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

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Abstract

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

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1 Introduction

Understanding the relationship between stock returns and inflation has long been a topic of interest in financial economics. While prior research has predominantly focused on the aggregate stock market, the information content of cross-sectional stocks has been less studied.[1] In this paper, we study the extent to which the information contained in cross-sectional stocks can tell us about inflation shocks. Specifically, with respect to inflation exposure, how does the impact of inflation vary across firms? 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-sectional aspect of the stock market is motivated by the 2021 inflation surge, which was missed by the policymakers, as well as the economists contributing to the survey-based inflation forecasts.[2] As both the policymakers 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 ascent 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. This informational channel is akin to the seminal paper of Roll (1984), which examines the market's information processing ability by relating orange-juice futures price changes with subsequent errors in temperature forecasts issued by the National Weather Service for the central Florida region where most juice oranges are grown.

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

Cross-Sectional Inflation Exposure – Another implication of our illustrative model is that the cross-sectional variation in cash flow exposure b_i can be mapped into the cross-sectional variation in return exposure β_i. To 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 five-year 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

[4] Cross-sectional variation of cash flows to inflation exposure is suggested and studied by Fama (1981) and Boudoukh et al. (1994). These studies focus on the predictability of stock returns via expected inflation, while our focus is on the predictability of inflation via cross-sectional differences in realized stock returns.

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 exposure 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 significantly for firms with a more negative pre-ranking β^{Ann}. Conversely, headline CPI shocks have a more negative impact on firms with a more negative pre-ranking β^{Full} during the contemporaneous month. Consistent with Fama and Schwert (1977), the aggregate stock market in general has a negative, albeit unstable, inflation beta, suffering in performance amid positive inflation shocks.[5] Relative to the aggregate market, stocks with more negative inflation betas suffer even more severely when inflation increases, and importantly, such cross-firm variations in inflation exposure are persistent over time.

Estimating β^{Full} and β^{Ann} for both the Treasury bond and the commodity market, we find the same pattern – inflation-sensitive securities co-move 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 to them as β^{Head} and β^{Core}, respectively.

The Cash Flow Mechanism – To add empirical support for the cash flow mechanism,

[5] Consistent with Fang, Liu, and Roussanov (2021), the negative inflation exposure is generally more pronounced for core CPI than for headline CPI. Unlike their focus on the aggregate stock market, 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.

a central ingredient of our illustrative model, we examine the cross-sectional drivers of the inflation betas and find a significant alignment between the return-based inflation beta and the cash flow-based inflation beta. Specifically, firms with higher β_i^{Core} tend to experience an increase in their quarterly cash flows in response to inflation shocks, leading to a higher cash flow inflation beta b_i. Moreover, we find that firms with higher β^{Core} in general have lower duration and more immediate cash flow (e.g., higher dividend payouts). By contrast, firms with lower β^{Core} are more likely to be growth firms.

Further supporting the cash flow mechanism, we demonstrate that firms with more positive β^{Core} tend to experience, over the subsequent quarter, better sales growth, stronger cash flows, and higher IBES long-term growth forecasts in response to increased inflation expectations. Specifically, a one standard deviation increase in inflation expectation predicts a 3.2% standard deviation increase in cash flow over the next quarter for firms in the top β^{Core} quintile relative to those in the bottom quintile. This evidence highlights the channel through which inflation shocks can have a heterogeneous impact on firms' future cash flows, forming the basis for active price discovery of inflation news among cross-sectional stocks.[6]

Inflation Forecasting with IP Portfolios – Sorting stocks by their pre-ranking beta into quintile portfolios, we form 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 using the risk-based and headline-focused β^{Head}. Compared to the aggregate market, the IP portfolios effectively cancel out aggregate noise and common factors affecting all stocks universally. Our hypothesis is that, when informed by higher inflation expectations, investors will underprice stocks in the bottom portfolio more severely than those in the top portfolio. Hence, as the model implies, a higher than usual IP is therefore a reflection of heightened inflation expectations and can help predict the inflation yet to be realized.

We use the 30-day return of IP$^{\text{Core}}$, observed at the end of month t, to predict month-$t+1$ inflation shocks, which are realized in month $t+1$ and announced in the middle of month $t+2$. A one standard deviation increase in IP$^{\text{Core}}$ predicts a 2.2 bps (t-stat=2.98) increase in

[6]Different from the cash flow channel, we do not find empirical support for the risk premium channel. In particular, using our β^{Core}-sorted portfolios, we do not have a significant risk premium for the core inflation risk.

core-CPI innovations and a 7.9 bps increase (t-stat=6.54) in headline-CPI innovations. Given that the standard deviations of core- and headline-CPI innovations are 16 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 a similar magnitude, it cannot predict core-CPI movements. Thus, although IP^{Head} better captures the inflation risk premium, for inflation forecasting, IP^{Core}, constructed based on the announcement-day beta, proves 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 ability to forecast core inflation is very 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 source. Between the time our inflation forecast is observed (end of month t) and the announcement of the month-$t+1$ CPI (mid-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) beyond other market-based predictors. A one standard deviation increase in IP^{Core} predicts an increase of 2.3 bps (t-stat=3.10) and 3.8 bps (t-stat=4.22), 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.

Further supporting the active discovery of inflation news, we show that the predictability of IP^{Core} is stronger in firms with better information environments. When investors have limited capacity or face constraints to arbitrage, inflation expectations may not be quickly reflected in stock prices. Consequently, we expect stronger price discovery in firms with superior information environments. Consistent with this, the predictability of IP^{Core} is more evident in larger firms, those with greater analyst coverage, and higher institutional ownership, which serve as proxies for a better information environment.

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 appeared to misjudge 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.

Against this backdrop, we show that, prior to the 2021 inflation surge, IP^{Core} had already signaled a sequence of alerts – the signal for the April CPI was at 3.7-sigma above the average. Over the 24 months from October 2020 through the peak of core CPI in September 2022, the predictability of IP^{Core} increases significantly, with an R-squared of 17.7%. When using the market-based predictors, including IP^{Core}, TIPS-UST, and GSCI, to jointly forecast core CPI during this period, IP^{Core} emerges as the only significant predictor, dominating the other predictors in both economic and statistical significance. This increased predictive power for core CPI, especially amid heated debates at the time, indicates that the information contained in cross-sectional stocks can be useful for policymakers and economists for the purpose of forecasting core inflation shocks.

As a parallel to 2021, the 1973 experience is often revisited to shed light on the recent runaway inflation. Tracking the performance of IP^{Core} in the 24 months during the core-CPI run-up period from May 1973 to April 1975, we observe a similar pattern: IP^{Core} significantly predicts core-CPI innovations with a much improved R-squared of 28.4% and an economic magnitude of 19.5 bps (t-stat=3.43). Moreover, similar to the case of 2021-22, this enhanced predictability is captured exclusively by our core-focused inflation portfolio, rather than 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} provides the most timely and valuable information when inflation emerges as an important risk factor in the capital markets. Further exploration reveals that the predictability of IP^{Core} is significantly stronger when inflation risk is more volatile and when economists strongly disagree about inflation movements.

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 funds 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.

Finally, we show that 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 4-6%, a performance unmatched by any other predictors in our analysis.[7] In contrast, the out-of-sample enhancements provided by GSCI and TIPS-UST for predicting core inflation are significantly weaker, at less than 3%. Additionally, 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, utilizing all historical observations for beta estimation, and excluding the industry component.

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

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 exposure, which is found elusive for inflation risk in the stock market. Given the weak contemporaneous correlation between stock returns and inflation documented by Fama and Schwert (1977), the common belief is that the 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. This distinction enhances our understanding of how inflation expectations are priced into equities and provides a more nuanced view of the relationship between inflation and stock market returns.

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

[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 that survey forecasts perform the best, outperforming the information from the Treasury yield curve, macro variables, and time-series models using past inflation growth. Relative to this literature, our paper documents the unique and important role played by the cross-section of stocks in forecasting inflation, particularly the elusive core inflation. We find that inflation forecasts from the cross-section of stocks outperform the bond-based predictor by a wide margin and consistently forecast the errors made by economists, especially when inflation emerges as a significant risk factor in the economy.

Conceptually, the closest paper to ours is Downing, Longstaff, and Rierson (2012), who uses industry portfolios from the equity market to track inflation growth over the subsequent month, and Titman and Warga (1989), who studies the predictability of aggregate stock market returns on inflation. Our focus and implementation, however, differ significantly from theirs. Instead of tracking inflation growth, 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 the data, and Section 3 outlines the methodology for estimating the inflation beta. In Section 4, we introduce the model and the cash flow mechanism related to predictability. Section 5 examines the ability of cross-sectional inflation portfolios to predict inflation shocks and economists' forecasting errors. Section 6 discusses robustness checks and additional tests, and Section 7 concludes.

2 Data

We obtain monthly data on the Consumer Price Index (CPI), including Headline, Core, and Energy CPI from the U.S. Bureau of Labor Statistics (BLS).[9] The CPI announcement dates are also collected from the BLS. Following Chen, Roll, and Ross (1986), Ang, Bekaert, and Wei (2007), Bekaert and Wang (2010), CPI growth is defined as the difference in the

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

natural logarithm of monthly CPI: $\pi_t = \ln(P_t) - \ln(P_{t-1})$, where P_t is the level of CPI for month t.

For each type of CPI series, CPI innovation is constructed using the ARMA(1,1) time series model, following Fama and Gibbons (1984), Ang, Bekaert, and Wei (2007), and Boons et al. (2020). The ARMA(1,1) model is estimated by maximum likelihood with the following specification:

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

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

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

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

Appendix Table D1 reports the summary statistics for CPI innovations. Headline-CPI innovation has a mean of -0.01 bps with a standard deviation (STD) of 26 bps, and core-CPI innovation has a mean of -0.07 bps with a STD of 16 bps. The close-to-zero average value of CPI innovations suggests that the ARMA(1,1) model does a good job of capturing the overall inflation pattern. Consistent with the intuition that core CPI, which excludes food and energy components, is generally more persistent than its non-core counterparts, the standard deviation of core CPI is smaller than that of headline CPI. We also use economists' forecasting errors, constructed as the actual monthly CPI growth value minus the median forecast by Bloomberg economists, to capture surprises in CPI announcements. The headline forecasting error on average is 0.1 bps with a STD of 13 bps, and the core forecasting error is on average -0.23 bps with a STD of 10.9 bps.

Data on cross-sectional stocks are obtained from the Center for Research in Security Prices (CRSP), and accounting information is from Compustat. We include all common stocks traded on the NYSE, Amex, and NASDAQ. Stock returns are adjusted for delisting

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

3 Measuring Inflation Exposure

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

3.1 Methodology: Announcement Day vs. Full Month

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

We therefore use two approaches to estimate securities' inflation exposure. The announcement-day inflation beta is constructed by regressing securities' announcement-day excess returns

[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.

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

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

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

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

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

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

3.2 Inflation Exposures in Cross-Sectional Stocks

We first estimate individual stocks' pre-ranking inflation betas using a rolling five-year window, as specified by equations (3) and (4). Appendix C details the timeline for the estimations. Each month, after the CPI announcement A_t, we construct the announcement-day inflation beta for firm i using data from announcement A_{t-59} to announcement A_t, requiring at least 24 months of data out of the last 60 months available. Similarly, we estimate the full-month beta, β^{Full}, using monthly stock returns and inflation innovations from month M_{t-59} to month M_t. Since data on CPI innovations start from 1967, with five-year estimation periods, the individual stocks' CPI beta estimates begin in 1972.[11]

We construct the announcement-day and full-month (pre-ranking) inflation betas for each

[11] Appendix Table D5 confirms the robustness of results using betas estimated from all historical observations, following the methodology in Boons et al. (2020).

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.[12] The two size groups are defined by the 50th percentile of NYSE market capitalization at the end of the previous month, following Fama and French (1993). We hold the portfolio until the next CPI announcement day, at which point the new CPI innovation becomes available, allowing us to update the estimates of each stock's inflation exposure.

Table 1 reports the post-ranking announcement-day and full-month inflation betas for the pre-ranking beta sorted cross-sectional stock portfolios, with the two size groups combined. We find that cross-sectional stocks' core-inflation betas are significantly more negative than their headline betas, consistent with Fang, Liu, and Roussanov (2021). Additionally, core CPI has a much larger impact on stock returns on announcement days compared to headline and energy components. A one standard deviation increase in core-CPI innovation negatively affects the bottom quintile of core beta-sorted stocks by -14.7 bps (t-stat=3.23) on the CPI announcement days. In contrast, the same increase in headline- and energy-CPI innovations has a positive and trivial impact of 1.6 bps (t-stat=0.19) and 4.5 bps (t-stat=0.57), respectively.

As our focus is on the cross-sectional dispersion in individual stocks' inflation exposure, Panel B of Table 1 further reports the beta estimates while controlling for the aggregate stock market return, i.e., controlling for announcement-day market return and full-month market return in the estimation of β^{Ann} and β^{Full}, respectively. By removing the negative inflation exposure at the market level, the inflation estimates become generally less negative. However, we can still observe significant dispersion in cross-sectional stocks' post-ranking core-beta when estimated using announcement days. The row labeled "Quintile 5-1" refers to an inflation portfolio constructed with a long position in the top quintile (most positive inflation beta stocks) and a short position in the bottom quintile (most negative inflation beta stocks). A one standard deviation increase in announcement-day core innovation leads to a 4.6 bps (t-stat=2.49) return increase in the core beta-sorted portfolio, while such dispersion is absent for headline and energy beta-sorted portfolios on CPI announcement days. This

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

suggests significant cross-sectional variations in firms' core-inflation exposure, with firms showing strong sensitivity to core-CPI innovations on past announcement days continuing to respond significantly to core innovations in future announcements.

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

Overall, the cross-sectional stocks' inflation exposure suggests persistent cross-firm variations in inflation exposure, with the information-based announcement-day approach being most effective in capturing the core-inflation exposure and the contemporaneous approach most effective in capturing the headline exposure. This contrast is consistent with the intuition that non-core inflation components (like energy and food) are more observable and can be hedged using commodity instruments as investors experience inflation throughout the month. In contrast, core components (such as goods and services) are harder to observe and tend to cause larger surprises on CPI announcement days. Therefore, we refer to the announcement-day estimated core beta as β^{Core} and the full-month estimated headline beta as β^{Head} for short in our subsequent analyses.[13]

3.3 Inflation Exposures Across Asset Classes

Estimating the inflation betas for a wide range of inflation-sensitive assets, we observe a consistent contrast between announcement-day and full-month approaches. In particular, we estimate equations (3) and (4) for each asset using observations from the entire sample. To ensure comparability across asset classes, all variables – both dependent and independent

[13] Appendix Figure D1 shows that the individual stocks inflation beta estimation is highly persistent. For a stock in the top (bottom) quintile sorted based on month-t inflation beta, the probability of it remaining in the same quintile is 76% and 74% after 6 months.

– are standardized to have means of zero and standard deviations of one during the beta estimations.

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

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

The last two rows of Table 2 present the beta estimates for the aggregate stock market, along with the inflation betas estimated for the long-short portfolio formed from the cross-section of stocks (IP portfolio).[14] Comparing the two, it is evident that the IP portfolio behaves more like inflation-sensitive assets, in contrast to the aggregate stock market. This is due to the significant cross-sectional variations in firms' inflation exposure; some firms exhibit positive inflation exposure, while others exhibit negative exposure. The aggregate market sensitivity reflects the average of all firms. Thus, even if the market-wide inflation exposure may show an unstable and negative relation to inflation shocks (Fama and Schwert (1977), Bekaert and Wang (2010)), the relative cross-firm variation in inflation exposure remains stable and positive.[15]

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

[15]This announcement-day approach could also be applied to other macroeconomic announcements to identify variations in firms' macro exposure. However, it is essential that these announcements create significant cross-firm variations in returns, where some firms benefit while others are adversely affected. Announcements

3.4 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 a 3% standard deviation increase in β^{Core}, and this relationship remains consistent when controlling for firm characteristics and Fama-French 48 industry fixed effects. As for headline betas, a similar pattern is observed, although the coefficient becomes insignificant when industry fixed effects are included.

This suggests that return-based and cash flow-based betas align well with each other. In response to positive inflation shocks, firms with more positive β^{Core} experience significant increase in their quarterly cash flows, relative to the firms with a more negative β^{Core}. 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.[16] Table 3 suggests that firms with more positive β^{Core} tend to have lower growth potential, higher dividend payouts, and higher cash flows. This suggests a concentration of immediate cash flows realized in the near term but lower long-term cash flows, leading to a shorter cash flow duration. In contrast, firms with more negative core betas exhibit longer cash flow duration and are typically growth firms.

such as those from the FOMC and CPI might be suitable, whereas those like NFP and GDP, which tend to affect all firms in the same direction, may be less effective.

[16]Detailed descriptions of variables are provided in Appendix B.

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

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

4 An Illustrative Model and the Mechanism

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

4.1 An Illustrative Model

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

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

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

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

For market participants, however,

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

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

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

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

The short rate r_t is modeled as:

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

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

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

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

where the parameter b_i captures stock i's cash flow (dividend) exposure to inflation shocks

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

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

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

where, excluding the risk premium channel from the valuation problem, we take the expectation under the physical measure.[17] The price-dividend ratio can be further calculated as

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

where it is important to note that the time-t stock price contains the superior information possessed by the market participants, namely y_t. Moreover, the price dependence varies across firms via $b_i\sigma_\pi - \alpha$, where b_i enters via the cashflow channel and differs cross-sectionally, while α enters via the riskfree rate channel and is the same for all firms.[18]

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

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

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

Proposition 1. *For the cross-sectional inflation portfolio (IP) that takes a long position of \$1 in stock i and a short position of \$1 in stock j, the inflation exposure is given by*

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

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

$\beta_{ij} = \frac{b_i - b_j}{\sigma_y^2 + 1}$.

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

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

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

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

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

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

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

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

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

The population estimate of γ_{ij} *is*

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

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

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

4.2 The Cash Flow Channel

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

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

Across all specifications, inflation positively affects sales growth, cash flow, and the IBES long-term growth forecast more for firms with more positive β^{Core}. Focusing on sales growth in the first two columns, the coefficients of the interaction term are significantly positive. A 10% increase in IP^{Core} leads to a 7.8% standard deviation increase in sales growth when the quintile ranks of β^{Core} move from the bottom to the top quintile. After taking into account operational costs, we observe a similar magnitude of IP^{Core} on cash flows: A 10% increase in IP^{Core} at the end of quarter t predicts a 7.1% standard deviation increase in quarter-$t+1$ cash flow. A similar pattern is observed for the IBES long term growth forecast of EPS, indicating that analysts also update their beliefs about firm growth correspondingly.

Figure 1 offers a more intuitive graphical illustration. At the beginning of each quarter

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

4.3 Inflation Risk Premium

We further test whether or not the cross-firm variations in returns are driven by the inflation risk premium. If the variations in IP^{Core} are driven by the time-varying inflation risk premium, we would expect firms with higher β^{Core} to face lower required rates of return in the context of elevated inflation expectations. However, we do not find evidence in support of this risk premium channel. Following the same regression framework, the last two columns of Table 4 report the impact of IP^{Core} on firm returns. The coefficients of the interaction term are insignificant, indicating a lack of return dispersion between stocks with high and low β^{Core}.

Furthermore, Table 5 reports the inflation risk premium for the β^{Core} sorted quintile portfolios from January 1972 to December 2023, as well as for subsamples split around December 2002.[19] 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 1.2% (t-stat=1.06). The subsample analysis yields similar results: both in the pre-2002 and post-2002 subsamples, the return difference between the top and bottom portfolios

[19]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)).

is positive and insignificant. However, for the β^{Head} sorted portfolios, as reported in Panel B, we observe a different pattern. Annualized excess returns for β^{Head} sorted portfolios decrease from 9.8% for the bottom quintile to 7.6% for the top quintile, resulting in a top-minus-bottom return difference of -2.2% (t=-1.67) for excess return and -2.7% (t=-1.98) for CAPM alpha. In sum, β^{Head} and β^{Core} contain uniquely different information, with β^{Head} better capturing the risk premium and β^{Core} better capturing the information shocks.

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

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

The intercept measures the unconditional inflation risk premium, and β^{NRC} measures the increase in annualized portfolio return resulting from a one standard deviation increase in NRC. Focusing on the β^{Head} sorted portfolios in Panel B of Appendix Table D2, we find consistent evidence, as in Boons et al. (2020), that IP^{Head} strongly co-moves with the nominal-real covariance, reflecting a compensation for inflation risk. In contrast, as shown in Panel A, for β^{Core} sorted portfolios, the effect of NRC is insignificant, and the sign is even negative. This indicates that variations in IP^{Core}, and hence the predictability of IP^{Core} on inflation shocks, are not driven by the time-varying inflation risk premium.

5 Inflation Forecasting

In this section, we provide evidence that the cross-sectional IP portfolio contains unique predictive information about future inflation shocks not yet fully incorporated by economists, and such predictability is especially pronounced during important inflation episodes.

5.1 Predicting Inflation Innovations

We use the monthly rebalanced top-minus-bottom quintile inflation portfolios from Section 3.2 to predict inflation shocks. The core-focused inflation portfolio (IP^{Core}) is constructed using the announcement-day core-beta β^{Core}, while the headline-focused inflation portfolio (IP^{Head}) is constructed using the full-month headline beta β^{Head}. As discussed in Proposition 2, stocks in the bottom-ranked portfolio, whose inflation betas are ranked the lowest, suffer the most when inflation increases. Therefore, in anticipation of heightened inflation, sophisticated investors would underprice stocks in the bottom portfolio more severely than those in the top portfolio, leading to a positive return for the inflation portfolios. In other words, a higher-than-usual return for the inflation portfolio could serve as an early warning from the equity market about an upcoming surge in inflation.

5.1.1 Event Study around Extreme CPI Months

We begin by tracking the performance of inflation portfolios around extreme CPI events to understand the timing of price discovery. According to Lo and MacKinlay (1990), large stocks have better liquidity and often lead small stocks in incorporating market-wide information, so we focus on inflation portfolios constructed using large stocks.[20] We categorize all CPI events into quintiles based on headline- and core-CPI innovations, with the top (bottom) quintile capturing the events with very positive (negative) surprises. We then plot the cumulative performance of inflation portfolios (IP^{Core} and IP^{Head}) from $t = -50$ trading days before the start of the CPI month to $t = 50$ days afterward in Figure 2, with $t = 0$ marking the start of the CPI month.

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

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

shown by its stronger downward drift before the bottom-quintile CPI innovations. The lower graph, conditional on core-CPI innovations, shows similar evidence: an increase in IP^{Core} leads to higher-than-expected core-CPI innovations, and a decrease in IP^{Head} leads to lower-than-expected core-CPI innovations.

To pinpoint when the equity market starts incorporating next-month inflation expectations, Table 6 reports the predictability of inflation portfolio returns on CPI innovations, with returns estimated over 10-day intervals. For instance, the interval [-10,-1] denotes returns from 10 trading days before the CPI month to the last trading day before the CPI month. To compare with information discovery in other asset markets, we also include TIPS-UST returns to capture Treasury market dynamics, and GSCI returns for the commodity market. All regressors are standardized with means of zero and standard deviations of one for ease of interpretation.

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

5.1.2 Predictability of Core-Focused Inflation Portfolio

Building on the event window analysis in Section 5.1.1, we assess the performance of inflation portfolios in the 30-day period before the CPI month to predict upcoming inflation changes. We focus on the additional forecasting ability of IP^{Core}, comparing it with the headline-inflation portfolio and market-based signals from Treasury bond and commodity markets. Specifically, as shown in Appendix C, at the end of month t (M_t), we use the 30-

day returns observed by the end of month t to forecast CPI changes for month $t+1$ (M_{t+1}), which are announced on day A_{t+1}, using the following regression specification:

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

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

Table 7 shows the predictive power of $\mathrm{IP}^{\mathrm{Core}}$ on inflation innovations. A one standard deviation increase in the 30-day core beta inflation portfolio ($\mathrm{IP}^{\mathrm{Core}}$) observed at the end of month t predicts a 2.2 bps increase (t-stat=2.98) in core-CPI innovations and a 7.9 bps increase (t-stat=6.54) in headline-CPI innovations for month t+1. Given the sample standard deviations of core- and headline-CPI innovations are 16 bps and 26 bps, respectively, the economic significance of $\mathrm{IP}^{\mathrm{Core}}$ is non-trivial. This evidence confirms our finding in Section 5.1.1 that a significant portion of future inflation expectations is incorporated into cross-sectional stocks well before the start of the actual CPI month.

The predictability of $\mathrm{IP}^{\mathrm{Core}}$ 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.[21] Including GSCI with $\mathrm{IP}^{\mathrm{Core}}$ boosts the predictability on headline inflation from an R^2 of 9.1% to 24%, while adding TIPS-UST enhances the R^2 to 20.3%. In both cases, the coefficient estimate on $\mathrm{IP}^{\mathrm{Core}}$ 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 $\mathrm{IP}^{\mathrm{Core}}$ predicts a 2.4 bps increase in core-CPI innovations (t-stat=2.47),

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

whereas TIPS-UST and GSCI predict increases of 0.7 bps (t-stat=0.71) and 1.0 bps (t-stat=1.3), respectively. These findings suggest that while price discovery for headline CPI, particularly its energy component, is more active in the commodity and Treasury markets, the information embedded in cross-sectional stocks can still add significant value, especially in terms of core-CPI shocks.

Finally, columns (5)-(6) and (11)-(12) analyze the headline-focused portfolio ($\mathrm{IP}^{\mathrm{Head}}$) for predicting inflation. The forecastability of $\mathrm{IP}^{\mathrm{Head}}$ on headline inflation is similar to that of $\mathrm{IP}^{\mathrm{Core}}$. A one standard deviation increase in $\mathrm{IP}^{\mathrm{Head}}$ predicts a 7.4 bps (t-stat=5.78) increase in headline-CPI innovations, close to the 7.9 bps (t-stat=6.54) increase predicted by $\mathrm{IP}^{\mathrm{Core}}$. However, $\mathrm{IP}^{\mathrm{Head}}$ is less effective for core-CPI innovations. When controlling for TIPS-UST and GSCI in column (6), the coefficient for $\mathrm{IP}^{\mathrm{Head}}$ is an insignificant 0.9 bps (t-stat=1.47), as the headline portfolio's information is largely absorbed by Treasury and commodity market signals. Thus, compared to $\mathrm{IP}^{\mathrm{Head}}$, the core-focused $\mathrm{IP}^{\mathrm{Core}}$ 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.[22]

5.2 Do Economists Update Beliefs about Inflation?

Our $\mathrm{IP}^{\mathrm{Core}}$ forecaster is constructed at the end of month t, while the inflation data for month-$t+1$ is typically announced in the second or third week of month $t+2$. This results in a lag of over one month between the signal formation and the CPI announcement. This situation raises an intriguing question: Do economists update their inflation expectations based on market-based information, particularly that embedded in cross-sectional stock data? Alternatively, if economists do not fully incorporate the information from $\mathrm{IP}^{\mathrm{Core}}$, 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.[23] These surveys provide the most current consensus view of inflation just prior to

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

[23]Bloomberg Individual Economist Estimates are derived from a diverse group of forecasters, including

the announcement. We define the change in forecasts as the difference between economists' estimated value for month-$t+1$ inflation growth and the value predicted by the ARMA (1,1) model. The announcement-day forecasting error is then defined as the actual inflation growth for month $t+1$ minus the value estimated by Bloomberg economists.

Table 8 shows that although economists are generally responsive to market-based inflation signals 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 bps (t-stat=2.73) and 10.5 bps (t-stat=5.02) 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 2.3 bps (t-stat=3.1) and 3.8 bps (t-stat=4.22) in the core and headline CPI, respectively, which economists do not anticipate. Given that the standard deviations of core- and headline-CPI forecasting errors are 11 bps and 13 bps, respectively, the information from cross-sectional stocks is significant and can enhance economists' forecasting accuracy. Yet, this information, available over a month in advance, does not seem to be incorporated into the economists' forecasts.

traders, portfolio managers, think tanks, and academics.

5.3 Time-Varying Predictability

The influence of inflation on the economy and its effect on asset prices fluctuates 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 3 shows core-CPI (MoM) growth against Bloomberg economists' forecasts from October 2020 to September 2022. During critical months in 2021, the median forecasts missed the rapid ascent of core CPI by 10 bps in March, 60 bps in April, 20 bps in May, and 50 bps in June. The April 2021 forecast error was particularly notable, being a 5.5-sigma event given that the standard deviation of forecasting error is 10.9 bps in the whole sample.

In contrast to the failure of economists, the inflation portfolio ($\mathrm{IP}^{\mathrm{Core}}$) appeared to correctly anticipate the inflation surge during this period. The lower graph of Figure 3 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 3.7 times of its sample standard deviation. Meanwhile, $\mathrm{IP}^{\mathrm{Core}}$ co-moves well with the ups and downs of core CPI, successfully catching the local trough in July 2021 and the local peaks in April 2021 and June 2022.

In the form of a scatter plot, the upper left graph of Figure 4 further demonstrates the capability of $\mathrm{IP}^{\mathrm{Core}}$ 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 26.3 bps (t-

stat=2.31) increase in core-CPI innovations for month $t + 1$, with an R-squared of 17.7%. Amid doubts about the persistence of the inflation shock, possibly driven by temporary supply-chain disruptions post-COVID-19, $\mathrm{IP}^{\mathrm{Core}}$ 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 4 shows that TIPS-UST fails to predict core-CPI innovations and even exhibits a negative correlation. Panel A of Table 9 further reports regression estimates using various market-based predictors to forecast core-CPI innovations and economists' forecasting errors. $\mathrm{IP}^{\mathrm{Core}}$ emerges as the only significant predictor, with both economic and statistical significance far surpassing other predictors.[24] Importantly, the coefficient estimates of $\mathrm{IP}^{\mathrm{Core}}$ on core-CPI innovation and survey-based forecasting error are more than three times larger than the full-sample estimates, highlighting the importance of the core-focused inflation portfolio in the price discovery of inflation during the 2021 episode.

The Episode of 1973 – Drawing parallels to the inflationary surge of 2021, the 1973 experience is frequently revisited to provide insights into recent inflation dynamics. The buildup to the Great Inflation began in the early 1970s, and by the end of 1973, inflation had escalated to 8.6%, significantly exceeding the average inflation rate of 2.5% observed between 1947 and 1972. This surge was driven by stimulative fiscal policies under Nixon's presidency, excessive government spending for the Vietnam War, and the Arab oil shock. Both periods experienced highly accommodative monetary policies leading up to their respective inflationary episodes. In 1973, inflation persisted at elevated levels until Paul Volcker's appointment as Chair of the Federal Reserve in 1979, when he initiated a stringent monetary tightening campaign.

Similar to the 2021 scenario, economists and policymakers in the early 1970s severely underestimated the rate of inflation. However, the core-focused inflation portfolio demonstrated exceptional power in forecasting inflation during the 1973 episode. We form the 1973 episode by including 24 months after May 1973 to capture the run-up period of the Great

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

inflation. May 1973 is the first time when the year-over-year core-CPI growth crossed above 3% and stayed there afterward for a prolonged decade. The lower left graph of Figure 4 shows that a 10% increase in IP^{Core}, observed at the end of month t, can predict an increase of 76.2 bps (t-stat=3.43) in month-$t+1$ core-CPI innovations, with a much improved R-squared of 28.4%. This enhanced predictability on core-CPI innovations is uniquely captured by our IP^{Core}, mirroring the results observed in the 2021 episode. Columns (5) and (6) of Table 9 further report the predictability of bond and commodity-based forecasters together with IP^{Core}.[25] Among all these forecasters, IP^{Core} is again the only significant variable that predicts core-CPI innovations during the Great Inflation episode.

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

We use two proxies to capture the time-varying nature of inflation uncertainty: (a) |CPI Innovation|, the absolute value of CPI innovation in the last month; (b) CPI disagreement, the difference between the 75th percentile and 25th percentile of quarterly CPI forecasts from the Survey of Professional Forecasters (SPF) database.[26] Panel B of Table 9 reports the predictability of IP^{Core} on core-CPI innovations and the forecasting errors (survey-based surprises) for subsamples defined using the median cutoffs of the two proxies.

The forecasting power of IP^{Core} is much stronger when the last-month |CPI Innovation| and the CPI disagreement are above the median cutoff. For example, a one standard deviation increase in IP^{Core} predicts a 3.9 bps (t-stat=3.34) and 2.9 bps (t-stat=2.39) increase in core innovations and core forecasting errors during periods with above-median inflation risk. In contrast, during periods of low inflation risk, the predictive power is only 0.4 bps and 1.8 bps, respectively.[27] Overall, the evidence suggests that IP^{Core} can provide valuable

[25] 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.

[26] 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.

[27] We focus on predicting core CPI due to its crucial role in the Fed's decision-making process. The results

information about future inflation expectations when the market most needs it.

We further explore how monetary policies impact the time-varying informativeness of IP^{Core}. The Taylor rule provides a useful framework for describing activist monetary policy (Taylor (1993)). When prices deviate from the 2-3% inflation target, the central bank can implement monetary policy to restore the target. When the Fed aggressively combats inflation preemptively, inflation can be effectively contained, reducing the predictability of market-based forecasters. For instance, during the 1989-1991 inflation period, driven by the first Gulf War and rising oil prices, annual CPI rose to 5% in May 1989 but was controlled to below 3% by October 1991. The effective federal funds rate was maintained around 9%, successfully preventing runaway inflation. Hence, the Fed's timely intervention may limit the ability of market-based forecasters to predict inflation spikes. Conversely, when the Fed reacts sluggishly, as in 2021 and 1973, inflation becomes uncontrollable, and with the lack of Fed intervention, market-based forecasters could become more effective in predicting inflation.

To test the predictability of inflation indicators conditional on Fed monetary policy, we measure the extent to which the Fed is behind-the-curve by the distance between the Fed funds rate recommended by the Taylor rule and the actual federal funds rate. The recommended Fed funds rate is calculated as 2.5%+1.5*(Core-CPI YoY Growth-2%)+0.5*OutPut Gap, where the output gap is estimated by the percentage deviation of real output from the long-run trend (Taylor (1993)). We use response coefficients of 1.5 for inflation deviations and 0.5 for output gap, following Piazzesi (2022).[28] Panel B of Table 9 reports the subsample regression estimates, where "Behind" refers to the periods when the difference between the rate implied by the Taylor rule and the actual Fed funds rate is above the 67% percentile cutoff. A one standard deviation increase in IP^{Core} predicts a 3.7 bps (t-stat=2.8) increase in core-CPI innovations with an R-squared of 5.6%, when the Fed is behind the curve. For the rest of the periods, the predictability of IP^{Core} is 1.3 bps (t-stat=1.83) with an R-squared of 0.4%.

As a graphical illustration, Figure 5 plots the time-series predictive power of IP^{Core}. For

for headline-CPI predictions are qualitatively similar.

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

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.[29] On the right axis, the upper and lower graphs plot the volatility of inflation shocks and the extent to which the Fed is behind the curve, respectively. We observe a strong co-movment between the γ^{IP} estimate and the importance of inflation risk at the time. γ^{IP} peaks during significant core inflationary episodes in 1973–82 and 2021–2022. Zooming into these periods, the predictive power is consistently stronger at the beginning of the inflation run-up when the Fed is behind the curve in combating inflation. Conversely, when the Fed aggressively fights inflation, such as during the early 1980s under Paul Volcker and in late 2022 with aggressive rate hikes, the γ^{IP} estimate decreases dramatically.

5.4 Out-of-Sample Forecastability

Section 5.1 to 5.3 presents in-sample evidence that the core-focused inflation portfolio has strong predictive power for future inflation shocks, particularly the core component. To better reflect real-time information available to market participants, we follow the methodologies of Ang, Bekaert, and Wei (2007) and Faust and Wright (2013), examining the out-of-sample forecasting power of 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 $\pi_t = a + \sum_{k=1}^{N} b_k\, X_{t-1}^k + \epsilon_t$ using only publicly available information up to month t. Here, X_{t-1}^k represents the forecasting signal k observed at the end of month $t-1$, and π_t represents the inflation growth for month t. We then use the estimated coefficients to forecast inflation growth for month t+1. The forecasting error for month t+1 is calculated as the actual inflation growth minus the forecasted growth. Out-of-sample accuracy is measured by relative RMSE, which is the ratio of the root-mean-square forecasting error (RMSE) for a particular model relative to that of the benchmark model. We use an ARMA(1,1) time-series model as our benchmark. Additional forecasting signals such as IP^{Core}, commodity-based GSCI returns, and TIPS-UST returns are added to evaluate their incremental forecasting power. A relative RMSE

[29] Appendix Figure D2 plots the regression R-squared.

below 1 indicates that the indicator improves the benchmark model's performance. To ensure sufficient historical data for training the forecasting model, the out-of-sample period begins in May 2003, five years after the introduction of TIPS data in May 1998.

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

In addition to these market-based indicators, we include economists' and households' inflation forecasts from the Survey of Professional Forecasters (SPF) database and the Surveys of Consumers by the University of Michigan. Ang, Bekaert, and Wei (2007) and Faust and Wright (2013) show that subjective survey forecasts outperform those from Phillips curve or term structure models. The importance of household subjective expectations is also emphasized by Weber, Gorodnichenko, and Coibion (2023) and D'Acunto and Weber (2024). Since we are predicting month-$t+1$ inflation growth at the end of month t, we use the latest survey forecast available at that time.[30] Table 10 indicates that economists' preliminary forecasts at month t can improve the time-series model by only 1.7%. Motivated by the Phillips curve economic model (e.g., Stock and Watson (1999)), we also include real GDP growth, output gap, unemployment rate, labor income share, and CFNAI as proxies for economic activity in the forecasting model. Consistent with Ang, Bekaert, and Wei (2007), real activity measures do not add value.

Finally, Panel B of Table 10 reports the out-of-sample performance of IP^{Core} for subsamples when inflation is particularly significant to the economy. Consistent with Section 5.3, the forecasting power of IP^{Core} is stronger during periods when inflation plays a critical role.

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

The out-of-sample predictability for core and headline CPI improves by 6.4% and 11.2%, respectively, during the 2021 inflation episode. For periods when inflation risk is above the median or when there is significant noise from the Treasury market, improvements are 3.8% for core CPI and 8.3% for headline CPI. Overall, $\mathrm{IP}^{\mathrm{Core}}$ provides unique information about inflation both in-sample and out-of-sample, particularly during heightened inflation periods.

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 $\mathrm{IP}^{\mathrm{Core}}$ should be stronger among firms with a more opaque information environment, which we capture through analyst coverage.

Additionally, we examine the informativeness of stock prices conditional on the degrees of limits 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).[31] We then sort stocks within each category by their β^{Core} into quintiles. Table 11 reports the informativeness of the top-minus-bottom quintile $\mathrm{IP}^{\mathrm{Core}}$ portfolios constructed within each group. While $\mathrm{IP}^{\mathrm{Core}}$ (X$\leq$Median), constructed based on the stocks with

[31]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.

below-median information environments, is sometimes significant in predicting the core-CPI shocks, its predictive power is fully absorbed by IP^{Core} (X>Median) when included together in columns (3), (6), and (9). This evidence is consistent with our hypothesis and indicates a stronger active price discovery among larger firms with higher institutional ownership and analyst coverage.

6.2 Predicting Inflation-Linked Asset Returns

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

Table 12 reports the predictability of IP^{Core}, observed at the end of month t, on the change in inflation swap rates (Panel A) and the change in nominal yields (Panel B) from the end of month t to the announcement day when the actual inflation of month $t+1$ is publicly released. For ease of interpretation, IP^{Core} is standardized with a mean of zero and a standard deviation of one. A one standard deviation increase in IP^{Core} predicts a 19.4 bps (t-stat=2.93) increase in the one-year inflation swap rate, with the magnitude declining monotonically with maturity. This indicates that the information from the cross-section of stocks is mostly concentrated in the short run. Similarly, a one standard deviation increase in IP^{Core} also predicts an increase in nominal yields, with the magnitude decreasing from the highest of 11.7 bps for the one-year yield to the lowest of 4.5 bps for the 30-year yield. These yield changes align roughly with the monthly predictability of around 2.2 bps in forecasting CPI innovations. Overall, it suggests that IP^{Core} can capture information not yet incorporated by inflation-linked assets. A strategy formed based on the IP^{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 how we construct individual stock inflation betas. Panel A of Table 13 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 insurance 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 industry of shipping containers appears in the top 10 for β^{Core} with a positive core beta of 0.03 per announcement day but falls into the bottom 10 for β^{Head} with a negative headline beta of -0.14 per month. This contradictory behavior makes intuitive sense: while rising commodity prices are costly for firms running shipping containers, price increases for providing shipping services benefit them. 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 13 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 D3 demonstrates the predictability of IP^{Core}, observed at the end of month t, for month-$t+1$ CPI growth and for quarterly CPI growth. To account for serial correlation in CPI growth, we control for the lagged dependent variable, akin to controlling for an AR(1) series of CPI. Consistent with our baseline estimates in Table 7, a one standard deviation increase in IP^{Core} predicts a 2.0 bps increase (t-stat=2.93) in next-month core-CPI growth and a 6.5 bps increase (t-stat=5.72) in headline-CPI growth. For quarterly (three-month) CPI growth, a one standard deviation increase in IP^{Core} predicts a 7.3 bps increase (t-stat=4.03) in core-CPI growth and a 15.6 bps increase (t-stat=4.69) in headline-CPI growth over the next three months.

Risk Factors and Portfolio Alpha – Panel A of Appendix Table D4 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.

Beta Estimated By All Historical Observations – In our baseline specification, we estimate individual stocks' inflation betas using a simple five-year rolling window approach (Fama and French (1993)). Appendix Table D5 further presents results based on inflation betas constructed following the methodology in Boons et al. (2020), using a weighted least squares (WLS) regression with exponential weights over an expanding window that includes all historical observations. Firm i's announcement-day inflation beta ($\beta^{\text{Ann}}_{i,A_t}$) is given by:

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

where R_{i,A_τ} denotes firm i's excess return on the announcement day A_τ. The weight is given by $w(\tau) = \frac{\exp(-|t-\tau|/h)}{\sum_{\tau=1}^{t-1}\exp(-|t-\tau|/h)}$. Using $h = \log(2)/60$ means the half-life of the weights $w(\tau)$ converges to 60 months for large t. The full-month inflation betas are estimated similarly.[32]

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

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

[32]Following Elton et al. (1978), Cosemans et al. (2016), and Boons et al. (2020), the betas are further transformed using the Vasicek (1973) adjustment: $\widehat{\beta^v_{i,t}} = \widehat{\beta_{i,t}} + \frac{\text{var}_{TS}(\widehat{\beta_{i,t}})}{\text{var}_{TS}(\widehat{\beta_{i,t}})+\text{var}_{CS}(\widehat{\beta_{i,t}})} \times (\text{mean}_{CS}(\widehat{\beta_{i,t}}) - \widehat{\beta_{i,t}})$, where each $\widehat{\beta^v_{i,t}}$ represents a weighted average of the stock's beta derived from time-series data ($\widehat{\beta_{i,t}}$) and the cross-sectional beta average ($\text{mean}_{CS}(\widehat{\beta_{i,t}})$).

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 D6 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.

7 Conclusions

Motivated by the 2021 inflation surge and the collective failure of policymakers 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 in 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 runaway inflation episodes of 2021 and 1973, when the predictive R-squared for month-over-month core-CPI innovations increases to 17.7% and 28.4%, 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 3.7-sigma alert beforehand. By incorporating the equity market information into their information set, economists could enhance the predictive R-squared by 9.1% 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 policymakers 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 limitations 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 policymakers as well as economists in their decision making.

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Figure 1. Core Beta and Firm Future Cash Flows

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

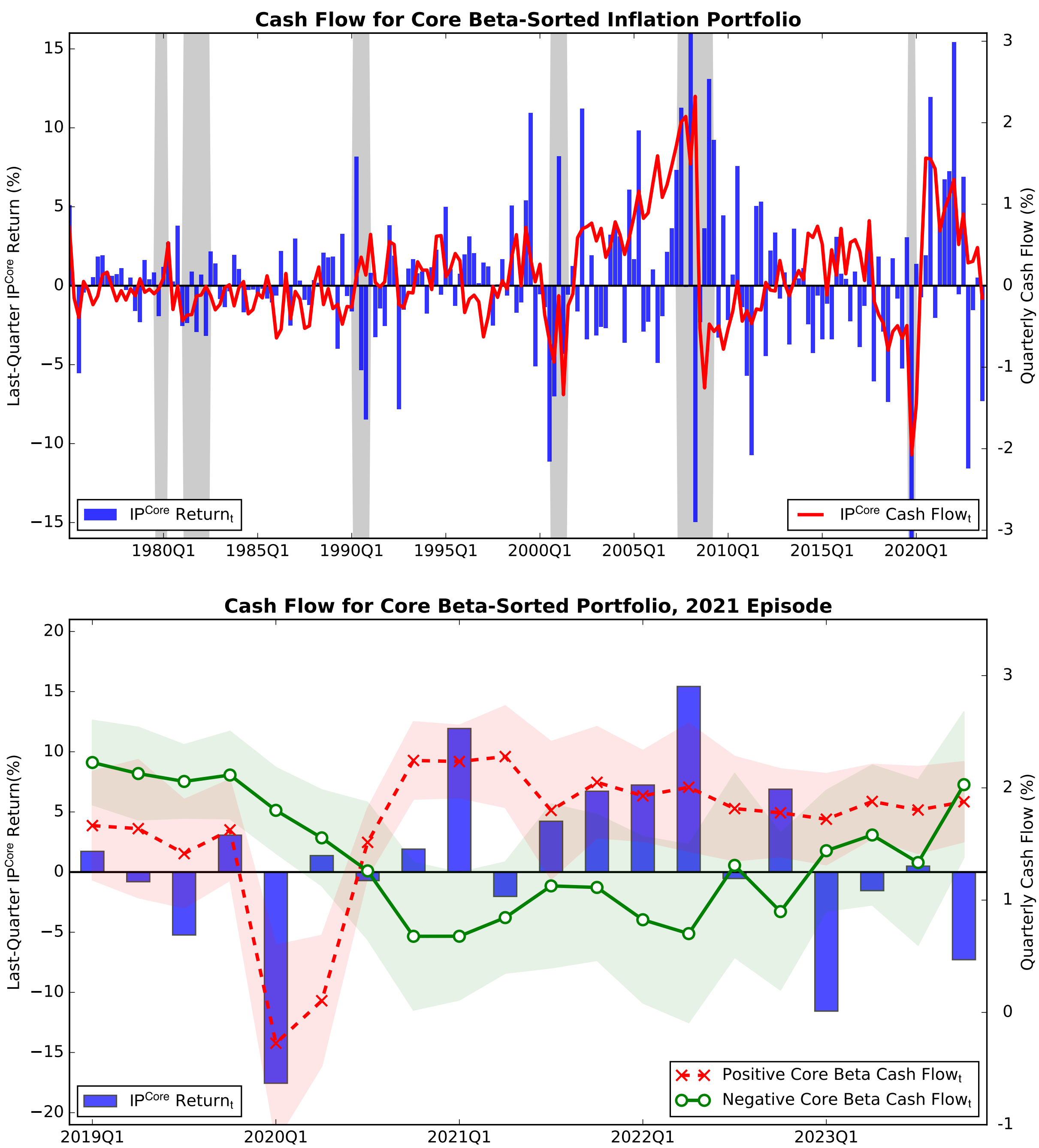
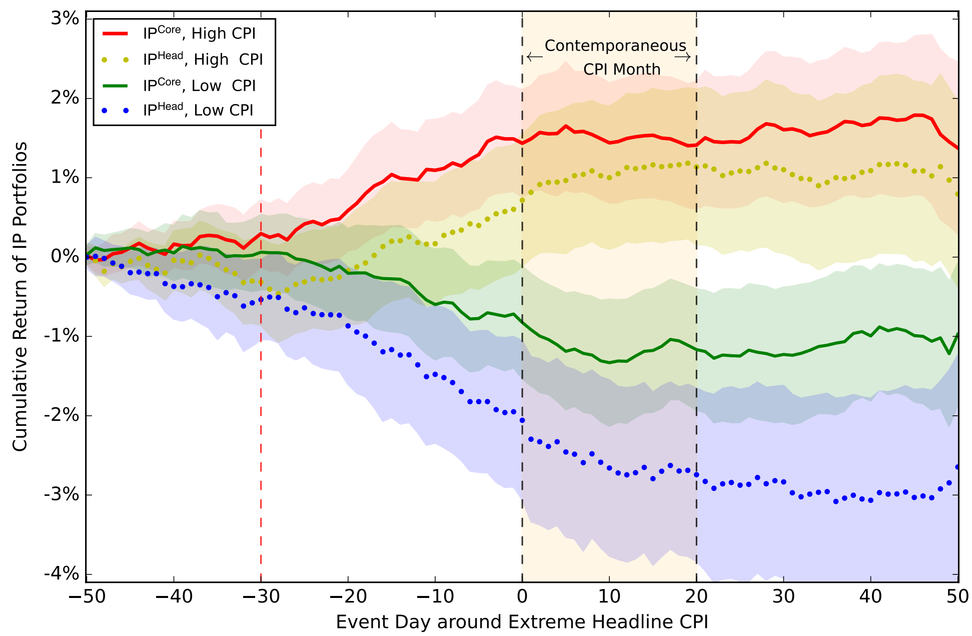


Figure 2. Performance of Inflation Portfolios around Extreme CPI Months

The upper graph illustrates the performance of IP^{Core} and IP^{Head} during the [-50, +50] trading day period surrounding extreme headline-CPI events, where t=0 denotes the beginning of the CPI data month. High (low) CPIs are categorized as those falling within the top (bottom) quintile among all CPI values. The lower graph depicts the corresponding performance of inflation portfolios when extreme CPI events are defined based on core-CPI innovations.



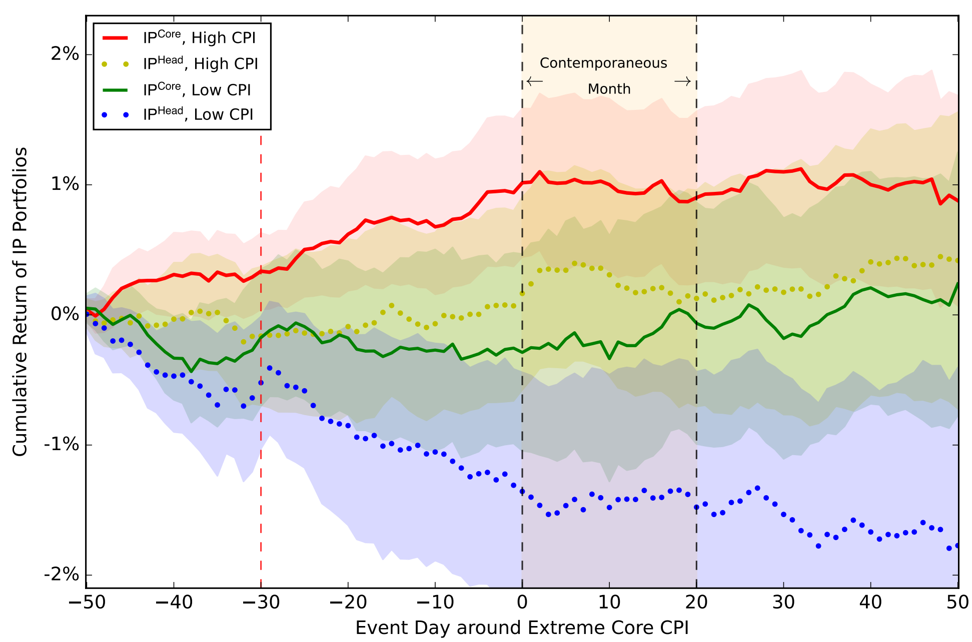


Figure 3. Economists' Forecasts and IP^{Core} in the 2021 Episode

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

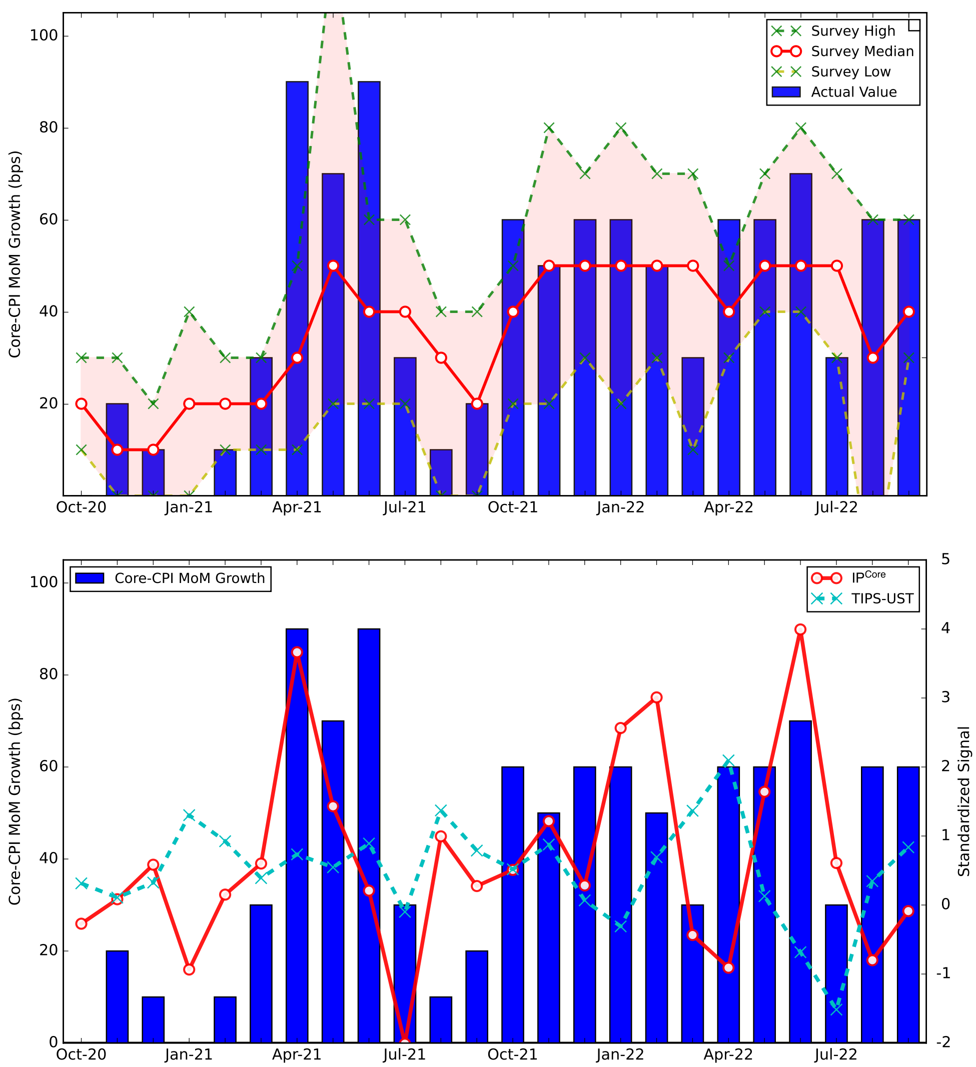


Figure 4. Predictability During Heightened Inflation Periods

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

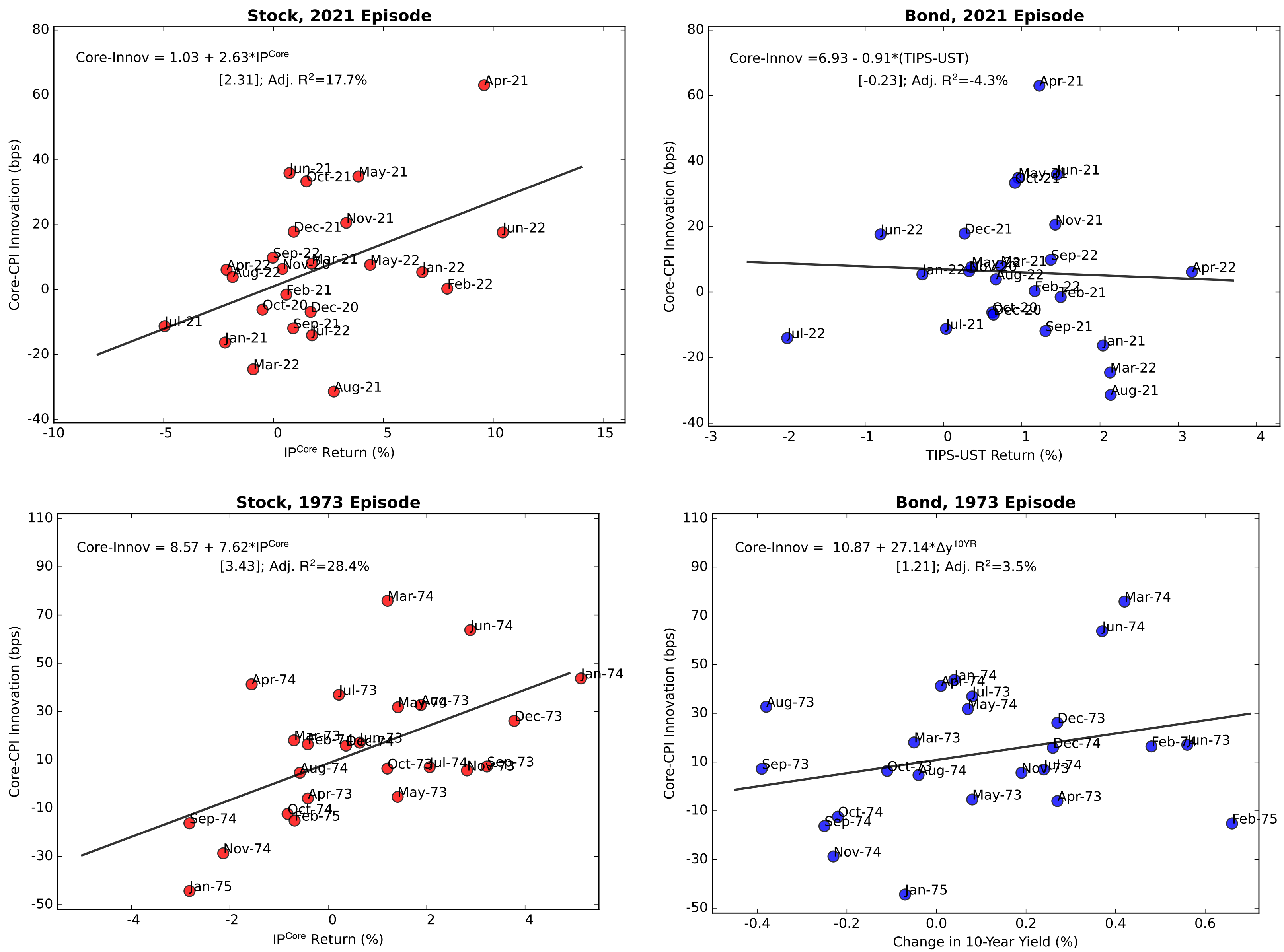
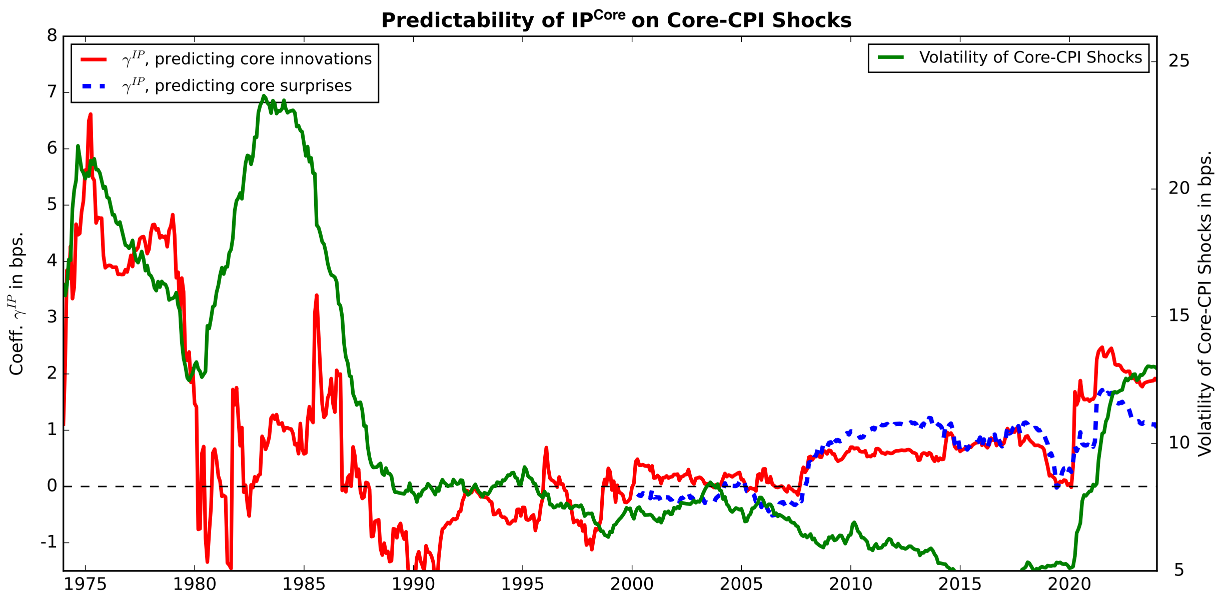


Figure 5. Predicting CPI Shocks using $\mathrm{IP}^{\mathrm{Core}}$

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



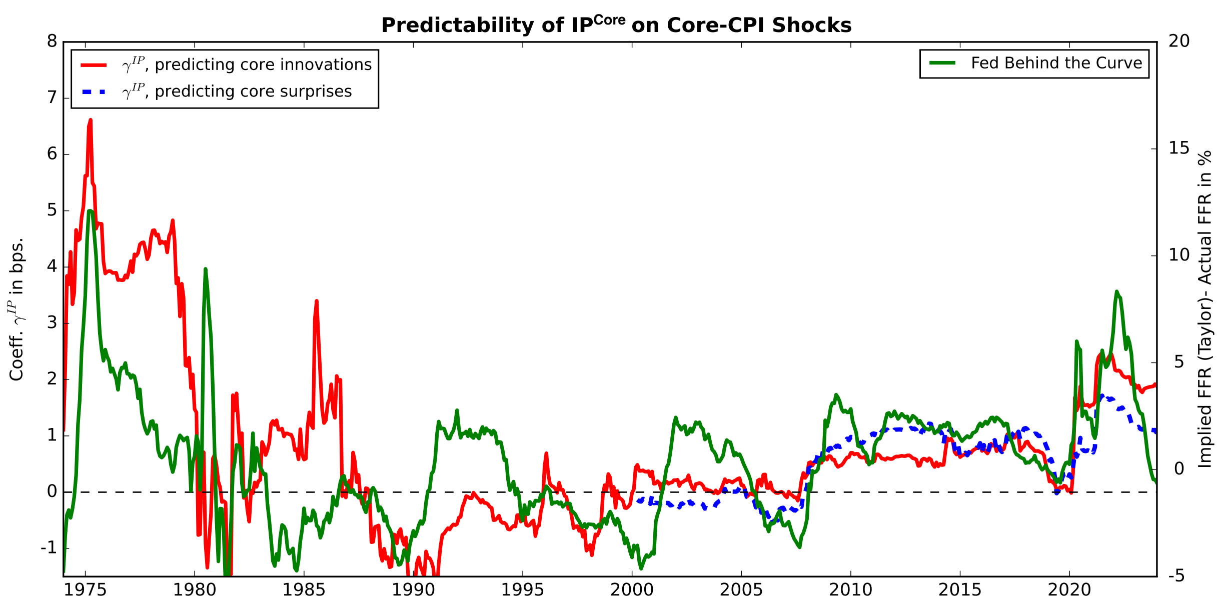


Table 1. Inflation Beta in Cross-Sectional Stocks: Ann-Day vs. Full-Month

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

Panel A. Post-Ranking Inflation Beta, Raw Model

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

Panel B. Post-Ranking Inflation Beta, CAPM Model

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

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

This table presents the announcement-day and full-month inflation betas across various asset classes. Announcement-day core, headline, and energy betas are derived by regressing announcement-day asset excess returns on announcement-day core-, headline-, and energy-CPI innovations, respectively. Full-month core, headline, and energy betas are estimated by regressing monthly asset excess returns on contemporaneous-month inflation innovations. We assess the inflation exposure for different assets, including the change in the 2-Year U.S. Treasury yield ($\Delta y^{2\mathrm{YR}}$), the change in 10-Year U.S. Treasury yield ($\Delta y^{10\mathrm{YR}}$), the negative value of the Bloomberg U.S. Treasury Index return (-UST), the difference between the Bloomberg U.S. Treasury Inflation Notes Index return and the Bloomberg U.S. Treasury Index return (TIPS-UST), the Goldman Sachs Commodity Index return (GSCI), the aggregate stock market return (VWRETD), and the cross-sectional IP return. To facilitate comparison, all variables (both dependent and independent) are standardized with means of zero and standard deviations of one. The sample spans from January 1972 to December 2023. Standard errors are adjusted for heteroskedasticity, and the *t*-stats are presented in parentheses.

	Announcement-Day (β^{Ann})			Full-Month (β^{Full})		
	Core	*Headline*	*Energy*	*Core*	*Headline*	*Energy*
$\Delta y^{2\mathrm{YR}}$	0.120	0.037	0.019	0.120	0.140	0.068
	(2.14)	(0.83)	(0.51)	(1.67)	(3.44)	(2.11)
$\Delta y^{10\mathrm{YR}}$	0.122	0.061	0.041	0.104	0.195	0.146
	(2.40)	(1.09)	(0.90)	(1.72)	(4.08)	(3.58)
-UST	0.156	0.090	−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)
Stock Market	−0.115	0.005	0.051	−0.105	−0.056	0.051
	(−2.82)	(0.06)	(0.60)	(−2.43)	(−0.94)	(0.95)
Cross-Section IP	0.107	0.068	−0.025	0.019	0.173	0.137
	(2.49)	(0.98)	(−0.39)	(0.35)	(2.96)	(2.23)

Table 3. Determinants of Inflation Beta

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

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

Table 4. Core Beta and Firm Future Cash Flows

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

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

Table 5. Inflation Beta Sorted Portfolios and Inflation Risk Premium

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

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

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

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

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

Table 6. Predicting Inflation Innovations Using Financial Assets

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

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

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

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

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

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

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

Panel A. Predicting Economist Forecasts of Core-CPI Growth

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

Panel B. Predicting Economist Forecasts of Headline-CPI Growth

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

Table 9. Time-Varying Predictability

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

Panel A. Heightened Inflation Episodes

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

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

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

Table 10. Out-of-Sample Forecastability

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

Panel A. Relative RMSE for the Whole Sample

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

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

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

Table 11. Firm Information Environment and Inflation Forecastability

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

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

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

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

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

Table 12. Forecasting Inflation Swaps and Nominal Yields

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

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

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

Panel B. Predicting Changes in Nominal Yields (%)

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

Table 13. 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. $\text{IP}^{\text{Core}}_{\text{Ind}}$ and $\text{IP}^{\text{Head}}_{\text{Ind}}$ are the 30-day cumulative returns for the industry-constructed inflation portfolios, with a long position in top-quintile CPI beta industries and a short position in bottom-quintile CPI beta industries. IP^{Core} and IP^{Head} are the 30-day cumulative returns for the stock-constructed inflation portfolios as in Table 7. All the IP returns are standardized with means of zero and standard deviations of one.

Panel A. Most and Least Inflation-Sensitive Industries

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

Panel B. Predictability of Industry vs. Stock Portfolios

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

Appendix A. Model Details

Derivations of formulas for the illustrative model are given below.

Stock Price

The stock price is given by

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

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

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

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

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

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

Stock Returns

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

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

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

The log capital-gains return is

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

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

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

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

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

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

the population estimate of β_i is

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

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

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

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

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

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

The population estimate of γ_{ij} is

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

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

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

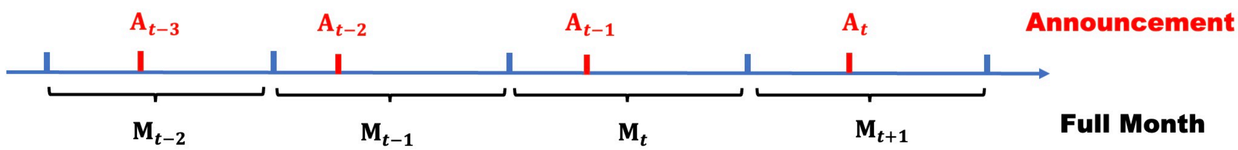
Appendix B. Variable Definition

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

Variable	Definition
CPI growth	$\pi_t = log(P_t) - log(P_{t-1})$, where P_t is the level of CPI for month t
CPI innovation	CPI-Innov$_{t+1} = \pi_{t+1} - \widehat{\pi_{t+1}}$, where $\widehat{\pi_{t+1}}$ is estimated using all the historical observations on and before month t from ARMA(1,1) time series model: $\pi_{t+1} = \mu + \phi\pi_t + \varphi\varepsilon_t + \varepsilon_{t+1}$
IP$^{\text{Core}}$	The cumulative return of the announcement-day core beta (β^{Core}) formed portfolio in the 30 days ([-30,-1]) before the end of month t
IP$^{\text{Head}}$	The cumulative return of the full-month headline beta (β^{Head}) formed portfolio in the 30 days before the end of month t
GSCI	Goldman Sachs Commodity Index return in the 30 days before the end of month t
TIPS-UST	Return difference between Bloomberg U.S. Treasury Inflation Notes Index and Bloomberg U.S. Treasury Index in the 30 days before the end of month t
Change in Forecasts	The Bloomberg economists' forecasting value of CPI growth minus the value predicted under the ARMA(1,1) model
Forecasting Error	The actual CPI growth minus the forecasting value by Bloomberg economists
CPI Uncertainty	Last-month absolute CPI innovations
CPI Disagreement	The difference between the 75th percentile and the 25th percentile of quarterly CPI forecasts from the Survey of Professional Forecasters database
Behind the curve	Periods when the difference between the Taylor rule implied Fed funds rate (2.5%+1.5*(Core-CPI YoY Growth-2%)+0.5*OutPut Gap) and the actual Fed funds rate is higher than the 67% percentile cutoff
QE	Periods of Quantitative Easing: November 2008 to March 2010, November 2010 to June 2011, September 2012 to October 2014, and March 2020 to March 2022
Output Gap	Log real GDP, detrended using the Hodrick–Prescott filter
CFNAI	A monthly index designed to gauge overall economic activity and related inflationary pressure
Log(Size)	The natural logarithm of a firm's market capitalization
Asset Growth	Growth rate of total asset: $AT_t/AT_{t-1} - 1$
Cash Flow	Income before extraordinary items plus depreciation and amortization, divided by total asset (Hennessy et al. (2007)): $\sum(IB_t, DP_t)/AT_t$
CF Beta	Cash flow betas 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: $(Sales_t - Sales_{t-1})/AT_{t-1}$

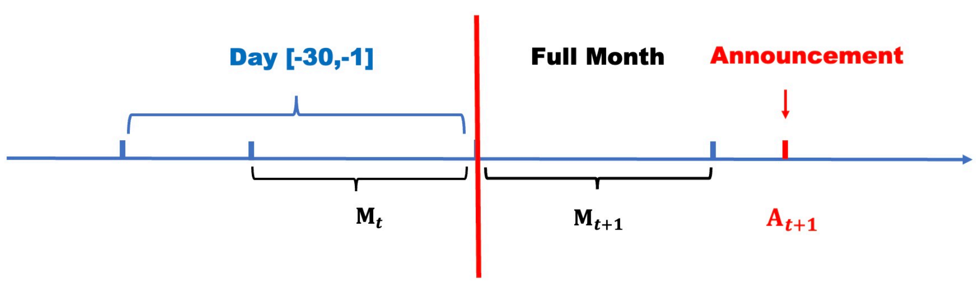
Appendix C. Illustration of the Time Line

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



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

The second approach estimates the inflation risk exposure by the sensitivity of monthly asset returns to the contemporaneous-month inflation innovations. Standing at announcement day A_t, firm i 's full-month beta is estimated using monthly returns from month M_{t-59} to M_t. For example, if we are estimating inflation beta on May 11, 2022, which is the CPI announcement day for April 2022, we use the monthly returns and monthly CPI innovations from May 2017 to April 2022 to estimate.



Forecasting with IP – To examine the forecastability of inflation portfolio returns, standing at the end of month t (M_t), we use the 30-day inflation portfolio returns observed by the end of month t (M_t) to predict the CPI innovations realized in month $t+1$ (M_{t+1}) and announced in day A_{t+1}. For example, to predict the CPI for month April 2022, i.e., M_{t+1} is April 2012, we construct our signal using the 30-day cumulative return from February 18, 2022 to March 31, 2022 (total 30 trading days). The predicted CPI is then materialized in month April 2022 and announced on day May 11, 2022.

Figure D1. Persistence of Inflation Beta

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

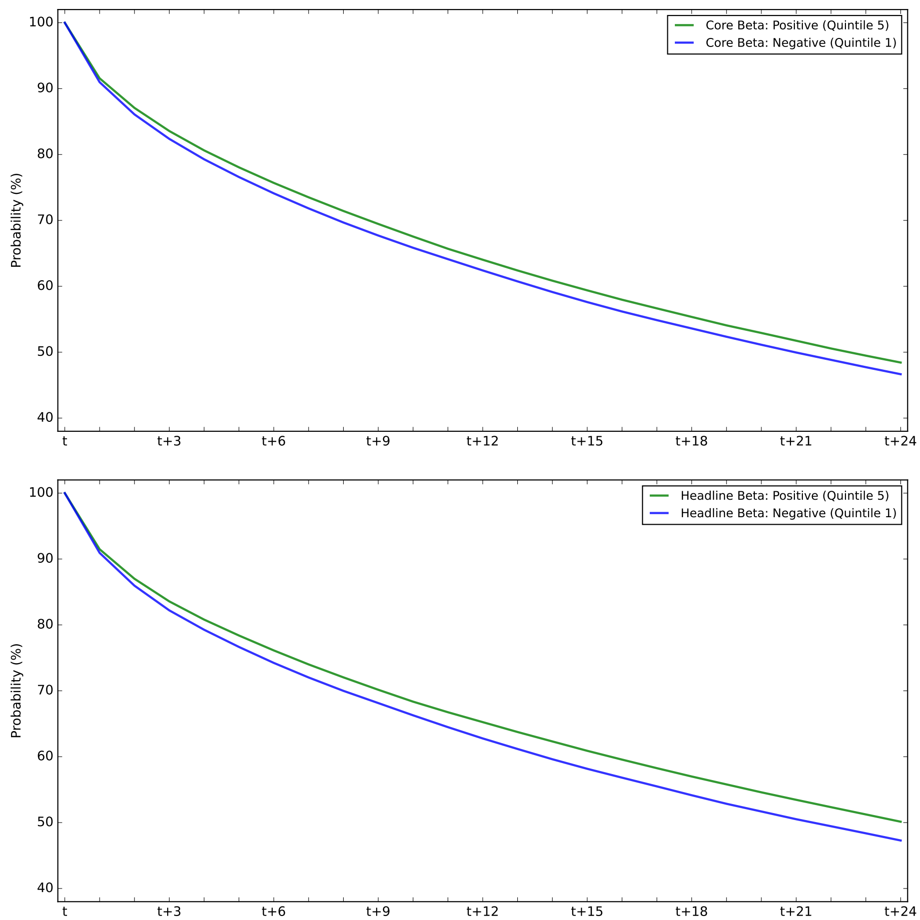
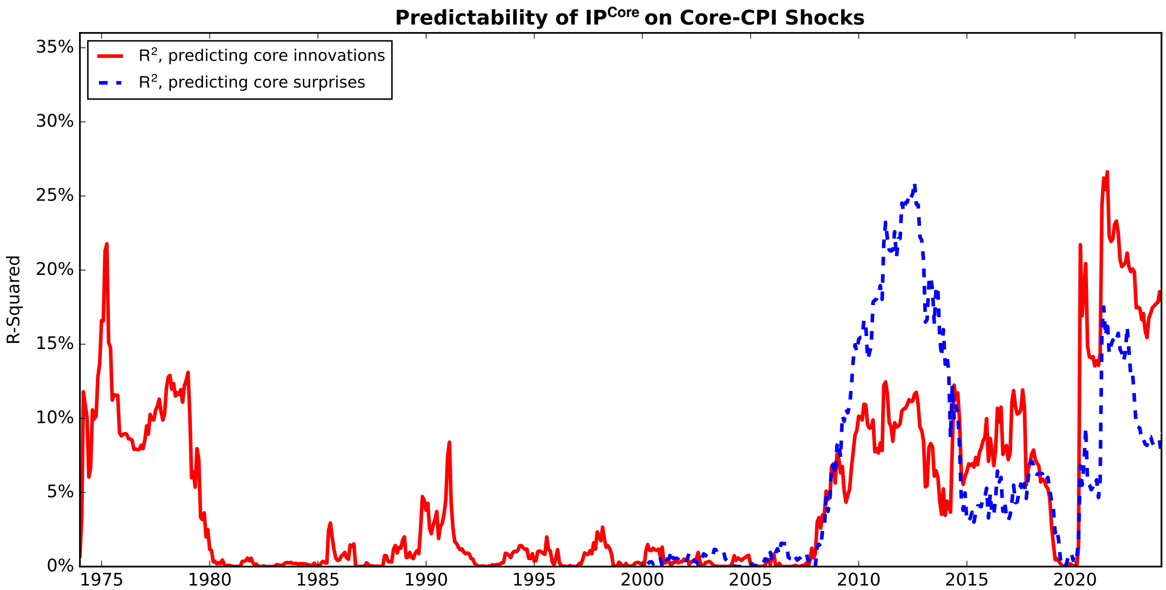


Figure D2. Predicting CPI Shocks using IP^{Core}, R-Squared

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



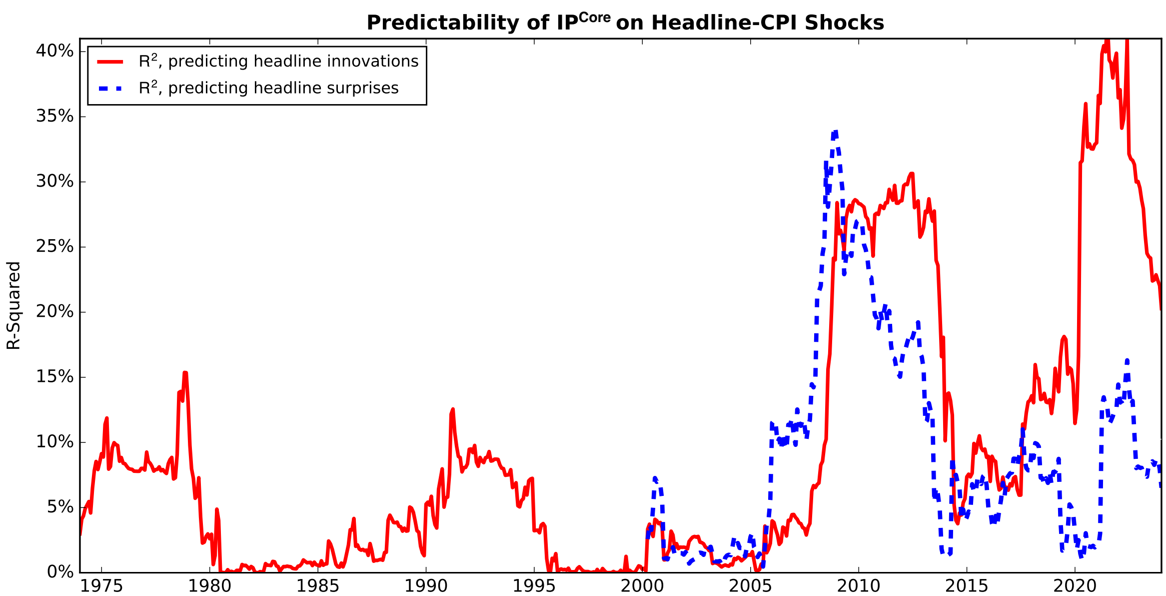


Table D1. Summary Statistics

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 returns of the β^{Core} and β^{Head} sorted portfolios observed at the end of month t. We also include statistics for asset returns, including the aggregate stock market return (VWRETD), changes in two-year and ten-year U.S. Treasury yields (Δy^{2YR} and Δy^{10YR}), the Goldman Sachs Commodity Index return (GSCI), and the return difference between the Bloomberg TIPS index and the U.S. Treasury index (TIPS-UST). The sample period is from January 1972 to December 2023.

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

Table D2. Inflation Risk Premium Conditional on Nominal-Real Covariance

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

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

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

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

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

Table D3. Predicting Inflation Growth Using Core Beta-Sorted Portfolio

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

Panel A. Predicting Month t+1 CPI Growth												
	Core-CPI Growth						Headline-CPI Growth					
IP^{Core}	1.998	1.490	2.561	2.537			6.493	3.806	8.114	4.390		
	(2.93)	(2.13)	(3.01)	(2.76)			(5.72)	(3.36)	(5.39)	(2.76)		
IP^{Head}					1.442	0.751					5.506	2.450
					(1.88)	(1.18)					(4.67)	(1.94)
GSCI		1.574		0.085		0.738		8.999		14.776		15.511
		(1.99)		(0.09)		(0.78)		(5.72)		(8.18)		(8.66)
TIPS-UST			1.254	1.214		1.221			8.413	3.189		3.127
			(1.84)	(1.74)		(1.71)			(3.08)	(1.18)		(1.15)
Lag (Y)	0.750	0.746	0.580	0.579	0.746	0.582	0.614	0.543	0.319	0.163	0.607	0.162
	(16.56)	(16.64)	(11.13)	(10.88)	(16.52)	(10.09)	(13.51)	(11.49)	(4.88)	(2.54)	(13.17)	(2.42)
Observations	624	624	308	308	624	308	624	624	308	308	624	308
Adj. R^2	56.6%	56.9%	39.1%	38.9%	56.3%	36.1%	43.5%	49.5%	37.2%	50.5%	42.4%	49.2%

Panel B. Predicting Next 3-Month CPI Growth												
	Core-CPI Growth						Headline-CPI Growth					
IP^{Core}	7.349	5.931	7.833	7.277			15.616	9.911	15.997	10.269		
	(4.03)	(3.13)	(3.62)	(3.10)			(4.69)	(2.96)	(4.27)	(2.67)		
IP^{Head}					3.868	1.820					15.020	4.945
					(1.97)	(1.26)					(3.87)	(1.07)
GSCI		4.390		2.012		3.995		17.861		20.447		22.383
		(2.33)		(0.84)		(1.64)		(5.39)		(4.52)		(4.87)
TIPS-UST			3.742	2.798		2.800			21.078	12.351		12.199
			(2.54)	(1.74)		(1.54)			(4.01)	(2.41)		(2.41)
Lag (Y)	0.804	0.801	0.495	0.491	0.799	0.491	0.615	0.582	0.131	0.081	0.611	0.082
	(19.16)	(19.07)	(6.57)	(6.45)	(18.78)	(6.16)	(14.32)	(12.97)	(1.96)	(1.17)	(13.89)	(1.13)
Observations	622	622	306	306	622	306	622	622	306	306	622	306
Adj. R^2	65.1%	65.5%	31.8%	31.8%	64.3%	28.0%	41.2%	45.1%	21.4%	26.8%	41.0%	25.3%

Table D4. The Predictability of Fama French 5-Factor Adjusted IP^{Core} Alpha

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

Panel A. FF5F Loading

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

Panel B. Predicting Month t+1 CPI Innovation

	Core-CPI Innovation						Headline-CPI Innovation					
IP^{Core} α	1.971	1.398	2.154	1.918			7.290	4.055	8.153	5.036		
	(2.87)	(2.12)	(2.58)	(2.21)			(6.33)	(3.58)	(5.01)	(2.84)		
IP^{Head} α					2.577	2.572					7.789	5.351
					(3.30)	(2.43)					(6.78)	(2.95)
GSCI		1.919		0.930		0.659		10.851		12.300		12.096
		(2.34)		(0.91)		(0.65)		(6.93)		(6.20)		(5.97)
TIPS-UST			1.574	1.116		1.032			8.655	2.600		2.397
			(1.90)	(1.42)		(1.32)			(2.80)	(0.82)		(0.75)
Observations	624	624	308	308	624	308	624	624	308	308	624	308
Adj. R^2	1.4%	2.7%	6.0%	6.2%	2.6%	8.1%	7.7%	23.5%	19.1%	30.8%	8.9%	31.1%

Table D5. Inflation Beta Constructed Using All Historical Observations

Panel A reports the post-ranking inflation betas of cross-sectional stocks, where the pre-ranking inflation betas are estimated using a weighted least squares (WLS) regression with exponential weights over an expanding window that encompasses all historical observations, following Boons et al. (2020). We control for market returns in estimating the betas. Panel B reports the inflation predictability of IP^{Core}, which is constructed based on the β^{Core} estimated in Panel A. The standard errors are adjusted for heteroskedasticity. The t-stats are in parentheses.

Panel A. Post-Ranking Inflation Beta, CAPM Model

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

Panel B. Predicting Month $t+1$ Inflation

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

Table D6. Inflation Beta Constructed using Ann-Day Surprise

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

Panel A. Post-Ranking Inflation Beta

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

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

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