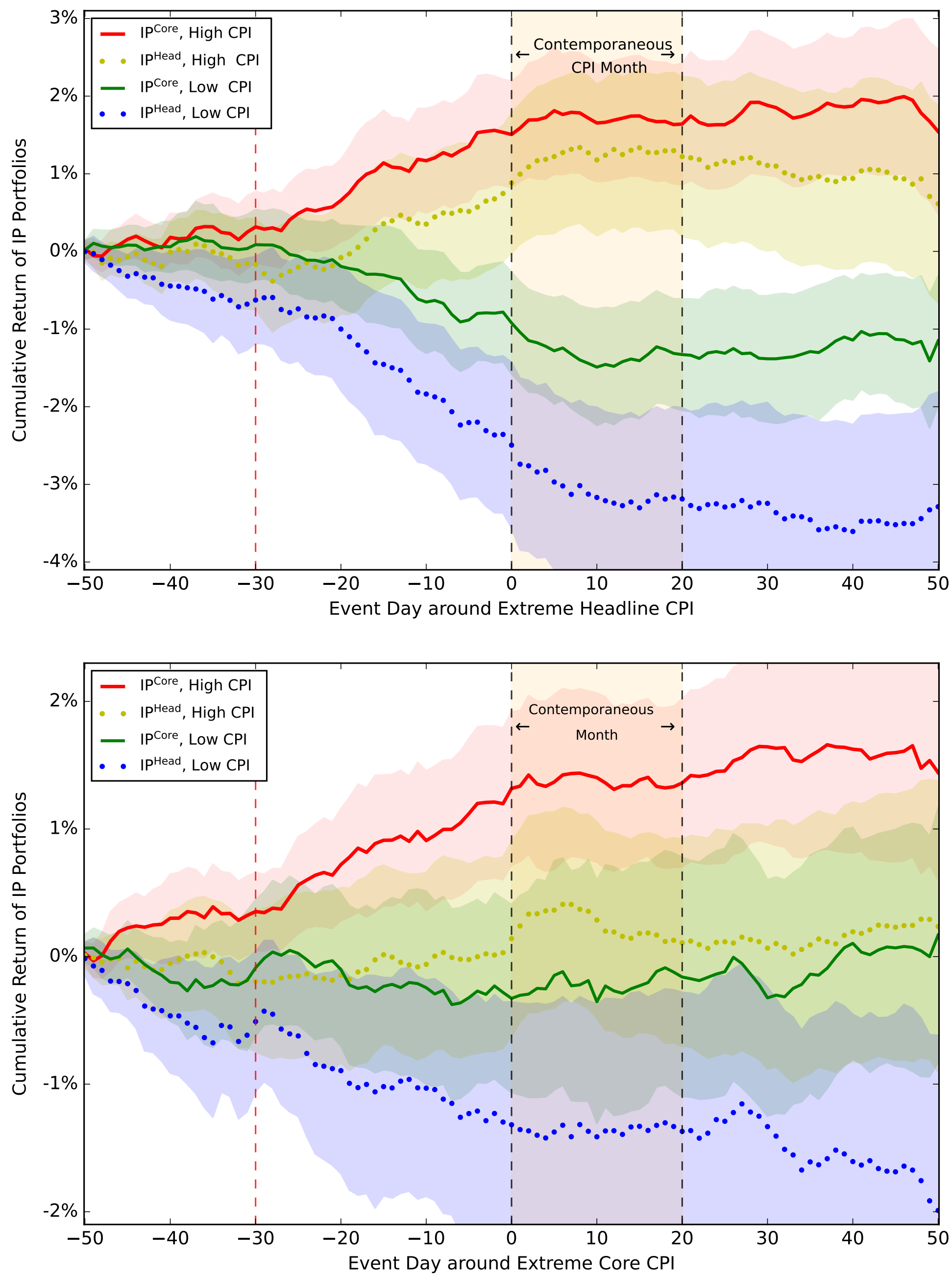


Figure 2. Economists' Forecasts and IP^{Core} in the 2021 Episode

The upper graph plots the month-over-month core-CPI growth for the period from October 2020 to September 2022. The solid red line denotes the median forecast value of core-CPI (MoM) 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.

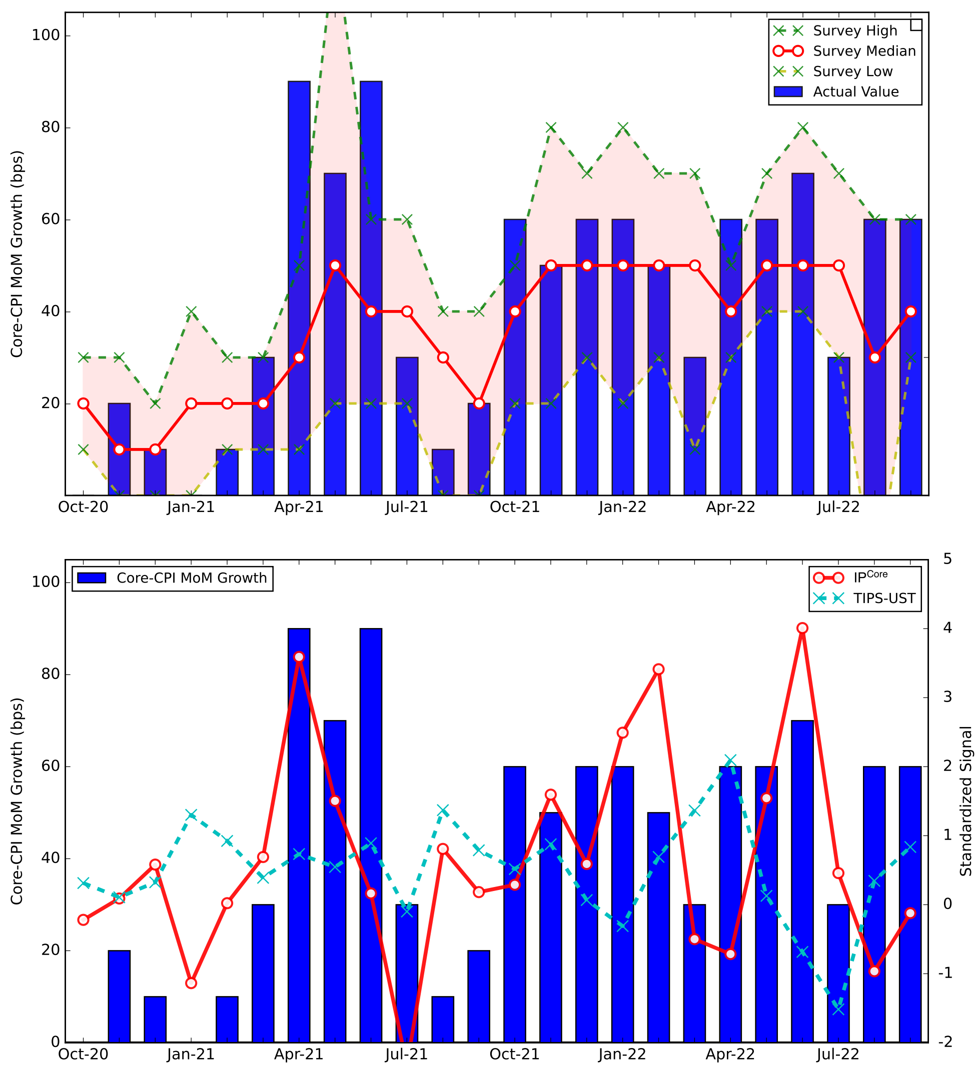


Figure 3. Predictability During Heightened Inflation Periods

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 U.S. Treasury yield as a substitute.

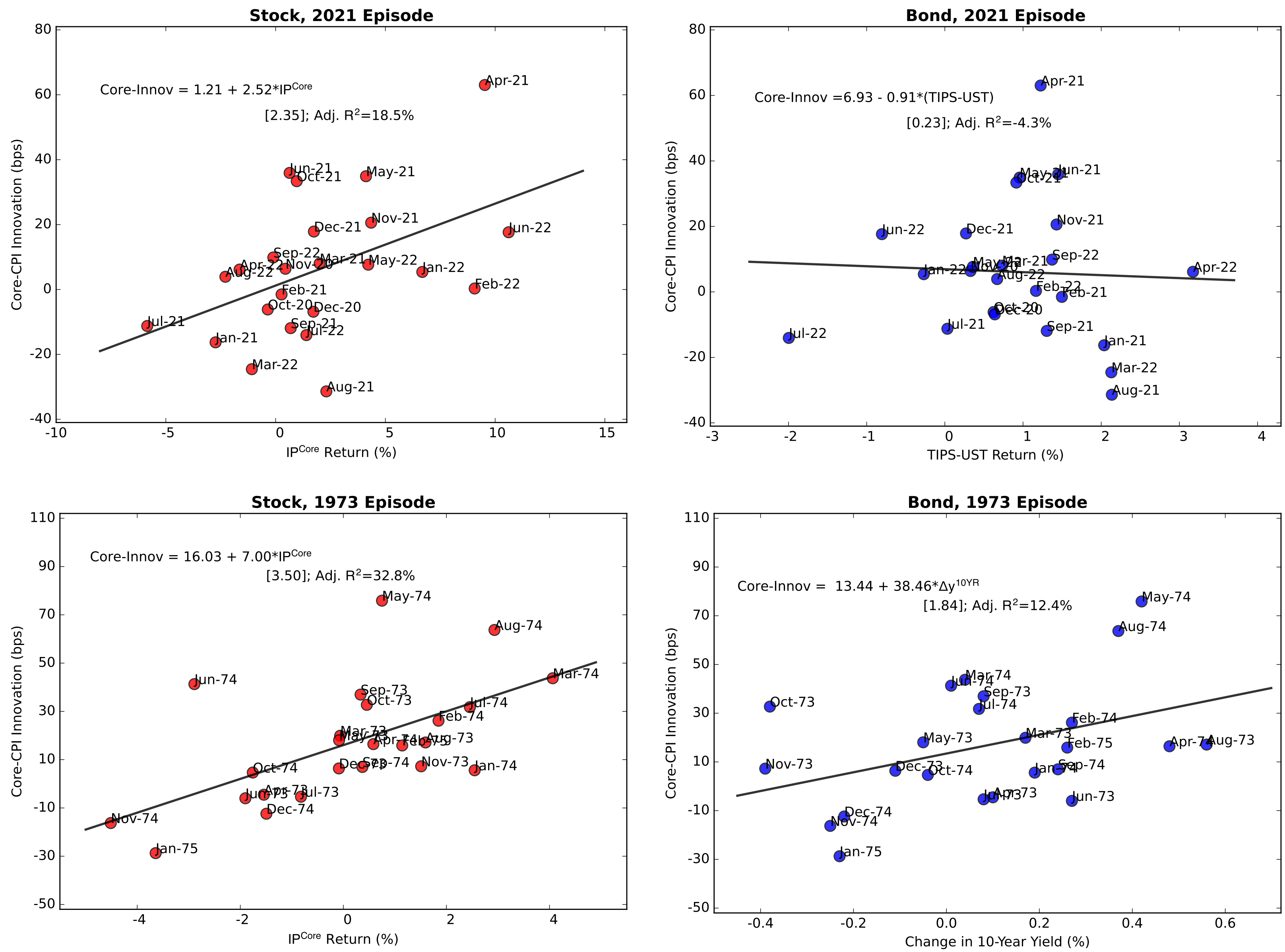
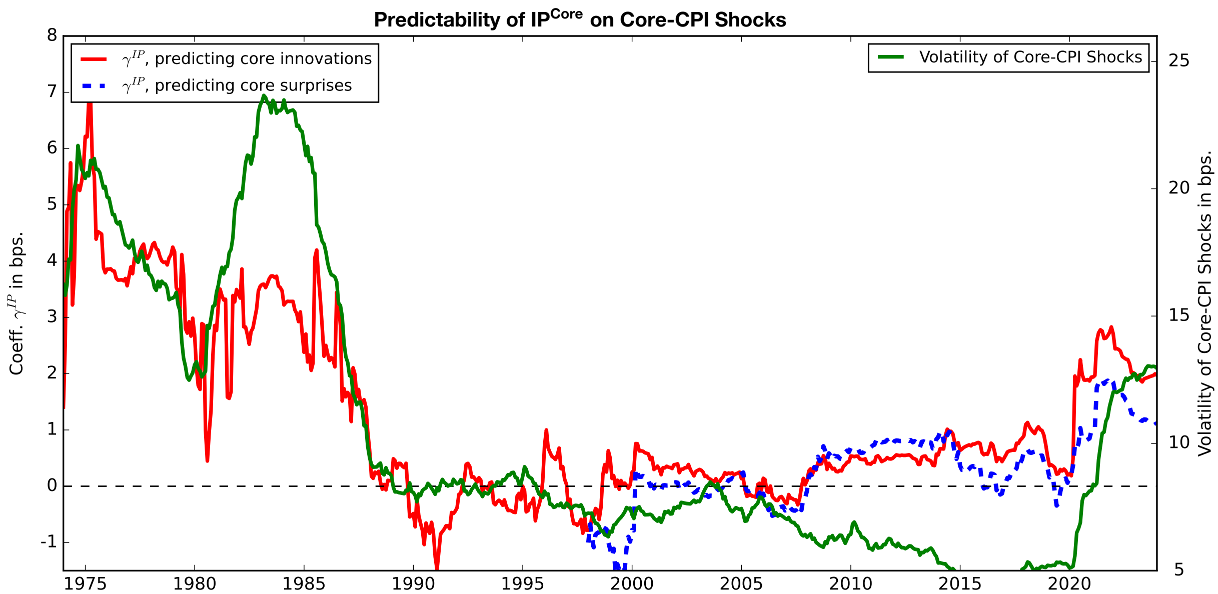


Figure 4. Predicting CPI Shocks using IP^{Core}

The graphs display the predictive coefficients, γ^{IP}, estimated using a rolling five-year window for core-CPI shocks. For each time t, we estimate the model: CPI Shock$_{t+1} = \alpha + \gamma^{IP} \times IP_t^{Core} + \epsilon_{t+1}$, using observations from $t-59$ to t. We require at least 24 months of observations. The sample period spans from December 1973 to December 2023. The red solid line shows the γ^{IP} with shocks measured by CPI innovations, while the blue dotted line represents CPI shocks measured by Bloomberg economist forecasting errors. In the upper graph, the right axis plots the volatility of core shocks, measured by the average absolute value of core-CPI innovations in the corresponding rolling five-year window. In the lower graph, the right axis plots the extent to which the Fed is behind the curve, calculated as the fed fund rate implied by the Taylor rule minus the actual fed fund rate.



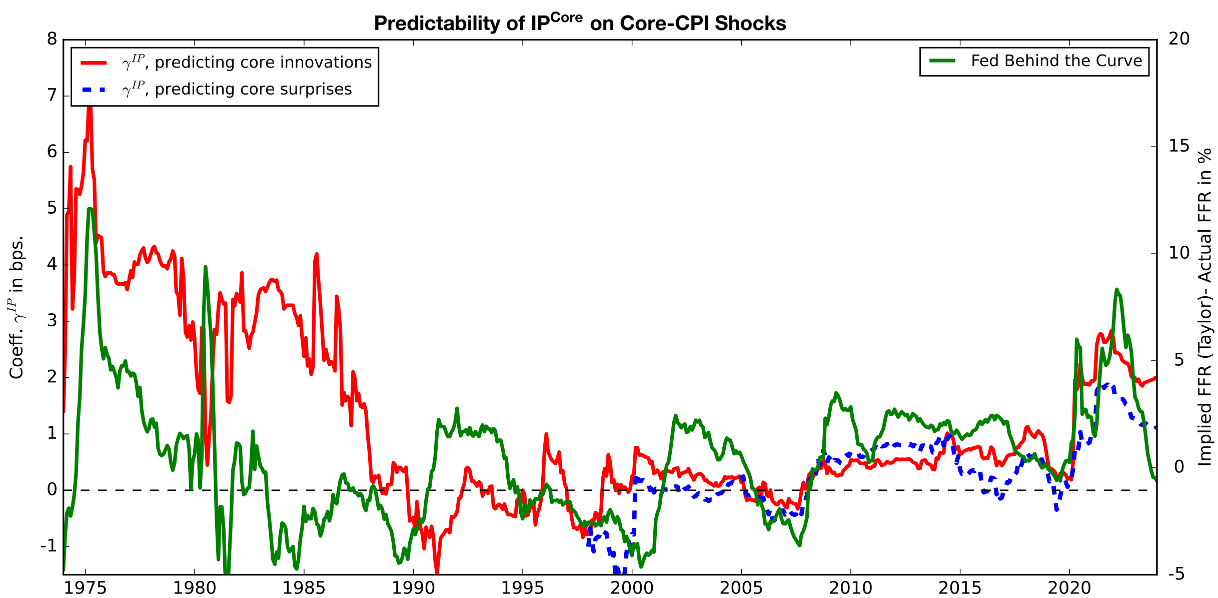
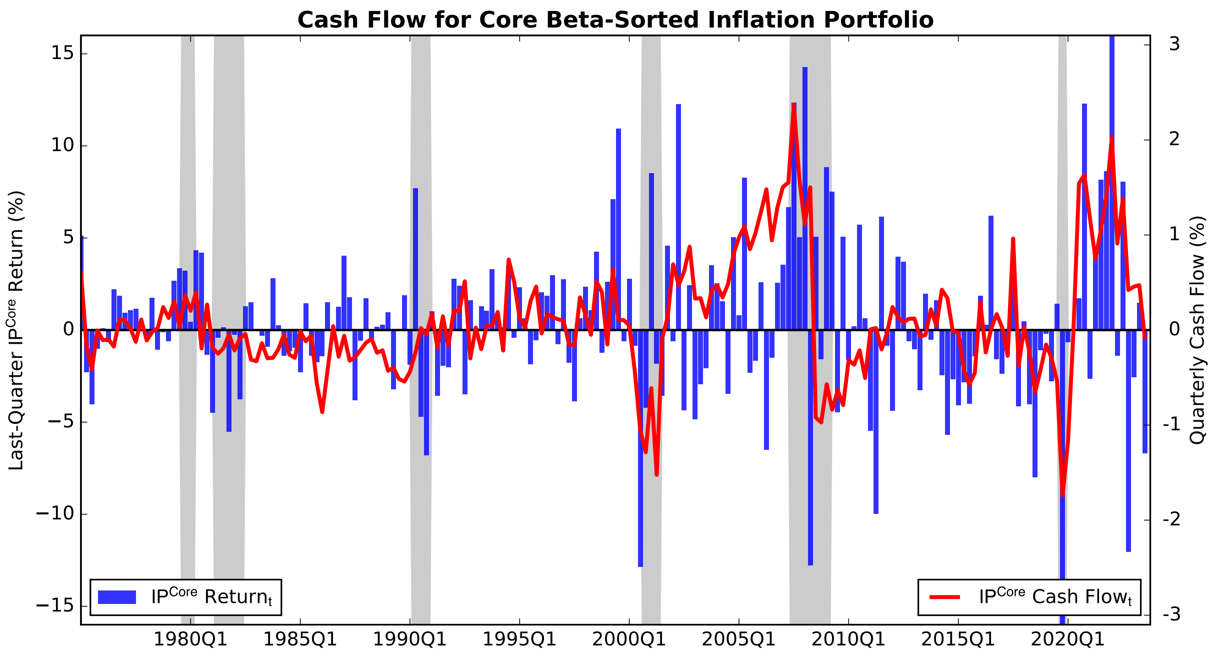


Figure 5. Core Beta and Firm Future Cash Flows

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



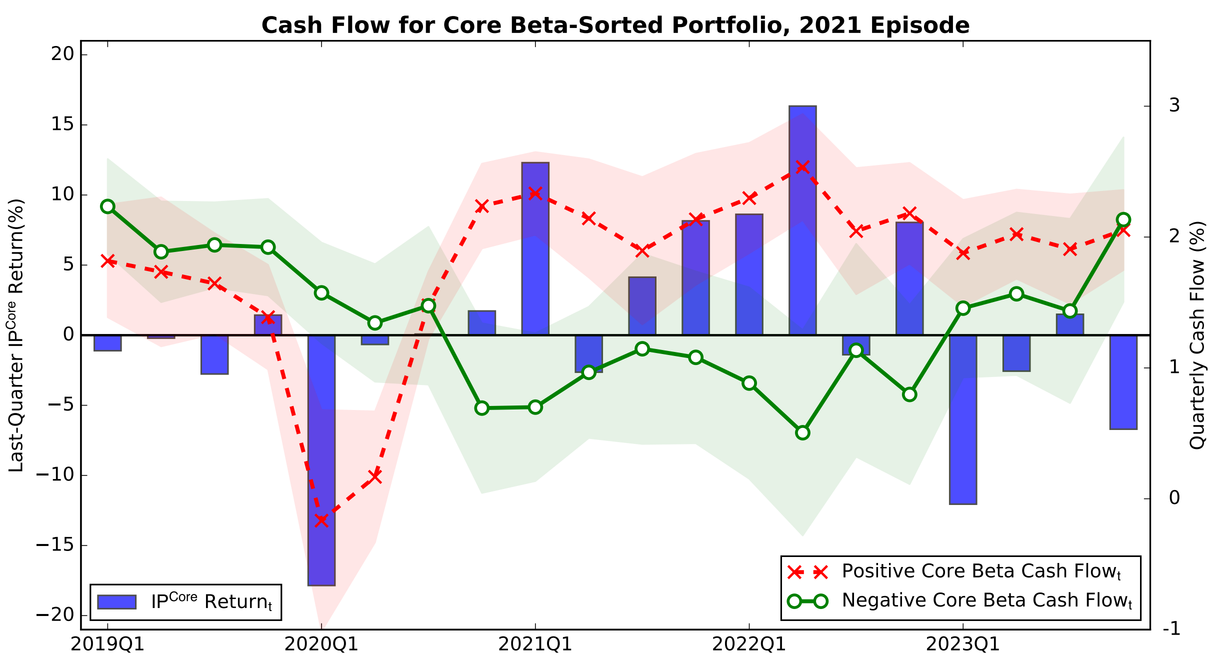


Table 1. Assets' Inflation Beta: Ann-Day vs. Full-Month

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 exposure for different assets, including aggregate stock market return (VWRETD), change in 2-Year US Treasury yield ($\Delta y^{2\mathrm{YR}}$), change in 10-Year US Treasury yield ($\Delta y^{10\mathrm{YR}}$), minus value of Bloomberg U.S. Treasury Total Return Index (-UST), 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)
$\Delta y^{2\mathrm{YR}}$	0.120	0.037	0.019	0.120	0.140	0.068
	(2.14)	(0.83)	(0.51)	(1.67)	(3.44)	(2.11)
$\Delta y^{10\mathrm{YR}}$	0.122	0.061	0.041	0.104	0.195	0.146
	(2.40)	(1.09)	(0.90)	(1.72)	(4.08)	(3.58)
-UST	0.156	0.090	−0.080	0.034	0.238	−0.221
	(2.97)	(1.18)	(−1.23)	(0.61)	(3.50)	(−3.20)
TIPS-UST	0.224	0.250	0.122	0.052	0.306	0.263
	(4.09)	(2.58)	(1.57)	(0.70)	(2.87)	(2.73)
GSCI	0.060	−0.010	−0.045	0.035	0.218	0.284
	(1.84)	(−0.20)	(−0.89)	(0.74)	(4.12)	(6.05)

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

Panel A. Post-Ranking Inflation Beta, Raw Model

	Announcement-Day (β^{Ann})			Full-Month (β^{Full})		
	Core	*Headline*	*Energy*	*Core*	*Headline*	*Energy*
Q1 (Low)	−14.23	2.02	5.15	−68.42	−38.51	22.57
	(−3.17)	(0.26)	(0.68)	(−2.61)	(−1.03)	(0.66)
Q2	−10.42	2.93	5.28	−63.82	−32.00	23.11
	(−2.50)	(0.34)	(0.63)	(−2.61)	(−0.99)	(0.80)
Q3	−9.48	1.98	5.91	−59.94	−24.47	25.65
	(−2.27)	(0.22)	(0.62)	(−2.58)	(−0.82)	(0.88)
Q4	−7.53	0.40	4.44	−63.77	−18.71	29.42
	(−1.70)	(0.04)	(0.44)	(−2.64)	(−0.65)	(0.99)
Q5 (High)	−9.74	0.55	2.77	−62.98	5.52	62.50
	(−2.09)	(0.05)	(0.24)	(−2.42)	(0.16)	(1.65)
Q5 − Q1	4.49	−1.48	−2.38	5.44	44.03	39.92
	(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*
Q1 (Low)	−2.20	−0.59	−0.61	−10.70	−7.45	−6.79
	(−1.20)	(−0.28)	(−0.31)	(−0.85)	(−0.61)	(−0.51)
Q2	0.52	2.07	−0.14	−12.46	−5.80	−1.96
	(0.29)	(1.10)	(−0.09)	(−1.39)	(−0.67)	(−0.21)
Q3	1.15	0.93	1.37	−14.32	3.33	−0.56
	(0.62)	(0.46)	(0.62)	(−1.71)	(0.39)	(−0.06)
Q4	2.79	1.85	−0.35	−11.71	7.54	5.92
	(1.31)	(0.84)	(−0.18)	(−1.27)	(0.77)	(0.56)
Q5 (High)	2.53	1.09	−1.58	−5.27	35.92	37.64
	(1.08)	(0.36)	(−0.69)	(−0.47)	(2.65)	(2.37)
Q5 − Q1	4.73	1.68	−0.96	5.43	43.37	44.43
	(2.38)	(0.55)	(−0.37)	(0.45)	(2.89)	(2.47)

Table 3. Determinants of Inflation Beta

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

	Core Beta (β^{Core})						Headline Beta (β^{Head})					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Size)	0.024	0.030	0.028	0.022	0.025	0.018	−0.017	−0.019	−0.017	−0.005	−0.002	−0.016
	(1.41)	(1.75)	(1.61)	(1.27)	(1.43)	(1.05)	(−0.86)	(−0.96)	(−0.87)	(−0.24)	(−0.09)	(−0.92)
CF Beta	0.028	0.028	0.029	0.027	0.029	0.027	0.033	0.034	0.034	0.029	0.029	0.015
	(2.41)	(2.39)	(2.41)	(2.14)	(2.26)	(2.09)	(3.18)	(3.35)	(3.38)	(2.45)	(2.44)	(1.30)
ME/BE		−0.047	−0.051	−0.044	−0.030	−0.007		−0.002	0.001	−0.026	−0.013	0.014
		(−2.78)	(−3.03)	(−2.72)	(−1.92)	(−0.44)		(−0.13)	(0.10)	(−1.90)	(−0.97)	(1.01)
Cash Flow			0.030	0.043	0.051	0.030			−0.019	0.030	0.038	−0.006
			(2.02)	(2.78)	(3.30)	(2.17)			(−1.73)	(2.14)	(2.75)	(−0.44)
Dividend Payout				0.016	0.015	0.006				0.010	0.009	−0.009
				(2.00)	(1.77)	(0.73)				(1.02)	(0.90)	(−1.04)
CF Duration					−0.041	−0.043					−0.04	−0.053
					(−2.49)	(−2.68)					(−2.28)	(−3.25)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	N	Y	N	N	N	N	N	Y
Observations	159,622	155,456	155,354	143,124	141,872	140,154	159,622	155,456	155,354	143,124	141,872	140,154
Adj. R^2	1.2%	1.4%	1.5%	1.6%	1.6%	4.6%	2.5%	2.5%	2.5%	2.5%	2.5%	8.7%

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$_{t+1}$				Headline-CPI Innovation$_{t+1}$			
	X=IP^{Core}	X=IP^{Head}	X=GSCI	X=TIPS-UST	X=IP^{Core}	X=IP^{Head}	X=GSCI	X=TIPS-UST
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X[-10,-1]	0.979	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]	−0.160	0.137	0.340	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. R^2	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 ($\mathrm{IP}^{\mathrm{Core}}$)

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). $\mathrm{IP}^{\mathrm{Core}}$ 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. $\mathrm{IP}^{\mathrm{Head}}$ 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$_{t+1}$						Headline-CPI Innovation$_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\mathrm{IP}^{\mathrm{Core}}$	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)		
$\mathrm{IP}^{\mathrm{Head}}$					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	2.620		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. R^2	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 reports the predictability of asset returns on economists' forecasts of inflation growth and their forecasting errors. Change in forecast (in bps) is calculated as the Bloomberg economists' forecasting value of month-$t+1$ CPI growth minus the value predicted 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_{t+1}						$\text{Forecasting Error}_{t+1}$					
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. R^2	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_{t+1}						$\text{Forecasting Error}_{t+1}$					
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. R^2	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. 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. The standard errors are adjusted for heteroskedasticity, and the t-stats are reported in parentheses.

Panel A. Heightened Inflation Episodes

	2021 Episode				1973 Episode	
	Core Innovation$_{t+1}$		Forecasting Error$_{t+1}$		Core Innovation$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
IP^{Core}	8.438	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 (Δy^{10YR})		6.361		10.067		9.639
		(0.83)		(1.40)		(1.11)
Observations	24	24	24	24	24	24
Adj. R^2	18.5%	15.7%	8.8%	11.3%	32.8%	31.7%

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

	Core Innovation$_{t+1}$	Forecasting Error$_{t+1}$	Core Innovation$_{t+1}$	Forecasting Error$_{t+1}$
	High Uncertainty		Low Uncertainty	
IP^{Core}	4.199	2.804	0.736	1.115
	(3.67)	(2.51)	(0.94)	(1.46)
Adj. R^2	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. R^2	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. R^2	4.9%	4.7%	1.5%	1.5%

Table 8. 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 inflation portfolios (IP^{Core}, IP^{Head}), financial assets (GSCI, TIPS-UST, VWRETD, $\Delta y^{2\text{YR}}$, and $\Delta y^{10\text{YR}}$), the latest survey forecasted inflation growth from SPF survey and Michigan survey, and Phillips curve (real GDP growth, output gap, unemployment rate (UNEMP), labor income share (Labor Share), and CFNAI). "Relative RMSE" reports the ratio of the root mean squared forecasting error estimated using the corresponding forecasting model, relative to that of the benchmark model of ARMA(1,1). The p-value is computed under the null that the RMSE for that model equals the RMSE for the ARMA(1,1), 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 7, including the 2021 episode, periods of high uncertainty, high disagreement, and behind-the-curve periods.

Panel A. Relative RMSE for the Whole Sample

	Core-CPI		Headline-CPI	
Forecasting Model	Relative RMSE	p-value	Relative RMSE	p-value
IP:				
IP^{Core}	95.78%	0.07	93.91%	0.00
IP^{Head}	100.52%	0.70	93.78%	0.00
Other Financial Assets:				
GSCI	97.59%	0.14	85.84%	0.00
TIPS-UST	101.18%	0.69	93.11%	0.11
VWRETD	100.99%	0.99	99.78%	0.38
$\Delta y^{2\text{YR}}$	99.49%	0.39	99.19%	0.06
$\Delta y^{10\text{YR}}$	99.46%	0.38	99.49%	0.26
Survey:				
SPF Survey	104.34%	0.92	98.33%	0.30
Michigan Survey	99.42%	0.27	100.47%	0.66
Phillips Curve:				
Real GDP Growth	101.47%	0.79	101.09%	0.96
Output Gap	105.53%	0.97	101.34%	0.99
UNEMP	103.27%	0.99	100.99%	0.98
Labor Share	100.92%	0.88	100.75%	0.88
CFNAI	102.41%	0.60	103.51%	0.83

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

	Core-CPI		Headline-CPI	
Subsample	Relative RMSE	p-value	Relative RMSE	p-value
2021 Episode	91.84%	0.05	88.60%	0.06
High Uncertainty	93.66%	0.05	93.75%	0.01
High Disagreement	95.42%	0.09	93.30%	0.00
Behind the Curve	94.72%	0.08	92.71%	0.03

Table 9. 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-$t+1$ firm sales growth, cash flow, change of IBES long-term growth forecast of EPS (IBES LTG), and quarterly return. The independent variables include the interaction of the quintile rank of β^{Core} ($\beta^{\text{Core}}_{\text{Rank}}$) with IP^{Core}, $\beta^{\text{Core}}_{\text{Rank}}$, Log(Size), asset growth, ME/BE, and dividend payout, all observed at the end of quarter t. To control for the persistence in firm fundamentals, we also include the quarter-t value of the dependent variable as controls (Y_t). All variables (except $\beta^{\text{Core}}_{\text{Rank}}$ and IP^{Core}) are standardized with means of zero and standard deviations of one for ease of interpretation. Time and firm fixed effects are included. Standard errors are double clustered by quarter and firm, and the t-stats are presented in parentheses.

	Sales Growth$_{t+1}$		Cash Flow$_{t+1}$		IBES LTG$_{t+1}$		Return$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\beta^{\text{Core}}_{\text{Rank}} \times \text{IP}^{\text{Core}}_{\text{t}}$	0.206	0.201	0.207	0.179	0.176	0.213	0.036	0.023
	(3.65)	(3.54)	(3.88)	(3.90)	(2.68)	(2.75)	(0.31)	(0.20)
$\beta^{\text{Core}}_{\text{Rank}}$	0.004	0.004	−0.003	0.001	0.000	0.001	0.002	0.003
	(1.28)	(1.42)	(−0.98)	(0.32)	(−0.15)	(0.43)	(0.46)	(0.67)
Log(Size)	−0.024	−0.086	0.195	0.104	−0.008	−0.005	−0.533	−0.472
	(−2.30)	(−7.53)	(12.85)	(8.30)	(−0.97)	(−0.67)	(−16.34)	(−16.65)
Y_t	−0.304	−0.343	0.289	0.289	−0.079	−0.079	−0.004	−0.012
	(−19.40)	(−21.62)	(20.04)	(17.85)	(−6.07)	(−6.06)	(−0.30)	(−0.82)
Asset Growth		0.187		0.02		0.008		0.002
		(15.44)		(5.23)		(3.29)		(0.63)
ME/BE		0.086		0.166		0.013		−0.02
		(10.32)		(17.66)		(2.63)		(−1.84)
Dividend Payout		0.005		−0.034		0.018		−0.024
		(1.21)		(−9.07)		(4.62)		(−5.12)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	167,559	150,573	168,021	150,917	137,358	124,181	173,512	152,867
Adj. R^2	11.1%	14.2%	48.4%	47.5%	2.7%	3.5%	29.2%	29.2%

Table 10. Inflation Beta Sorted Portfolios and Inflation Risk Premium

This 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 excess returns (minus risk-free rate) and CAPM alpha for the full sample from January 1972 to December 2023, as well as for subsamples split around December 2002. Standard errors are adjusted for heteroskedasticity, and the t-stats are presented in parentheses.

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

	Whole sample		Pre-2002		Post-2002	
	Ex.Ret.	α_{CAPM}	*Ex.Ret.*	α_{CAPM}	*Ex.Ret.*	α_{CAPM}
Q1 (Low)	8.43	0.55	6.76	1.03	10.91	−0.19
	(3.20)	(0.66)	(1.95)	(1.01)	(2.69)	(−0.13)
Q2	9.31	2.48	7.54	2.59	11.93	2.29
	(4.10)	(3.69)	(2.50)	(2.71)	(3.48)	(2.62)
Q3	9.13	2.31	7.79	3.02	11.10	0.93
	(4.01)	(3.19)	(2.65)	(2.91)	(3.09)	(1.10)
Q4	8.98	1.88	7.58	2.66	11.05	0.33
	(3.78)	(2.46)	(2.52)	(2.70)	(2.87)	(0.28)
Q5 (High)	9.78	1.37	8.03	2.05	12.38	0.11
	(3.45)	(1.41)	(2.21)	(1.84)	(2.72)	(0.06)
Q5 − Q1	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	
	Ex.Ret.	α_{CAPM}	*Ex.Ret.*	α_{CAPM}	*Ex.Ret.*	α_{CAPM}
Q1 (Low)	10.06	2.33	9.56	3.85	10.80	0.21
	(3.85)	(2.49)	(2.72)	(3.03)	(2.80)	(0.16)
Q2	9.66	2.76	8.38	3.41	11.56	1.72
	(4.18)	(3.66)	(2.73)	(3.07)	(3.31)	(1.97)
Q3	9.11	2.29	7.65	2.88	11.26	1.12
	(4.01)	(3.30)	(2.61)	(2.90)	(3.14)	(1.32)
Q4	9.18	2.07	6.89	1.96	12.56	1.85
	(3.92)	(3.27)	(2.32)	(2.37)	(3.30)	(2.00)
Q5 (High)	7.70	−0.79	5.32	−0.62	11.22	−1.43
	(2.67)	(−0.74)	(1.44)	(−0.45)	(2.41)	(−0.82)
Q5 − Q1	−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)

Table 11. Firm Information Environment and Inflation Forecastability

This table reports the predictability of $\mathrm{IP}^{\mathrm{Core}}$ conditional on the firm's information environment. The dependent variables are core-CPI innovations (Panel A) and headline-CPI innovations (Panel B) in basis points. We use firm size, residual institutional ownership, and residual analyst coverage to measure the information environment. Residual institutional ownership and analyst coverage are computed by orthogonalizing with respect to firm size. We sort stocks into 2×5 groups, first by their information environment proxy (X) and then by β^{Core}. The two size groups are defined by the median cutoff of NYSE market capitalization. The predictive regressors are the top-minus-bottom quintile portfolio returns within each group of X. $\mathrm{IP}^{\mathrm{Core}}$ returns are standardized with 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)
$\mathrm{IP}^{\mathrm{Core}}$ ($X >$ 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)
$\mathrm{IP}^{\mathrm{Core}}$ ($X \leq$ 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. R^2	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)
$\mathrm{IP}^{\mathrm{Core}}$ ($X >$ 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)
$\mathrm{IP}^{\mathrm{Core}}$ ($X \leq$ 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. R^2	8.1%	1.9%	8.0%	4.8%	1.5%	4.6%	3.4%	2.9%	3.6%

Table 12. Forecasting Inflation Swaps and Nominal Yields

This table reports the predictability of IP^{Core}, observed at the end of month t, on the changes 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 end of month t 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. R^2	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. R^2	2.7%	2.5%	2.7%	2.0%	1.6%	1.4%	1.9%	1.2%

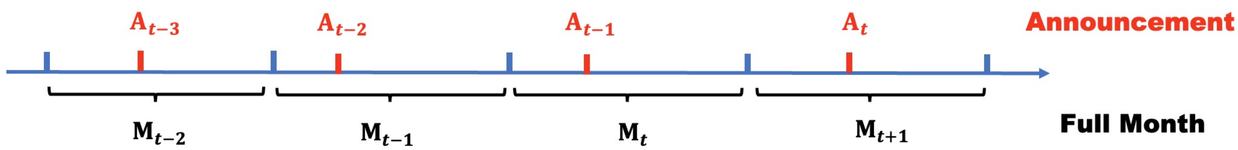
Appendix A. Variable Definition

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

Variable	Definition
CPI growth	$\pi_t = log(P_t) - log(P_{t-1})$, where P_t is the level of CPI for month t
CPI innovation	CPI-Innov$_{t+1} = \pi_{t+1} - \widehat{\pi_{t+1}}$, where $\widehat{\pi_{t+1}}$ is estimated using all the historical observations on and before month t from ARMA(1,1) time series model: $\pi_{t+1} = \mu + \phi\pi_t + \varphi\varepsilon_t + \varepsilon_{t+1}$
IP$^{\text{Core}}$	The cumulative return of the announcement-day core beta (β^{Core}) formed portfolio in the 30 days ([-30,-1]) before the end of month t
IP$^{\text{Head}}$	The cumulative return of the full-month headline beta (β^{Head}) formed portfolio in the 30 days before the end of month t
GSCI	Goldman Sachs Commodity Index return in the 30 days before the end of month t
TIPS-UST	Return difference between Bloomberg U.S. Treasury Inflation Notes Index and Bloomberg U.S. Treasury Index in the 30 days before the end of month t
Change in Forecasts	The Bloomberg economists' forecasting value of CPI growth minus the value predicted under the ARMA(1,1) model
Forecasting Error	The actual CPI growth minus the forecasting value by Bloomberg economists
CPI Uncertainty	Last-month absolute CPI innovations
CPI Disagreement	The difference between the 75th percentile and the 25th percentile of quarterly CPI forecasts from the Survey of Professional Forecasters database
Behind the curve	Periods when the difference between the Taylor rule implied Fed 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
Output Gap	Log real GDP, detrended using the Hodrick–Prescott filter
CFNAI	A monthly index designed to gauge overall economic activity and related inflationary pressure
Log(Size)	The natural logarithm of a firm's market capitalization
Asset Growth	Growth rate of total asset: $AT_t/AT_{t-1} - 1$
Cash Flow	Income before extraordinary items plus depreciation and amortization, divided by total asset (Hennessy et al. (2007)): $\sum(IB_t, DP_t)/AT_t$
CF Beta	Cash flow betas are estimated by regressing changes in quarterly cash flows on quarterly CPI innovations, using a rolling window of 5-year
ME/BE	The market value of total assets divided by the book value of total assets: ME_t/BE_t
Dividend Payout	Dividends divided by income: DVC_t/IB_t
CF Duration	Cash flow duration, constructed following Weber (2018)
Sales Growth	Change of gross sales divided by total asset: $(Sales_t - Sales_{t-1})/AT_{t-1}$

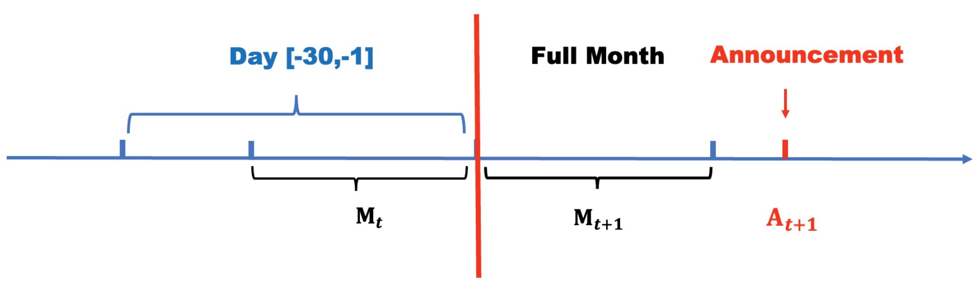
Appendix B. Illustration of the Time Line

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 exposure 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.

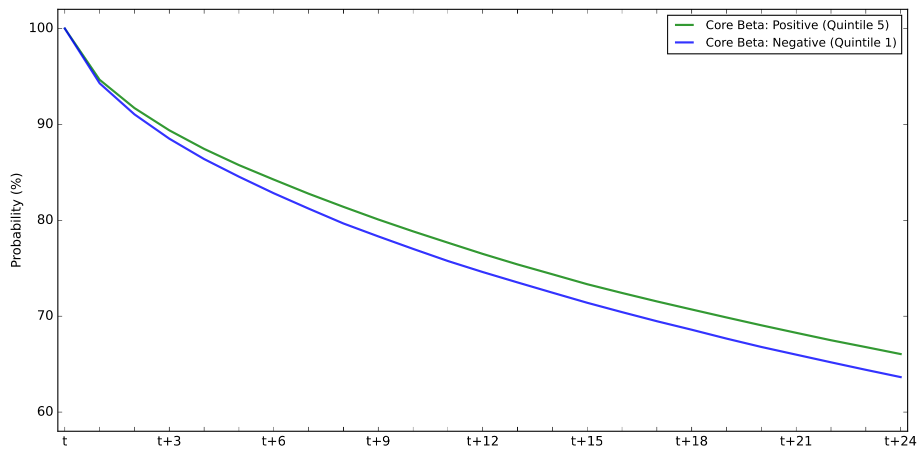
The second approach estimates the inflation risk exposure by the sensitivity of monthly asset returns to the contemporaneous-month inflation innovations. Standing at announcement day A_t, firm i 's full-month beta is estimated using monthly returns from month M_1 to M_t. For example, if we are estimating 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.



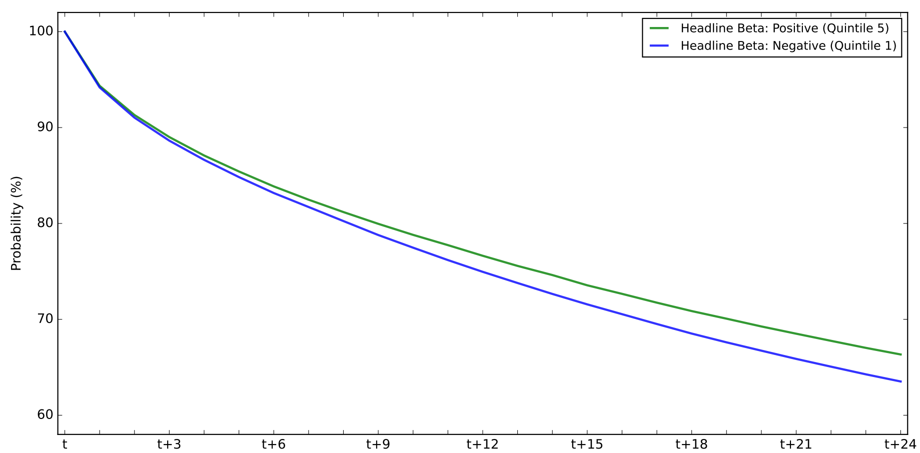
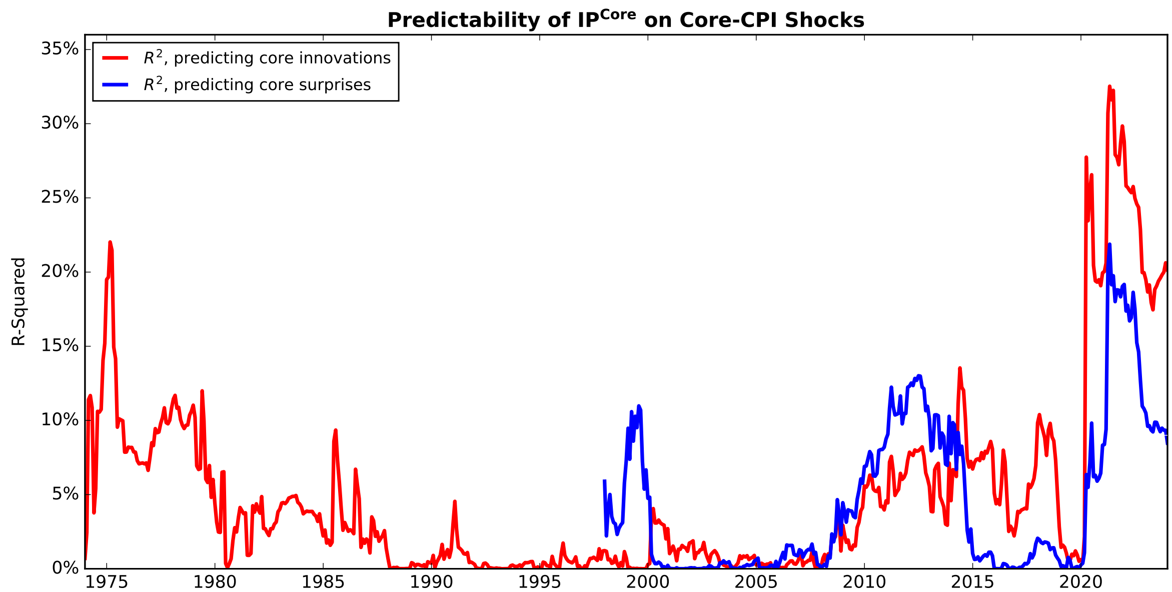


Figure C2. Predicting CPI Shocks using IP^{Core}, R-Squared

The upper and lower graphs display the predictive regression R-squared, estimated using a rolling five-year window for core- and headline-CPI, respectively. For each time t, we estimate the model: $\text{CPI Shock}_t = \alpha + \gamma^{IP} \times IP^{Core}_{t-1} + \epsilon_t$, using observations from $t-59$ to t. We require at least 24 months of observations. The sample period spans from December 1973 to December 2023. The red solid line shows the regression R-squared with shocks measured by CPI innovations, while the blue dotted line represents CPI shocks measured by Bloomberg economist forecasting errors. The blue (green) shaded area plots the volatility of Core (Headline) CPI shocks, measured by the average absolute value of CPI innovations in the corresponding rolling five-year window. The grey shaded area indicates the period when the Fed is behind the curve.



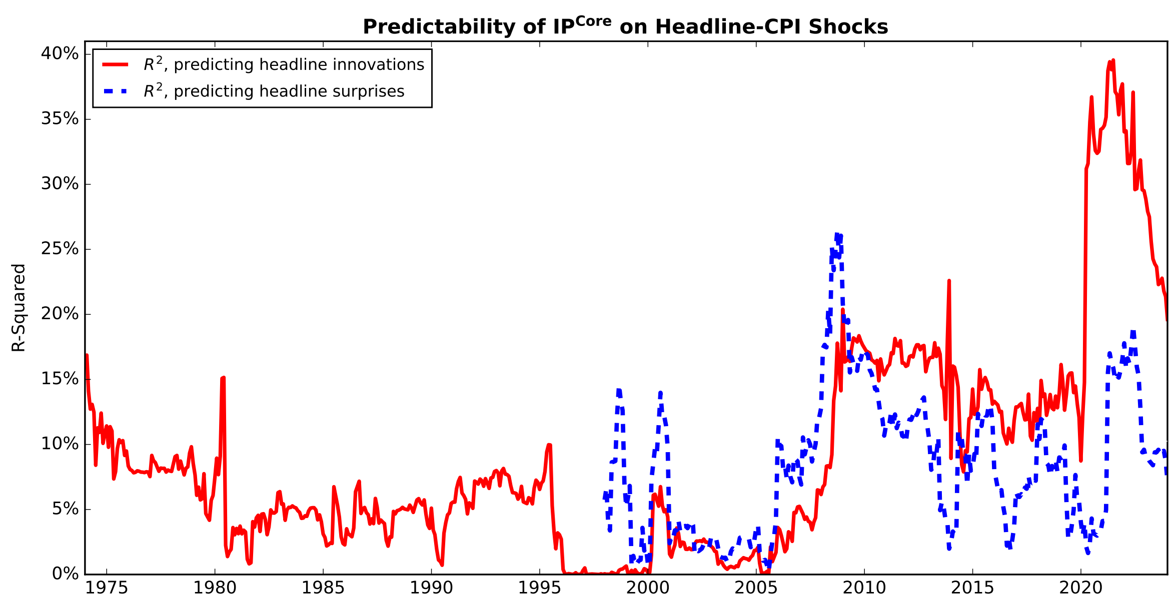


Table C1. Summary Statistics

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-Surprise$_{t+1}$ and Core-Surprise$_{t+1}$, are constructed as the actual CPI monthly growth minus the median forecast by Bloomberg economists. IP^{Core} and IP^{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 (Δy^{2YR} and Δy^{10YR}), 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-Surprise$_{t+1}$ (bps.)	308	0.10	0.00	−10.00	10.00	13.00
Core-Surprise$_{t+1}$ (bps.)	307	−0.23	0.00	−10.00	10.00	10.92
IP^{Core} (%)	624	0.21	0.05	−1.23	1.48	2.60
IP^{Head} (%)	624	−0.26	−0.21	−1.73	1.58	3.41
VWRETD (%)	624	1.23	1.70	−1.42	4.43	5.21
Δy^{2YR} (%)	571	−0.01	−0.01	−0.25	0.18	0.53
Δy^{10YR} (%)	624	0.00	−0.01	−0.21	0.20	0.40
GSCI (%)	624	0.95	1.42	−3.06	5.00	6.74
TIPS-UST (%)	308	0.17	0.19	−0.33	0.88	1.43

Table C2. Inflation Risk Premium Conditional on Nominal-Real Covariance

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

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

	$K=1$		$K=3$		$K=12$	
	Intercept	β^{NRC}	Intercept	β^{NRC}	Intercept	β^{NRC}
Q1 (Low)	12.73	−1.58	12.91	−1.40	13.41	−1.60
	(4.65)	(−0.61)	(5.37)	(−0.58)	(5.86)	(−0.67)
Q2	13.61	−1.69	13.74	−1.69	14.22	−2.01
	(5.85)	(−0.72)	(6.78)	(−0.78)	(7.51)	(−1.02)
Q3	13.43	−1.94	13.53	−1.99	13.98	−2.37
	(5.80)	(−0.81)	(6.78)	(−0.92)	(7.69)	(−1.27)
Q4	13.27	−2.55	13.37	−2.62	13.81	−3.10
	(5.51)	(−1.01)	(6.46)	(−1.15)	(7.39)	(−1.60)
Q5 (High)	14.08	−2.26	14.19	−2.20	14.59	−2.51
	(4.88)	(−0.78)	(5.70)	(−0.84)	(6.53)	(−1.15)
Q5 − Q1	1.35	−0.68	1.36	−0.86	1.48	−0.89
(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}
Q1 (Low)	14.36	−3.14	14.58	−3.17	15.07	−3.65
	(5.28)	(−1.17)	(6.14)	(−1.27)	(7.00)	(−1.69)
Q2	13.96	−2.44	14.09	−2.52	14.66	−2.98
	(5.89)	(−1.02)	(6.90)	(−1.17)	(7.65)	(−1.53)
Q3	13.40	−2.16	13.51	−2.20	14.04	−2.61
	(5.79)	(−0.90)	(6.72)	(−1.00)	(7.39)	(−1.30)
Q4	13.48	−1.31	13.61	−1.29	14.08	−1.53
	(5.63)	(−0.54)	(6.53)	(−0.57)	(7.34)	(−0.76)
Q5 (High)	12.00	−1.04	12.07	−0.80	12.38	−1.03
	(4.07)	(−0.35)	(4.76)	(−0.30)	(5.25)	(−0.44)
Q5 − Q1	−2.36	2.10	−2.25	2.05	−2.08	2.16
(IP^{Head})	(−1.58)	(1.40)	(−1.69)	(1.51)	(−1.50)	(1.68)

Table C3. Industry vs. Stock-Level Inflation Exposure

Panel A lists the top 10 and bottom 10 industries that are the most and least sensitive to announcement-day core-CPI innovations and full-month headline-CPI innovations, respectively. We construct industry CPI betas in a similar manner to individual stock CPI betas, by regressing Fama and French 48 Industry returns (%) on CPI innovations (standardized) under the "CAPM Model". We report the time series average industry betas beside the industry names. Panel B compares the predictability of industry- and stock-constructed inflation portfolios on CPI innovations. $\mathrm{IP}^{\mathrm{Core}}_{\mathrm{Ind}}$ and $\mathrm{IP}^{\mathrm{Head}}_{\mathrm{Ind}}$ are the 30-day cumulative returns for the industry-constructed inflation portfolios, with a long position in top-quintile CPI beta industries and a short position in bottom-quintile CPI beta industries. $\mathrm{IP}^{\mathrm{Core}}$ and $\mathrm{IP}^{\mathrm{Head}}$ are the 30-day cumulative returns for the stock-constructed inflation portfolios as in Table 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$_{t+1}$						Headline-CPI Innovation$_{t+1}$					
$\mathrm{IP}^{\mathrm{Core}}_{\mathrm{Ind}}$	1.009		−0.151				5.621		2.992			
	(1.69)		(−0.26)				(4.32)		(2.11)			
$\mathrm{IP}^{\mathrm{Core}}$		2.669	2.733					7.466	6.197			
		(3.40)	(3.23)					(6.83)	(5.05)			
$\mathrm{IP}^{\mathrm{Head}}_{\mathrm{Ind}}$				1.505		0.543				5.82		1.43
				(2.69)		(0.79)				(4.53)		(1.13)
$\mathrm{IP}^{\mathrm{Head}}$					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. R^2	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 C4. 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. R^2	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. R^2	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 C5. The Predictability of Fama French 5-factor Adjusted IP^{Core}

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

Panel A. FF5F Loading

		Mktrf	SMB	HML	CMA	RMW	Obs.	Adj. R^2
IP^{Core}	Coeff.	0.049	0.135	0.128	−0.087	−0.007	624	5.8%
	t-stat	(1.73)	(2.83)	(1.79)	(−0.94)	(−0.09)		
IP^{Head}	Coeff.	0.037	−0.080	−0.008	−0.179	−0.418	624	12.6%
	t-stat	(1.08)	(−1.62)	(−0.12)	(−2.04)	(−6.00)		

Panel B. Predicting Month t+1 CPI Innovation

	Core-CPI Innovation						Headline-CPI Innovation					
IP^{Core} α	2.33	1.811	2.215	1.986			6.799	3.655	7.406	4.117		
	(3.20)	(2.64)	(2.62)	(2.27)			(5.90)	(2.74)	(4.13)	(1.91)		
IP^{Head} α					2.934	2.641					6.625	3.89
					(3.55)	(2.35)					(6.09)	(1.85)
GSCI		1.819		0.873		0.657		11.017		12.548		12.661
		(2.26)		(0.87)		(0.67)		(6.61)		(5.97)		(6.00)
TIPS-UST			1.676	1.236		1.179			9.145	2.819		2.632
			(2.00)	(1.53)		(1.47)			(2.81)	(0.87)		(0.81)
Observations	624	624	308	308	624	308	624	624	308	308	624	308
Adj. R^2	2.1%	3.2%	6.3%	6.4%	3.4%	8.5%	6.7%	23.1%	17.8%	29.9%	6.4%	29.7%

Table C6. 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*
Q1 (Low)	−2.19	−1.10	−1.29	−9.50	−1.51	−4.69
	(−1.14)	(−0.52)	(−0.64)	(−0.70)	(−0.12)	(−0.35)
Q2	0.75	1.27	0.10	−9.23	−4.64	−3.72
	(0.44)	(0.62)	(0.06)	(−1.04)	(−0.55)	(−0.38)
Q3	1.75	1.20	1.02	−16.29	−4.85	1.71
	(0.92)	(0.59)	(0.45)	(−2.09)	(−0.63)	(0.21)
Q4	2.10	2.55	0.96	−13.74	3.89	8.53
	(1.01)	(1.11)	(0.44)	(−1.56)	(0.44)	(0.90)
Q5 (High)	2.37	1.43	−2.09	−5.57	40.75	32.33
	(1.01)	(0.50)	(−1.05)	(−0.47)	(2.73)	(1.91)
Q5 − Q1	4.56	2.53	−0.80	3.93	42.25	37.02
	(2.49)	(0.98)	(−0.39)	(0.35)	(2.96)	(2.23)

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^2	1.9%	7.5%	4.1%	4.2%	9.1%	31.3%	8.2%	13.1%

Table C7. Inflation Beta Constructed using Ann-Day Surprise

Panel A reports the post-ranking inflation betas for stock portfolios formed when pre-ranking betas are constructed by regressing announcement-day stock excess returns on announcement-day economists' forecasting errors of Core CPI (β^{Surp}), Changes in 2 year Inflation Swap Rates (β^{ISWAP2YR}), Changes in 5 year Inflation Swap Rates (β^{ISWAP5YR}), Changes in 2 year UST yield (β^{UST2YR}) and Changes in 5 year UST yield (β^{UST5YR}) under the "CAPM Model". Panel B examines the predictability of IP^{Surp}, $\text{IP}^{\text{ISWAP2YR}}$, $\text{IP}^{\text{ISWAP5YR}}$, $\text{IP}^{\text{UST2YR}}$ and $\text{IP}^{\text{UST5YR}}$ constructed based on Panel A's betas, observed at the end of month t, on core-CPI innovations and headline-CPI innovations at month-$t+1$. Standard errors are adjusted for heteroskedasticity, and the t-stats are in parentheses.

Panel A. Post-Ranking Inflation Beta

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q5 − Q1
β^{Surp}	−10.09	−4.80	−0.65	1.70	2.91	13.00
t-stat	(−2.81)	(−1.81)	(−0.22)	(0.47)	(0.73)	(2.64)
β^{ISWAP2YR}	−17.69	−5.14	−0.61	−0.73	9.60	27.29
t-stat	(−2.56)	(−1.22)	(−0.16)	(−0.18)	(1.80)	(3.57)
β^{ISWAP5YR}	−17.07	−6.27	−2.51	3.27	8.98	26.05
t-stat	(−2.60)	(−1.52)	(−0.67)	(0.81)	(1.76)	(3.58)
β^{UST2YR}	−3.79	0.09	1.82	3.25	6.30	10.09
t-stat	(−0.95)	(0.04)	(0.77)	(1.34)	(2.05)	(2.63)
β^{UST5YR}	−1.58	0.42	1.05	2.61	4.20	5.77
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. R^2	2.9%	4.6%	2.9%	1.3%	0.8%	7.3%	7.7%	12.4%	0.9%	0.3%