In the Core of the Storm: Revisiting Inflation Hedging Properties Within and Across Asset Classes

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Abstract

The recent surge in inflation has reignited discussions on hedging inflation risks, forming the focal point of this study. In our paper we consider conventional asset classes from 1968 to 2023 as well as alternative assets from 2020 to 2023 and find that no asset class provides a statistically significant hedge against core inflation shocks, while commodities and currencies can hedge headline and energy inflation risk. Consequently, our analysis highlights a consistent negative risk premium associated with core inflation risk across all time periods considered, which remains robust for both in-sample and out-of-sample shocks. Notably, the isolation of active trading strategies reveals an insignificant positive core inflation risk premium, opening a potential avenue to mitigate the price of inflation risk within portfolios. Moreover, we find that the negative beta of bonds and stocks on core inflation shocks can help to explain the changing sign of the bond-stock correlation.

JEL Classification: G11, G12, G14, G15

Keywords: Inflation hedging, Inflation risk premium, Inflation forecasting, Bond-stock correlation

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1. Introduction

Believed to be dead not so long ago, inflation has resurged in recent years and managed to consistently surprise to the upside, posing major challenges for policy makers, companies, individual households, and ultimately financial investors. In this thesis, our goal is to enrich the limited asset pricing literature concerning inflation risk hedging, unveiling characteristics that can offer valuable guidance for investor portfolio decisions.

The consequences of the resurgence of inflation for investors are far reaching, ranging from the potential devaluation of assets due to expected higher interest rates, which elevate cost of capital and may ultimately slow down the economy, to alterations in their liabilities. This is particularly relevant for asset managers with real liabilities, such as pension funds, as their nominal costs increase with inflation, while their assets lose value. Hedging against inflation is therefore key to survival for many financial institutions. Given the volatile nature of inflation and the uncertainty associated with unexpected inflation for investors, however, our research focuses particularly on hedging against inflation innovations, defined as the difference between expected and realized inflation. Also, we intend to shed light on how different components of headline inflation have varying effects on asset classes. For this purpose, we examine inflation shocks based on the US energy inflation index, which tends to be more volatile and transitory, as well as on the US core inflation index, which is the most persistent component of headline inflation as it excludes energy and food inflation, and is often perceived as more harmful for economic activity.

In order to account for structural shifts in the US economy and highlight how hedging properties manifested during the latest inflation spike, we segmented our study into three subperiods, while also considering the entire span from 1968 to June 2023. Similar to Fang et al. (2022), we examine one interval pre-dating the year 2000 and another commencing with the new millennium until 2019. The most recent segment begins in 2020 and concludes in mid-2023. This latest subperiod is characterized by a series of heterogeneous events, starting with an unprecedented demand shock caused by the outbreak of the Covid pandemic and followed by quantitative easing to stimulate the economy (Milstein and Wessel, 2021). In between, the US economy saw significant fiscal stimulus, with the level of US government debt increasing by more than 20 percent between 2019 and 2023, as reported by the United States Treasury (2023), and supply-chain disruptions due to sustained lock-downs in different parts of the world (Hernandez, 2023). Shortly after, the war in Ukraine started, causing disruptions in the energy market (Adolfsen et al., 2022), before central banks all over the world started hiking interest rates (Kozlowski and Jordan-Wood, 2023). In this environment, it is therefore even more relevant to understand inflation shocks as a driver of asset returns and explore strategies to hedge against unexpected inflation.

Motivated by the economic environment and significance of the subject at hand for the asset pricing literature, in this thesis we aim to answer the following key research questions. What are the hedging properties of different asset classes against headline inflation and its components, are they time-varying, and can any asset hedge against core inflation shocks? Is there a consistent risk premium or price of inflation risk? Does the price of inflation risk remain constant when we consider observable forecasting errors rather than in-sample VAR residuals as inflation shocks and is it impacted by the accuracy of the forecasting model? Can stock and bond return reactions to inflation risk explain the time-varying relationship of the two asset classes?

To approach the questions, we choose a structure which builds upon existing literature, but progressively extends and challenges current views. Each section offers an outline of our key findings as well as a discussion where we attempt to contextualise and explain the results. We begin by exploring the inflation hedging properties and price of risk of conventional asset classes, backing the latter analysis by constructing inflation risk factor mimicking portfolios, extending the analysis in Fang et al. (2022) to incorporate the 2020-2023 inflation surge. We then revisit the first two research questions by extending the asset pool to other asset classes, including various alternative assets and trading strategies, an area unexplored by Fang et al. (2022), to understand how these bear against inflation risk and whether the price of risk remains robust in their presence. To further strain the results, we then go beyond the methodology employed in existing literature and build a VAR inflation forecasting model, where we ultimately optimize the forecasting window, to test the hedging properties of asset classes and the price of inflation risk on out-of-sample forecast errors observable to investors. Equipped with all the preceding analysis, similarly to Fang et al. (2022), we then consider the final research question and explore the dynamics of the bond-stock correlation, offering a range of possible explanations of the relationship stemming from our research and existing literature. We conclude our analysis by dissecting stock returns into cash flow and discount rate news as a way to understand the key driver of the core inflation betas of stocks. Subsequently, we conduct a range of tests to strengthen the robustness of our results.

2. Literature Review

In the following section, we review the literature related to the topics discussed in our work. While the core of this thesis is based on a paper published by Fang et al. (2022) titled "Getting to the Core: Inflation Risks Within and Across Asset Classes", we extend the timeframe under consideration, as well as venture into topics not covered by the authors. This section aims to provide a solid academic background to support our methodology and enrich the discussion.

2.1 Inflation Modeling

The Vector Autoregressive Model (VAR) was first introduced by Sims (1980) and has been a cornerstone model for empirical macroeconomic analysis ever since, providing a simple framework to comprehensively capture dynamics between multiple time series (Stock and Watson, 2001). The VAR method served as a foundation for many influential papers studying causal relations between stock returns and macroeconomic variables such as interest rates, inflation and other, with multiple publications acting as examples of such (Lee, 1992; James et al., 1985; Cologni and Manera, 2008). Although many complex models originating from the VAR have been developed over time, as Stock and Watson (2001) point out in their publication dedicated to vector autoregressions, simple VAR models are still used as benchmarks for complex forecasting and modeling tools. The choice of state variables employed in the VAR differs across studies, which, as argued by Chen and Zhao (2009), can have a significant impact on the outcomes from the VAR models. In this paper, we follow the VAR system used by Fang et al. (2022) which supplements the New Keynsian VAR applied, for instance, by Bekaert et al. (2005), with the price-dividend ratio. Moving window VAR models, resembling the method we employ for inflation forecasting, have also been used in research concerning macroeconomic issues, exemplified, for instance, by Swanson (1998) in his paper on the relationship between money stock and real output.

2.2 Inflation Hedging Properties of Asset Classes

As per the Fisher theorem, expected nominal rates should co-move with expected inflation, and hence by extension one could infer that stocks should provide a hedge against rising price levels (Fisher, 1930). However, already early empirical work disproves this theoretical view, showing that stock returns are in fact negatively correlated with both expected and unexpected components of inflation (Bodie, 1976; Miller et al., 1976; Fama and Schwert, 1977). The robustness of these findings has been further reinforced in the following years with similar results obtained from studies using international stock market data (Solnik, 1983; Bekaert and Wang, 2010). While Bodie (1976) and Miller et al. (1976) focused on common stocks, Fama and Schwert (1977) also considered US government bonds and bills, which they find to be a hedge against both expected and unexpected inflation. Subsequently, Fama (1981) revisited this topic to find plausible explanations for the negative inflation beta of stocks, arguing it is driven by the negative relations between inflation and real activity. Katz et al. (2016) offer a different explanation, suggesting that nominal discount rates used by local stock investors are sticky and slow to adjust to increases in local consumption baskets, hence stock returns tend to lag changes in inflation levels.

Although the bulk of research focused on common stocks and bonds, some studies also covered inflation hedging properties of other asset classes. Ready et al. (2013) in their exploration of carry trades find a negative correlation of inflation to forward discounts and US-dollar denominated FX returns. Commodity futures, on the other hand, are found to be positively correlated with both expected and unexpected components of inflation, which Gorton and Rouwenhorst (2004) argue is due to futures including information about foreseeable trends in commodity prices. Later research confirms this thesis, however adds that the hedging abilities of commodity futures tend to vary over time (Spierdijk and Umar, 2015). With regards to real estate, often perceived as a good inflation hedge, early studies analysing returns of tangible real estate portfolios show promising results, suggesting real estate can shield from both expected and unexpected inflation components (Hartzell et al., 1987; Rubens et al., 1989). However, as suggested by Case and Wachter (2011), numerous factors make it challenging to determine the efficacy of real estate as an inflation hedge. In fact, a more recent study in this area conducted by Hardin et al. (2012) focused on REIT returns shows contrary results, with REITs displaying a negative relationship with inflation, particularly in the short-term.

The hedging properties of alternative asset classes such as digital assets, private equity or hedge fund strategies still remain an under-researched area. Existing studies suggest Bitcoin exhibits some inflation hedging properties, which were noticeable particularly during the recent pandemic (Choi and Shin, 2022), however the robustness of the results and the extent of the relationship remain uncertain. Neville et al. (2021) find that some active trading strategies, after factoring in the trading costs, can provide a hedge against unexpected inflation. These include, for instance, trend-following strategies within a range of asset classes or value strategies.

While the majority of research on inflation hedging properties of asset classes considers the relationship of asset returns with CPI headline inflation levels, Fang et al. (2022) decompose inflation into its components: headline, core and energy. The authors demonstrate that core and energy inflation exhibit different statistical properties and argue that hedging of core inflation shocks, which represent the persistent component of price level rises, is investors' main concern. As opposed to some prior research on headline CPI, Fang et al. (2022) find that, in general, real assets do not offer a statistically significant hedge against core inflation shocks within the 1963 to 2019 time frame. The paper, however, does not capture the recent inflationary period, which we consider in this thesis, along with other asset classes and perspectives unexplored by the authors.

2.3 Price of Inflation Risk

As a further step, to enhance the understanding of inflation within the realm of finance and asset pricing literature, many researchers explore the price of inflation risk or in other words the inflation risk premium, both within and across asset classes. Chen et al. (1986) found weak evidence of a time-varying inflation premium, prominent particularly in periods of high inflation variance. These findings sparked further research in the area, which over time provided more robust evidence supporting the significance of the inflation risk premium, as well as reinforced the idea of its time-varying properties (Evans, 1998; Buraschi and Jiltsov, 2005; Bekaert and Wang, 2010). Grishchenko and Huang (2013) expand the discussion showing that the inflation risk premium not only varies over time, but in fact changes its sign depending on the time period considered. Boons et al. (2020) argue that the inflation risk premium exists because inflation is a predictor of real consumption growth. In their recent study, Fang et al. (2022) show that the sign, significance and magnitude of the inflation risk premium depends on whether we consider headline, core or energy inflation. The researchers provide robust results supporting a statistically significant negative core risk premium over time, suggesting investors are willing to pay to hedge against core inflation risk. In line with prior research, they show time-variance in the magnitude of the risk premia. Interestingly, the results appear more robust for core inflation as opposed to headline risk premium, which was the main focus of preceding research.

Although most research focused on proving and trying to understand the existence of the inflation risk premium in the wider economy, some studies centred on the price of risk derived from particular assets. Hollifield and Yaron (2001), for instance, show that there is a very weak evidence of an inflation risk premium in currency markets. On the contrary, Andrews et al. (2020) show, in a recent paper, that inflation is a key factor in explaining the returns of currency carry trades and the time-variation in such. When it comes to commodities, Hou et al. (2023) show that a model-based commodity inflation risk premium has a statistically significant explanatory power for the cross-section of commodity returns. Fang et al. (2022) take this analysis a step further by examining the price of risk across multiple assets while breaking it down into headline, core and energy inflation as well as constructing inflation factor mimicking portfolios bearing the same pricing power. Interestingly, the core inflation risk appears consistently priced across asset classes bearing a negative risk premium, while the pricing of headline and energy inflation fluctuates across asset classes.

2.4 Bond-Stock Correlation

Numerous papers explore the nature of the bond-stock correlation, the two key financial instruments in many investors' portfolios, some attempting to explain the underlying drivers of the relationship. Early studies show a positive correlation of stock and bond prices, or rather a negative correlation of stock prices and changes in yields (Shiller and Beltratti, 1992). Although this was true for the period examined by the authors, Ilmanen (2003) later shows early proof of the correlation sign varying over time. Campbell et al. (2009)

add the changing covariance to a standard term structure model suggesting it is a key macroeconomic indicator that should be considered. More recent papers, such as the one written by Brixton et al. (2023), show that the bond-stock correlation changed its sign in early 2000's and remained negative throughout the 21st century. However recently, as shown by the authors, the sign of the correlation has moved closer to zero and changed to positive for equity returns in some sectors. Academic literature further found evidence of the properties of the bond-stock correlations differing across regions. Yang et al. (2009) suggests that in the US the correlations are weaker during recessions while the opposite is true in the UK.

Besides modeling the dynamics of the bond-stock correlation, past research has further attempted to explain that phenomenon, presenting a range of theories. Boyd et al. (2005), for instance, suggest the bond-stock correlation is higher with expansive monetary policies. Yang et al. (2009) suggest two key macroeconomic indicators that can predict the correlation: short rate and inflation rate. With those variables in mind, Brixton et al. (2023) offer a more complex explanation of the relationship, significant for this thesis. Armed with prior research on equity and bond sensitivity to inflation, they point out both asset classes are negatively correlated to inflation news, while the sign of their correlation to growth news differs. Hence, they consider demand shocks as key drivers of a negative stock-bond correlation in the 21st century. Their rationale is that demand side shocks drive inflation and growth in the same direction, with the correlation responding more strongly to growth shocks. As an alternative explanation, they argue that for most of the 21st century, inflation has been anchored and with low levels of uncertainty, hence growth shocks were a key driver of the negative bond-sock correlation. By extension, an environment where supply shocks drive inflation while hindering growth is one where the correlation is likely to turn positive again.

3. Methodology and Data

The following section will outline the methodology employed in our analysis. In order to ensure this paper can be replicated, this section will further detail the sources of data used for the purpose of this thesis.

3.1 Methodology

3.1.1 Inflation Shocks

Following the methodology of Fang et al. (2022), inflation shocks in our model are defined as the residuals from the following vector autoregression (VAR):

$$\begin{aligned}
\pi_{h,t} &= \pi_{c,t-1} + \pi_{e,t-1} + \pi_{f,t-1} + rf_{t-1} + pd_{t-1} + gdppot_{t-1} + \varepsilon_t \\
\pi_{c,t} &= \pi_{c,t-1} + \pi_{e,t-1} + \pi_{f,t-1} + rf_{t-1} + pd_{t-1} + gdppot_{t-1} + \varepsilon_t \\
\pi_{f,t} &= \pi_{c,t-1} + \pi_{e,t-1} + \pi_{f,t-1} + rf_{t-1} + pd_{t-1} + gdppot_{t-1} + \varepsilon_t \\
\pi_{e,t} &= \pi_{c,t-1} + \pi_{e,t-1} + \pi_{f,t-1} + rf_{t-1} + pd_{t-1} + gdppot_{t-1} + \varepsilon_t,
\end{aligned} \tag{3.1}$$

where π_t is the observed headline, core, food as well as energy inflation for period t, π_{ct-1} the core inflation, π_{et-1} the energy inflation, π_{ft-1} the food inflation, rf_{t-1} the monthly risk-free rate, pd_{t-1} the price-dividend ratio and $gdppot_{t-1}$ the output gap. All the right hand side variables are lagged by 1 period. We conduct regressions with headline, core, and energy inflation as dependent variables from the beginning of 1968 to mid-2023 on a quarterly basis, deriving quarterly shocks, ε_t, based on an in-sample estimation approach. Notably, as our research focus excludes food inflation due to its relatively minor contribution to headline inflation shocks as Table 16 in the Appendix shows, it was solely utilized as an independent variable in the VAR model.

Furthermore, given our analysis also delves into the most recent inflation episode from 2020 to mid-2023, we modify the methodology used by Fang et al. (2022) by conducting VARs on a monthly basis to augment the number of data points for this period. To increase comparability with the quarterly VAR, the regression is run using the whole sample period spanning from 1968 to June 2023. However, to account for the fact that markets can only react to inflation shocks as soon as inflation numbers are published, which occurs after the month ends, we lag core inflation shocks by one month prior to running regressions to determine hedging properties. For headline and energy inflation, we choose not to lag them, considering that headline inflation is primarily driven by energy and food inflation shocks, as depicted in Table 16 in the Appendix, and we assume that both energy and food inflation shocks predominantly result from fluctuations in prices of tradeable commodities, which can be incorporated by markets immediately[1].

Given that the inflation shocks, as outlined above, are derived from the residuals of an in-sample VAR, they do not correspond to shocks that financial markets can in fact experience. To address this, we adopt an out-of-sample methodology using an expanding VAR window, thereby extending the inflation shock modelling approach of Fang et al. (2022). For this purpose, we consistently employ the most recent coefficients and data points to forecast inflation for the subsequent quarter. Consequently, the inflation shocks represent the difference between the forecasted and actual inflation during the respective quarter.

Finally, we aim to identify the optimal window length that minimizes out-of-sample forecasting errors, thereby reducing inflation shocks. This involves running VAR models with any possible window length and calculating the mean forecasting error for each length. However, to avoid errors in the VAR, the minimum window length was set to 7. Ultimately, we select the window length with the lowest mean forecasting error for headline, core and energy inflation shocks. These optimal window lengths are consequently utilized to minimize inflation shocks, which we then employ in subsequent analyses as detailed below.

3.1.2 Inflation Hedging

Consistent with Fang et al. (2022), the exposure of each asset to inflation shocks is determined through the following regression analysis:

$$r^e_{i,t} = \alpha_i + \beta^i_\pi \varepsilon_t + u_{i,t}. \tag{3.2}$$

In this specification, $r^e_{i,t}$ represents the realized return of asset i in excess of the risk-free rate. β^i_π denotes the exposure of asset i to the inflation shocks and ε_t refers to the inflation

[1]Tables 17 and 18 in the Appendix demonstrate that, across the entire sample period, lagging solely core inflation shocks yields the most consistent exposures to inflation shocks and prices of risk when comparing it to the quarterly results (see Table 3).

shock as defined in the VAR equation (3.1). To derive the exposure to headline inflation shocks, we perform a single regression, while we run a joint regression to obtain the exposures to core and energy inflation shocks. The t-statistics we report are adjusted in accordance with the Newey and West (1987) methodology to account for heteroskedasticity and autocorrelation inference in the time series.

Building on the betas derived from the first step regression (3.2), similarly to Fang et al. (2022), we perform Fama and MacBeth (1973) cross-sectional regressions to estimate the price of risk associated with each type of inflation. This estimation involves regressing average returns onto asset betas:

$$E(r_{i,t}) = \alpha_i + \lambda\beta_i + u_{i,t}, \tag{3.3}$$

where $E(r_{i,t})$ represents the average annual return of asset i, β_i the exposure of asset i to the inflation shocks and λ the risk premium. As in the first step regression, we run a single regression to derive the price of headline inflation risk, while we employ a joint regression to calculate the price of core and energy inflation risk. We then report White adjusted t-statistics to account for heteroskedasticity.

To assess how the exposure of each asset class to inflation evolves over time, we employ monthly first step regressions in a rolling five-year window. As next step, we assess how fluctuations in volatility and overall inflation levels influence the exposures to inflation risk. This is achieved by calculating the monthly differences in betas for each type of inflation. Subsequently, we conduct a regression analysis on these time series with the monthly differences in the level and volatility of inflation as joint explanatory variables and the changes in betas for each inflation type as dependent variables. This allows us to further explore the relationship between betas and the average level and standard deviation of inflation. We choose a five-year rolling window and monthly inflation data to strike a balance between responsiveness to short-term fluctuations and the ability to capture longer-term trends. This differs from the section in Fang et al. (2022) on time-varying exposures, as we do not use a local least square estimator and we also aim to identify the relationship between inflation risk exposures in relation to both the level and volatility of inflation.

To determine whether markets consistently price in inflation risk across assets, we construct inflation factor mimicking portfolios using the standard Fama-MacBeth procedure, replicating the methodology outlined by Pukthuanthong et al. (2019). Given that we conduct this exercise both within specific asset classes and for all assets combined, we always adjust the data to ensure the beginning and end dates are consistent across assets. We use the following equation to determine the asset weights in the mimicking portfolios:

$$w^* = V^{-1}\beta\,[\beta' V^{-1}\beta]^{-1}, \tag{3.4}$$

where V^{-1} is the covariance matrix of returns and β is the inflation shock beta of asset returns. When w^* derived from the above equation are applied to corresponding assets to create a portfolio, the portfolio will have a unit exposure to the given inflation risk ($\beta = 1$). We perform the above procedure at every time period in our sample separately for headline shocks in a univariate manner as well as core and energy shocks jointly. As a result, we obtain three portfolios with varying weights in each period, maintaining a beta exposure of 1 to headline, core and energy inflation shocks respectively.

Finally, following Fang et al. (2022), we aim to investigate how one of the most fundamental hedging properties in financial markets, namely the correlation between stocks and bonds, behaves in the context of inflation shocks. For this purpose, we calculate how much of the covariance between stocks and bonds is attributable to the covariance driven by inflation shocks:

$$Cov_{S,B}^{expl.} = Cov_{S,B}^{fitted} / Cov_{S,B}^{sample}. \tag{3.5}$$

In this specification, $Cov_{S,B}^{expl.}$ represents the proportion of covariance attributed to inflation shocks, $Cov_{S,B}^{fitted}$ signifies the covariance between the fitted values for stocks and bonds derived from the first step regression (3.2), where core and energy inflation shocks serve as the explanatory variables, and $Cov_{S,B}$ denotes the covariance between the excess returns of stocks and bonds in the respective sample.

3.1.3 Discount Rate News vs Cash Flow News

We follow the standard Campbell (1991) approach to decompose stock returns into discount rate and cash flow news. The following steps are performed on a range of stock market, industry and value-growth portfolios which we outline further in the data section. As a first step, we run a VAR with the following specification:

$$\begin{aligned} r_{i,t} &= r_{i,t-1} + pd_{t-1} + rf_{t-1} + \pi_{h,t-1} + \varepsilon_t \\ pd_t &= r_{i,t-1} + pd_{t-1} + rf_{t-1} + \pi_{h,t-1} + \varepsilon_t \\ rf_t &= r_{i,t-1} + pd_{t-1} + rf_{t-1} + \pi_{h,t-1} + \varepsilon_t \\ \pi_{h,t} &= r_{i,t-1} + pd_{t-1} + rf_{t-1} + \pi_{h,t-1} + \varepsilon_t, \end{aligned} \tag{3.6}$$

where $r_{i,t}$ represents the returns of asset i, pd_t represents the price-dividend ratio, rf_t is the risk free rate and $\pi_{h,t}$ is level headline inflation. Conscious that the choice of state variables for the VAR may have a significant impact on the outcome (Chen and Zhao, 2009), we choose to follow the choice made by Fang et al. (2022). As per the standard VAR approach, the right-hand-side is composed of lagged variables, in this case by one quarter. We then use the VAR results to derive the discount rate news, applying the following formula from Campbell (1991):

$$N_{DR,t} = e1^{'}\lambda u_t, \tag{3.7}$$

where λ is defined as $\rho\Gamma(\Gamma - \rho\Gamma)^{-1}$. In this configuration, u_t is a matrix of residuals from the VAR, $e1^{'}$ is a vector whose first element is equal to 1 and other elements are 0, Γ is the matrix of VAR coefficients and ρ is the discount coefficient. In this paper, we set ρ to 0.967, which is the optimal discount coefficient derived by Vuolteenaho (2002). We then proceed to derive the cash flow news using the indirect method which, as per Campbell and Vuolteenaho (2003), is advantageous given it does not require to understand short-run dynamics of dividends. We use the following equation to back out cash flow news:

$$N_{CF,t} = (e1^{'} + e1^{'}\lambda)u_t. \tag{3.8}$$

We then regress the cash flow and discount rate news on core and energy inflation shocks jointly.

3.1.4 Robustness Checks

To strengthen the validity of our analyses, we consider three distinct robustness checks employed by Fang et al. (2022). First, we assess whether the price of inflation risk is still present when we introduce other exogenous macroeconomic variables. These variables are included as independent variables when running regressions to determine the exposure of each asset to inflation shocks. In the second step regression, we then estimate both the price of inflation risk and the price of the risk associated with the specific macroeconomic variable under consideration.

Secondly, we aim to examine whether it is the exposure to inflation shocks or the exposure to expectations for future inflation that explains excess returns. For this purpose, we conduct a two-step regression analysis. In the first step, we run a regression of excess returns on the current level of inflation:

$$r^e_{i,t} = \alpha_i + \beta^i_{\text{level}} \pi_t + u_{i,t}. \tag{3.9}$$

In this specification, β^i_{level} denotes the exposure to the level of inflation. In the second step, we decompose the level of inflation into its unexpected and expected components. Similar to our initial specification of inflation shocks, we use the residuals from the quarterly VAR to capture unexpected inflation. For the expected inflation component, we obtain the fitted values from the VAR, which represent the expectations at $t-1$ for the level of inflation at t. Subsequently, we conduct a joint regression of excess returns, incorporating both the fitted values and residuals:

$$r^e_{i,t} = \alpha_i + \beta^i_e (E_{t-1}\pi_t) + \beta^i_u \varepsilon_{\pi,t} + u_{i,t}, \tag{3.10}$$

where β^i_e represents the exposure to expected inflation, $(E_{t-1}\pi_t)$ the inflation expectations for period t in $t-1$, β_u the exposure to unexpected inflation, and $\varepsilon_{\pi,t}$ the unexpected inflation in t.

As a last robustness check, we consider a different approach to determining inflation shocks. Rather than employing the VAR to back out inflation shocks, we use the inflation expectations from the Survey of Professional Forecasters and determine the shocks through the following equation:

$$u_{i,t} = \pi_{t,\text{level}} - \pi_{t,\text{survey}}, \tag{3.11}$$

where $\pi_{t,\text{level}}$ represents level inflation, $\pi_{t,\text{survey}}$ is the expected headline inflation from the survey and their difference $u_{i,t}$ is the inflation shock. Given expected core inflation data from the Survey of Professional Forecasters is only available from 2007, we follow the approach suggested by Fang et al. (2022) and use headline expectation as the expected inflation for both headline and core inflation. As energy inflation is largely unpredictable and very volatile, we use level energy inflation as the shock itself. We then run Equation 3.11 separately for core and energy inflation in all quarters from Q3 1981 to Q2 2023 in order to determine inflation shocks. Once shocks are determined, we then follow the previously outlined procedure to determine inflation hedging properties (3.2) and the price of risk (3.3) and compare it to the regression results obtained when the shocks were backed out from the VAR.

3.2 Data

3.2.1 Vector Autoregressive Model

Inflation data for the vector autoregression (VAR) analysis was sourced from the Federal Reserve Economic Data (FRED) database. Specifically, we used the Consumer Price Index for All Urban Consumers in the US, distinguishing between All items, All items Less Food and Energy, Food and Beverages and Energy, consequently referred to as headline, core, food and energy inflation, respectively. This data is seasonally adjusted and was retrieved both on a monthly and quarterly basis, with inflation representing the change in the Consumer Price Index on a month-on-month or quarter-on-quarter basis. Additionally, the dataset for the US output gap was sourced from FRED, representing the relative difference between the real gross domestic product and real potential gross domestic product. For the risk-free rate, we use the monthly risk-free rate from Kenneth R. French's research website, while the price-dividend ratio for the US stock market was retrieved from Robert Shiller's research website. The time span covered by the data for the VAR analysis extends from the beginning of 1968 to mid-2023.

3.2.2 Test Assets

In our analysis, we use various portfolios within asset classes as well as their respective market portfolios. For assets where we faced constraints in accessing market level data, we construct market portfolios manually, using the methodology outlined below. All our time series of returns, obtained from various sources, assume reinvestment of dividends. For REIT data, where the total return time series was not available, we constructed it based on available spot prices and the dividend yield.

We obtain our data from various sources: the stock market and international stock returns are obtained from MSCI indices. This includes returns of the US stock market, as well as Europe and Far East. Industry portfolio returns are downloaded from Kenneth R. French's website and encompass consumer, manufacturing, high tech and healthcare. Treasury data is pulled from CRSP, we get the agency and corporate bond returns from ICE Bofa Agency and Corporate indices. We gather returns of the fixed income assets for a range of maturities depending on particular availability. Commodity returns are obtained from GSCI indices and include livestock, agriculture, industrial metal, precious metal and energy. We use the S&P US REIT index as the proxy for the REIT market in our analysis. We further obtain currency data for multiple carry portfolios from the MIT Sloan School of Management database, which time frame we then extend as outlined in a subsequent paragraph. Additionally, in our discount rate vs cash flow news analysis, we use a range of portfolios sorted from value to growth, which we download from Kenneth R. French's website. Returns of different asset classes have different start dates. Our longest time series are for treasuries as well as industry and value portfolios from Kenneth R. French's website for which we have data from the beginning of 1968. However, treasury data only spans until the end of 2022. The stock market returns for the US and other regions are available from the beginning of 1970, so are the returns of the commodity market portfolio, livestock and agriculture. Other commodity returns have shorter available time series, with precious metal originating in 1973, industrial metal starting in 1977 and energy in 1983. Currency return data spans from the beginning of 1984. The REIT return data is available from Q3 in 1989. Our shortest time series are the returns of agency bonds and corporate bonds which are accessible from 1997.

Given constraints in accessing the data, we manually construct the market portfolios for treasury and currency returns. We do so by taking the equal weighted average of the returns of respective assets within each asset specification, hence implicitly assuming the market portfolio is composed of the embedded assets in equal proportions. For currencies, we only use the carry 1-6 portfolios in the market portfolio construction.

To extend the availability of currency excess returns for carry portfolios 1-6, as originally constructed by Lustig et al. (2011), and dollar carry excess returns, as formed in a subsequent paper (Lustig et al., 2014), we compile these portfolios for the missing time frames up to 2023. Following the methodology established by Lustig et al. (2011), we source data for 26 currency pairs from Eikon. This dataset includes monthly spot and 1-month forward prices quoted in terms of USD, spanning from 2007 to 2023. For carry portfolios 1-6, we calculate the 1-month forward discount for each currency pair at the end of period t. We then sort these currency pairs into six portfolios, with those exhibiting the highest forward discount relative to the USD assigned to portfolio 6, and those with the lowest discount allocated to portfolio 1. Next, we compute the average excess return of all currency pairs present in each respective portfolio in the subsequent month.

For the dollar carry excess return, we determine the average of all forward discounts for the 26 currency pairs. Similar to Lustig et al. (2014), we take a long position if an average discount is observed across all portfolios in period t and a short position if an overall premium is present on average. Subsequently, the excess return in the following month (t+1) is computed as the average excess return, with a positive sign when we were long and a negative sign when we were short in the previous month.

For all portfolios, we then conduct regressions of our currency excess returns on the available excess returns. These regressions yield correlations ranging from 0.89 to 0.95 for the six carry portfolios and 0.93 for the dollar carry portfolio, suggesting that our methodology in place is close to the one employed by Lustig et al. (2011) as well as Lustig et al. (2014) and the currency returns are thus comparable over time. Finally, we project the excess returns for the remaining time frame based on our currency returns and the regression coefficients.

In addition to traditional asset classes, we expand our analysis to include alternative assets and trading strategies. As alternative assets, we examine Bitcoin and include Treasury Inflation-Protected Securities (TIPS), for which we use the PIMCO 1-5 Year U.S. TIPS index ETF and the PIMCO 15+ Year U.S. TIPS index ETF to differentiate between short-term and long-term inflation-protected bonds. Our selection of active strategies encompasses merger arbitrage, represented by the IQ Merger Arbitrage ETF; event-driven strategies, captured by the BlackRock Event Driven Equity Fund; market-neutral strategies, for which we use the IQ Hedge Market Neutral Beta index, and trend following strategies, reflected by the Eurekahedge CTA/Managed Futures Hedge Fund index. Moreover, we consider different equity hedge fund strategies, including the Bloomberg Equity Long/Short Hedge Fund index, the Bloomberg Equity Hedge Fund index, Bloomberg Equity Multi-Strategy Hedge Fund index, the Bloomberg Equity Long Biased Hedge Fund index, as well as the Bloomberg Equity Long Only Hedge Fund index. Additionally, we use the S&P Listed Private Equity index as a proxy for private equity investments. Finally, we consider the most commonly known risk factors from Kenneth R. French's website, including Small Minus Big (SMB), High Minus Low (HML), Winners Minus Losers (WML), Conservative Minus Aggressive (CMA) and Robust Minus Weak (RMW) for the North American market. Due to varying data availability for alternative assets and trading strategies, we restrict our dataset to the period from 2020 to mid-2023, ensuring consistency in our analysis.

3.2.3 Data for Robustness Checks

To enhance the robustness of our results, we include five exogenous macroeconomic control variables in our analysis: change in personal consumption expenditures, change in personal consumption expenditures for durable goods, industrial production, total nonfarm employees and the employment rate. This data is seasonally adjusted and was retrieved from the FRED database for the US economy. As a further robustness check, we use data from the Survey of Professional Forecasters run by the Federal Reserve Bank of Philadelphia as the expected inflation, rather than using VAR to distinguish between expected and unexpected components of inflation. The survey results represent expectations for one year ahead inflation levels. It is conducted on a quarterly basis and its headline component runs from mid-1981 to mid-2023. Given data for core inflation is only available from 2007, we use headline as a proxy for both core and energy expectations, following the approach presented in the paper published by Fang et al. (2022).

4. Empirical Findings and Discussion

The purpose of this chapter is to present the key findings of our thesis. We further supplement it with a discussion of the interpretation and significance of our results.

4.1 Inflation Properties

4.1.1 Descriptive Statistics

As depicted in Panel A of Table 1, the average level of headline, food and core inflation has been vastly similar over the whole sample period. However, differences in standard deviations and autocorrelations between the three are relatively more pronounced. Overall, the standard deviation of core inflation has proven to be the lowest, while showing the highest degree of autocorrelation, suggesting that core inflation has been the most consistent and predicable inflation component over the whole sample period. In contrast, energy inflation exhibits a higher average level, with limited predictability due to a considerably higher standard deviation and low autocorrelation of 0.08.

When examining monthly inflation data since the start of 2020, we observe not only a higher level of inflation for all inflation components, but also a divergence of averages, with average food and energy inflation being higher by roughly two percentage points, while core inflation was higher only by 0.3 percentage points. With respect to autocorrelations, a reversal of the pattern for energy inflation is observable. In the most recent inflation episode, it has amounted to 0.37, indicating increased persistence. Core inflation, on the other hand, has become relatively less predictable, as indicated by its reduced autocorrelation.

Panel B provides a breakdown of the components comprising headline inflation over the entire sample period. Core inflation constituted the majority at 72 percent, followed by food inflation at 20 percent, and energy inflation at 8 percent. In the most recent 3.5 years, the composition has remained relatively stable, with food inflation contributing marginally more, while core inflation constituted proportionally less.

As Panel C shows, the correlation between headline inflation and its components is highest with core inflation throughout the entire sample period, which has remained high, albeit decreasing slightly, in the latest inflation period. Conversely, energy inflation has seen an increase in correlation with headline inflation most recently. Notably in this context, despite core inflation showing a relatively lower correlation with headline inflation, the correlation between core and energy inflation has increased in the recent period. For food inflation, a significant drop in correlation with headline inflation has been recorded, declining from 0.59 to 0.18.

Table 1. Inflation Summary Statistics

A. Summary Statistics

	Full Sample			2020-2023		
	Mean	SD	Autocorr	Mean	SD	Autocorr
Headline	4.04	1.69	0.60	4.66	1.26	0.57
Core	3.99	1.38	0.75	4.26	0.87	0.66
Food	4.06	1.95	0.50	5.99	1.24	0.65
Energy	5.05	10.26	0.08	6.82	11.57	0.37

B. Headline Composition

	Full Sample		2020-2023	
	β	s.e.	β	s.e.
Core	0.72	0.01	0.67	0.01
Food	0.20	0.01	0.23	0.01
Energy	0.09	0.00	0.09	0.00

C. Correlation Matrix

	Full Sample				2020-2023			
	Headline	Core	Food	Energy	Headline	Core	Food	Energy
Headline	1.00				1.00			
Core	0.81	1.00			0.77	1.00		
Food	0.59	0.47	1.00		0.18	0.09	1.00	
Energy	0.69	0.21	0.15	1.00	0.84	0.33	-0.04	1.00

Note: This table provides summary statistics for headline, core, food and energy inflation components. Panel A presents summary statistics for each inflation component, including their mean, standard deviation and auto-correlation. All values are annualized. Panel B reports the regression results of headline inflation on core, food and energy inflation. Panel C reports the correlation matrix.

4.1.2 Inflation Shocks

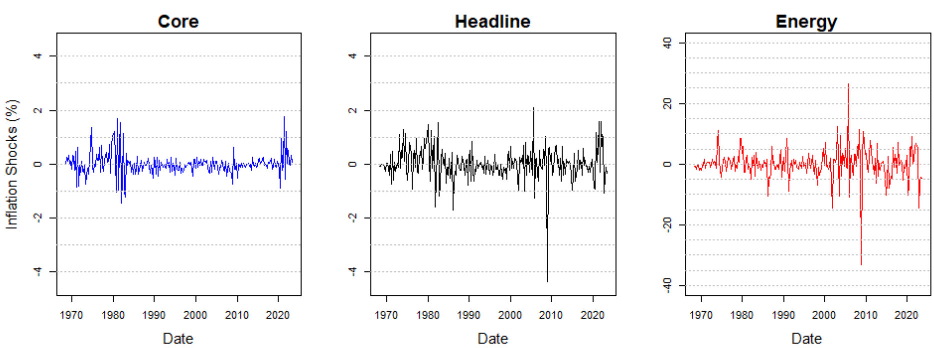
Figure 1 plots core, headline and energy inflation shocks from our vector auto regression model. As can be inferred from the graph, the time series of shocks exhibit different properties depending on the inflation metric.

The core inflation shock time series is the least volatile, with shocks fluctuating mostly within a $+/-$ 1 percent bound and never differing from zero by more than 2 percent. This result is intuitive, given core inflation exhibits the highest autocorrelation and lowest variance among the three inflation measures we analyse. Interestingly, periods of high core shocks tend to be clustered and last a relatively short time.

Energy inflation is substantially the most volatile. Shocks frequently breach a $+/-$ 10 percent bound, suggesting this component of headline inflation is extremely difficult to forecast. The shocks appear less clustered, however are characterized by significant and sudden spikes.

Headline inflation shocks are more volatile as compared to core shocks, however still significantly less volatile than energy shocks, predominantly staying within a $+/-$ 2 percent bound. Notably, when comparing headline to energy shocks it is noticeable that energy shocks drive the volatility of headline inflation, particularly in periods where energy inflation experiences major spikes. The headline shock time series thus seems comparable to the energy shocks plot, however its volatility appears significantly dimmed by the core inflation component. The observation of energy inflation shocks being the main driver of headline inflation shocks is also supported by Table 16 in the Appendix, which shows that energy inflation shocks can explain 64 percent of the variation in headline inflation shocks over the full sample period.

Figure 1. Time Series of Inflation Shocks



Note: This figure illustrates the time series of core, energy, and headline inflation shocks, being the error terms, ε_t, from the VAR specified in (3.1).

4.2 Inflation Hedging

4.2.1 Inflation Hedging Properties of Assets Classes

As shown in Panel A of Table 2, we find positive beta coefficients in response to headline inflation shocks for currencies, commodities and REITs over the entire sample period, with REITs not showing any statistical significance. Currencies exhibit almost perfect inflation hedging properties in response to unexpected headline inflation, indicating that an unexpected 1 percent inflation shock is associated with a 0.91 percent increase in the value of the currency portfolio. Commodity portfolios exhibit even more robust inflation hedging properties, implying an expected return of 8.19 percent in response to the same shock. Stocks and bonds were negatively correlated with inflation shocks throughout the entire sample period, with only treasury and agency bonds being statistically significantly exposed to headline inflation shocks.

As Panel A further illustrates, a clearer picture emerges for the exposure to core inflation shocks. All assets examined had negative core inflation betas, ranging from −4.47 for international stocks to −0.14 for agency bonds. However, only the coefficients for treasuries and domestic as well as international stocks are statistically significant. For energy inflation shocks, most asset classes exhibit beta coefficients close to zero, except for commodities, which display a beta of 1.15. Despite showing relatively low values for betas, the coefficients for treasury and agency bonds, as well as currencies and commodities, are statistically significant.

Accordingly, the hedging properties of real assets, such as stocks, commodities, REITs, and currencies, are confirmed only for currencies and commodities in response to headline and energy inflation shocks. The almost perfect hedging properties of the currency market portfolio in relation to headline inflation indicate that the market mechanism of currency devaluation in response to a headline inflation innovation works well. This implies the USD depreciates when US headline inflation unexpectedly rises, causing foreign currencies to appreciate, resulting in a strong performance of the currency portfolio, which consists of a basket with forward contracts to buy foreign currencies. However, this mechanism does not appear to function when core inflation is unexpectedly high. Combining the argument presented by Fang et al. (2022) of higher core inflation subsequently leading to lower real activity as well as consumption, with the argument of Lustig et al. (2011) of foreign currencies with high interest rates depreciating against the USD when US consumption growth is low, while currencies with low interest rates do not, we suggest that markets interpret core inflation shocks as increased US consumption risk and, in their search for safety, buy securities denominated in USD, acting as a counterweight to the currency devaluation mechanism described above.

Table 2. Asset Return Exposure to Inflation Shocks

	Mean	S.D.	Headline β	t-stat	Core β	t-stat	Energy β	t-stat
A. Full Sample Period								
Stock	7.27	16.92	-0.96	-0.57	-4.09	-2.46	0.17	0.97
Treasury	2.11	7.28	-2.40	-7.12	-1.92	-2.12	-0.21	-4.00
Agency	1.93	3.45	-0.90	-3.72	-0.14	-0.39	-0.10	-3.11
Corporate	3.19	5.93	-0.31	-1.15	-0.62	-0.48	-0.02	-0.48
Currency	1.53	6.88	0.91	2.41	-0.56	-0.68	0.13	2.56
Commodity	5.01	22.85	8.19	4.87	-0.41	-0.21	1.15	6.10
REIT	6.62	19.74	3.19	1.40	-1.59	-0.43	0.37	1.21
Int Stock	6.31	18.89	-0.55	-0.31	-4.47	-3.61	0.21	1.11
B. 1968-1999								
Stock	7.82	16.77	-5.61	-4.08	-4.72	-2.55	-0.35	-1.37
Treasury	1.70	7.51	-2.93	-6.30	-2.56	-3.04	-0.20	-2.17
Agency	0.83	3.48	-0.63	-0.97	3.62	3.66	-0.25	-2.60
Corporate	0.71	3.82	-1.07	-1.22	2.89	2.08	-0.26	-2.03
Currency	2.18	7.99	0.12	0.09	0.18	0.08	0.07	0.30
Commodity	6.64	19.83	3.98	1.74	-0.02	-0.01	0.66	1.62
REIT	-0.54	15.30	-8.03	-1.79	-5.08	-0.89	-0.67	-0.97
Intl Stock	7.90	18.91	-5.39	-3.50	-4.61	-2.68	-0.58	-1.93
C. 2000-2019								
Stock	5.52	16.13	2.68	1.79	-5.98	-1.12	0.33	1.61
Treasury	3.63	6.48	-2.23	-5.44	-1.23	-0.74	-0.22	-4.16
Agency	2.76	3.23	-1.04	-4.98	-0.52	-0.65	-0.10	-3.92
Corporate	4.53	5.26	-0.18	-0.73	-0.66	-0.29	-0.01	-0.21
Currency	1.40	6.15	1.22	4.14	-1.71	-0.85	0.15	2.52
Commodity	1.46	24.87	11.91	8.64	-1.05	-0.25	1.26	5.73
REIT	11.05	20.84	3.96	1.42	-7.16	-1.19	0.45	1.09
Intl Stock	3.96	18.29	3.55	2.97	-6.14	-0.91	0.45	2.14
D. 2020-2023								
Stock	12.91	20.31	1.21	0.33	-5.25	-1.73	0.27	1.00
Treasury	-3.72	7.29	-1.99	-2.50	0.78	0.67	-0.20	-2.73
Agency	-1.88	3.45	-0.87	-4.36	-0.06	-0.13	-0.08	-4.32
Corporate	-2.16	9.01	-0.11	-0.09	-2.20	-2.51	0.01	0.18
Currency	-0.73	4.04	1.20	2.24	-0.41	-0.49	0.09	1.61
Commodity	12.70	28.58	13.52	1.95	-8.04	-1.61	1.30	2.17
REIT	4.19	23.00	3.77	0.71	-3.92	-1.40	0.53	1.22
Int Stock	6.26	19.49	2.44	0.72	-6.18	-2.12	0.40	1.50

Note: This table reports the regression results of the following specification; $r^e_{i,t} = \alpha_i + \beta^i_\pi \varepsilon_t + u_{i,t}$, where $r^e_{i,t}$ are excess asset returns and $\varepsilon_{i,t}$ is the error term from the VAR (see Equation 3.1). We run a univariate regression for headline shocks, while for core and energy inflation shocks we run the regression jointly. The t-statistics we report are adjusted in accordance with the Newey-West methodology. All mean returns and standard deviations reported are annualized. We report the results for separate time periods and the full sample period.

The correlation between core inflation and subsequent real growth could also serve as explanation of why commodities can only hedge against headline and energy inflation. As Baffes and Kabundi (2023) show, commodity prices are increasingly driven by the global business cycle, suggesting a slow-down in the US economy would lead to a decline in demand for commodities. Nevertheless, the coefficient of above 1 for energy inflation shocks gives evidence for the hedging capabilities commodities have against unexpected inflation, indicating that some components in the commodity portfolio react even stronger to energy shocks than energy prices as measured in the consumer price index.

Unlike currencies and commodities, stocks and REITs exhibit no hedging properties at all since they are either negatively exposed to inflation shocks or fail to show statistical significance. In the context of performance of real estate investments Case and Wachter (2011) point out that, while they theoretically should have perfect hedging properties, a number of different factors make it difficult to assess the effectiveness of real estate as an inflation hedge, including differing degrees of long-term and short-term leverage, the ability to pass on prices to tenants and differing effects of supply and demand shocks on the real estate market. Thus, our analysis supports the assumption that REITs do not behave in a particular stipulated manner in response to inflation shocks.

For stocks, we aim to explore in Section 4.2.7 whether the lack of ability to hedge against any type of inflation shocks is predominantly driven by cash flow news or discount rate news. However, there seems to be a consistent pattern linking the hedging properties of domestic and international stocks to the exposure of the currency portfolio. As Table 2 demonstrates, if currencies have a positive exposure to inflation shocks, international stocks yield a better performance in response to inflation shocks than domestic stocks, and vice versa, indicating that the hedging properties of international stocks also correlate with the hedging properties of the currency portfolio.

Although bonds in general exhibit negative correlations with all types of inflation shocks, we observe that agency and corporate bonds consistently have lower exposure to unexpected inflation compared to treasury bonds. In this context, Kang and Pflueger (2015) argue that higher than expected inflation leads to a real devaluation of nominal debt claims, meaning corporations and agencies have relatively less debt compared to their earnings, which are expected to increase with inflation. This in turn leads to corporations and agencies having relatively less credit risk, offsetting some of the negative effects of prospective interest rate rises. As treasury bonds are considered risk-free, we do not observe a corresponding positive effect on creditworthiness.

Remarkably in this context, the exposure of all bonds to energy inflation shocks is sensitive to changes in the volatility of energy inflation shocks as Table 19 in the Appendix shows. This means that an increase in the annualized inflation volatility of 1 percent leads to a decrease in the beta of 0.03, 0.01 and 0.01 for treasury, agency and corporate bonds, respectively, indicating the loss in bond values is particularly pronounced in response to an upward inflation shock if uncertainty associated with energy inflation is high with similar implications for headline inflation shocks.

Table 2 further dissects the hedging properties of the eight asset classes into three periods, namely a period from 1968-1999, one from 2000-2019 and one from 2020-2023. A paradigm shift appears to have occurred from the first to the second period in terms of how markets perceive core inflation. While five out of eight assets exhibit statistically significant coefficients during the first period, none of the core inflation coefficients were significant in the latter period. Also, corporate and agency bonds as well as currencies switched their sign from positive to negative, with now all core shock betas being negative in the second subsample, indicating that there were no assets that could effectively hedge against core inflation innovations. Energy inflation shocks, on the other hand, appear to have become more important for asset returns, with headline inflation shock betas moving in the same direction as energy inflation shocks. In this context, Fang et al. (2022) argue that core inflation has been more volatile in the early sample, while energy inflation has become more volatile starting in the late 1990s, causing energy inflation shocks to contribute relatively more to headline shocks.

Fang et al. (2022) further suggest that energy inflation shocks were mainly driven by supply shocks in the first subsample period, with demand shocks becoming the main driving force of energy inflation shocks after 2000 until 2019. Following the argument outlined by Ready (2017), who finds supply shocks to be strongly negatively correlated with stock returns as well as future economic output, and demand shocks to have a strong positive relation, this can explain why the sign of stock's headline and energy betas switched from negative to positive in the second subsample. A similar interpretation could apply to REITs, whose exposure to headline and energy inflation shocks has also changed between the first and second subsample.

The differences between the core exposures of treasuries compared to agency and corporate bonds in the first subsample period, on the other hand, might be a product of the shorter availability of agency and corporate bonds, with both time series starting in 1997, and thus we can not effectively compare them between each other. Additionally Fang et al. (2022) find negative and statistically significant betas for corporate and agency bonds for their 1963-1999 subsample using a longer time series of data, therefore we do not consider the coefficients as enough evidence to conclude that those fixed income instruments had hedging properties against inflation shocks in this particular subsample period.

In the latest subsample, no major changes in the exposure to headline and energy inflation shocks can be observed. Only stocks have lower but still positive betas in the most recent subsample, which, in light of Ready's (2017) findings, indicates that there might have been counterweighting forces at play, with the negative shock to demand during the first phase of the Covid-19 outbreak suppressing demand for oil and the war in Ukraine and the subsequent ban of Russian oil representing a shock to the supply side.

Core inflation shocks, on the contrary, have become significant for international stocks and corporate bonds, with stocks and commodities approaching the five percent significance level. This suggests that core inflation overall has become again more relevant for financial markets most recently, especially given the fact that we have roughly half of the data points compared to the period before, which makes it relatively more difficult to find statistically significant relationships. While the signs or the magnitude of most beta coefficients changed over time, the exposure of stocks to core inflation shocks is relatively consistent between all three subsample periods, indicating there is something inherently detrimental in unexpected core inflation for stocks.

Notably, corporate and agency bonds have been consistently less exposed to headline and core inflation shocks in all subsample periods with only one exception in the most recent subsample. Here, corporate bonds exhibit a statistically significant negative beta in response to core inflation, while treasury and agency bonds display insignificant positive betas or betas close to zero. In this context, the behaviour of corporate bonds during recessions could serve as a possible explanation for the negative exposure. As Bordo and Duca (2021) argue, in times of recessions the spread between corporate bond yields and treasury yields typically widens, meaning investors anticipate a higher default risk and want to be compensated for that. In fact, the Sahm Rule Recession indicator (Sahm, 2023) was more than three times higher, on average, in the latest subsample period compared to the first subsample period and almost four times higher compared to the second subsample period. The behaviour of bonds in recessions will be further evaluated in Section 4.2.4 where we include the full set of assets.

When examining the evolution of the hedging properties of commodities over time, we observe contrasting trends for headline inflation and core inflation. While the magnitude of commodities' positive exposure to headline inflation shocks has increased over the three subsample periods, the opposite trend is observed for commodities in response to core inflation shocks. Here, the coefficients have become increasingly more negative and significant, indicating that commodities have become less capable of hedging against core inflation. This is consistent with the view that core inflation risk approximates consumption growth risk and the findings of Baffes and Kabundi (2023) regarding commodities becoming progressively more aligned to the global business cycles.

Finally, it appears that currencies have started to act as hedges against headline inflation only since 2000. The reasons for this change, however, are beyond the scope of this thesis.

4.2.2 Price of Inflation Risk

In this section, we define the price of risk an investor is willing to pay to hedge against inflation based on the betas and the average returns for all available conventional assets. A more detailed explanation of the test assets used in this analysis will be provided in Section 4.2.4. As Table 3 illustrates, we find an insignificant positive coefficient for headline and a significant positive coefficient for energy inflation for the whole sample period, indicating it is free or even rewarded to hedge against unexpected headline and energy inflation. The price of hedging against core inflation shocks, on the other hand, is significantly negative amounting to -1.10. This means investors require a compensation of 1.10 percent of excess return if the negative exposure to core inflation shocks rises by 1 percent. Vice versa, investors are willing to pay 1.10 percent of excess return in order to get a positive exposure of 1 to core inflation shocks, meaning if core inflation rises by 1 percent unexpectedly, their portfolio value would rise proportionally.

Table 3 further provides details of how the price of inflation risk evolves over time. For headline inflation shocks, we observe only a minor intertemporal variation. For core inflation, the changes are relatively modest as well, although the price of core inflation risk increases by roughly 1 percent in the latest subsample period, indicating investors were willing to pay more to hedge against core inflation shocks in the most recent inflation episode. Although we use monthly rather than quarterly data for the subsample spanning from 2020 to 2023, when comparing the core lagged results from Table 18 in the Appendix run on monthly data with the full sample λ from Table 3 run on quarterly data, the risk premia are very similar. Hence, this suggests the stark increase of the price of core inflation risk in the most recent subsample period is unlikely to be driven predominantly by the modified methodology, but rather uncovers some interesting insights on investors' aversion to core inflation shocks after 2019.

The price of energy inflation risk, on the other hand, varies drastically between the subsamples. While the premium is not statistically significant in the first and last subsample, it is significant and positive in the period spanning from 2000 to 2019. As previously shown, the volatility of energy inflation shocks was the highest between 2000-2019 and driven predominantly by demand shocks (Fang et al., 2022). This suggests that, when energy inflation is driven by demand side shocks, investors expect a risk premium to be compensated for their exposure to energy inflation risk, which in the 2000-2019 subsample period amounted to a significant 5.86 percent. Additionally, given that energy inflation shocks explained 91 percent of headline shocks in the 2000-2019 period as Table 16 in the Appendix shows, we argue the shift in how markets perceive energy inflation risk contributes to explain the statistically significant headline shock risk premium in that period.

Finally, Table 3 provides evidence of the importance of decomposing headline inflation into core and energy inflation as the explanatory power consistently increases in the model where core and energy inflation shock betas are used to explain returns compared to the model where only headline inflation is employed. Interestingly, the explanatory power of the Fama-MacBeth regressions increases over time, indicating that inflation risk has gained importance as a risk factor in the markets since the start of the millennium.

Table 3. Fama-MacBeth Regression Results

	A. Full Sample		B. 1968-1999	
Headline λ	0.09		0.00	
t-stat	0.24		0.00	
Core λ		-1.10		-0.63
t-stat		-7.31		-2.65
Energy λ		2.43		1.57
t-stat		4.25		0.48
R^2	0.01	0.72	0.00	0.38
	C. 2000-2019		D. 2020-2023	
Headline λ	0.68		0.96	
t-stat	4.28		0.99	
Core λ		-0.61		-1.60
t-stat		-5.47		-2.51
Energy λ		5.86		-0.41
t-stat		3.71		-0.05
R^2	0.39	0.67	0.34	0.59

Note: This table presents the price of risk estimated from 35 asset portfolios, using the standard Fama-MacBeth approach with the following specification; $E(r_{i,t}) = \alpha_i + \lambda\beta_i + u_{i,t}$, where $E(r_{i,t})$ represents the average annualized return of an asset, β_i is the asset's inflation shock beta and λ is the price of risk. The regression is run separately for headline and jointly for core and energy inflation shocks. We present the results for subsamples and the full sample period. The t-statistics in the table are adjusted in accordance with White's approach.

4.2.3 Inflation Factor Mimicking Portfolios

In this section, we construct factor mimicking portfolios to assess whether inflation risk is consistently priced across asset classes. This technique is frequently employed in asset pricing research to model risk factors which are not directly tradable, given the Fama-MacBeth replicated portfolios have unit exposure to to the chosen factor, and hence bear the same risk-reward characteristics (Huberman and Kandel, 1987; Breeden, 1979). We hereby utilize this methodology on an asset level as it allows to reduce the noise from running a two-step Fama-MacBeth procedure (Kleibergen and Zhan, 2014) to estimate the price of inflation risk within asset classes, while providing the same intuition.

Table 4 shows the mean returns and standard deviations of portfolios mimicking core, energy and headline inflation as risk factors. The mean returns of the factor mimicking portfolios replicating core inflation risk are in line with the previously discussed findings for the price of core inflation risk. With the exception of commodities, the core inflation risk is consistently negatively priced across assets, which provides robustness to our prior findings.

This image is not as clear for energy and headline inflation. The mean returns of portfolios replicating the risk of the former vary significantly, which is reflective of the high volatility of energy inflation shocks (see Section 4.1.2). This volatility can be seen directly through the increased standard deviation of energy shock factor mimicking portfolios as compared to core or headline. Similarly, headline inflation mimicking portfolio returns, while less volatile, are not consistently priced across asset classes. This result could be anticipated given, as previously shown, headline inflation risk often does not bear a statistically significant risk premium. Additionally, its sign exhibits time-varying patterns differing across assets (see Section 4.2.1), which translates to inconsistent returns of portfolios mimicking headline inflation risk.

Table 4. Mean Returns and Standard Deviations of Inflation Factor Mimicking Portfolios

	Stock	Treas	Agency	Corp	Curr	Comm	REIT	Intl	All
A. Core									
Mean	-0.97	-0.17	-0.61	-0.37	-0.55	0.27	-1.28	-1.26	-0.28
SD	2.75	2.16	4.89	3.23	1.04	1.70	10.50	3.30	0.82
B. Energy									
Mean	1.21	-5.80	-8.98	-7.15	10.22	1.45	-7.73	14.14	0.19
SD	32.88	24.98	31.61	46.96	23.17	19.43	81.06	60.37	16.93
C. Headline									
Mean	-0.44	-0.64	-0.02	2.39	-0.01	0.32	0.39	-2.47	-0.22
SD	2.89	2.61	3.72	14.42	2.00	2.17	5.70	8.27	1.71

Note: This table displays the percentage annualized mean returns and standard deviations of the factor mimicking portfolios constructed from assets within separate asset classes as well as all the assets combined. The factor mimicking portfolios are constructed following the standard Fama-MacBeth factor mimicking portfolio weight allocation procedure, where $w^* = V^{-1}\beta\,[\beta' V^{-1}\beta]^{-1}$, (see Equation 3.4).

4.2.4 The Full Set of Asset Classes

To explore whether expanding the asset universe yields statistically significant inflation hedges in the last 3.5 years, this section includes the full set of test portfolios consisting of 35 conventional assets as well as 18 additional alternative assets and trading strategies. We further explore the changes to the price of inflation risk when alternative assets and trading strategies are considered.

With regards to the exposure of assets to inflation innovations, we find conventional assets to have somewhat similar hedging properties within asset classes with a few exceptions and patterns observable as Table 20 in the Appendix indicates. Most notably, while all treasury and agency bonds are more negatively exposed to energy inflation shocks the longer their maturity, the opposite is true in response to core inflation shocks, with their exposure becoming more positive as their maturity gets longer. For corporate bonds, however, we observe no difference between maturities in response to energy inflation shocks, whereas their exposure increases with maturity in response to core inflation shocks. In this context, Bauer (2011) argues that core CPI inflation surprises tend to affect the shorter end of the yield curve more than the longer end, with long term forward yields increasing approximately half as much as short-term forward rates in response to a higher than expected core CPI. However, given that longer-maturity bonds have higher duration and are thus more sensitive to interest rate changes, we would expect bonds in general to fall more in response to unexpected inflation the longer their maturity. This assumption is also consistent with the findings of Fang et al. (2022), which show all bonds to be relatively more exposed to any type of inflation shock when their maturity is longer.

As alternative explanation, we propose that there has been a difference between how markets have interpreted energy and core inflation shocks in the last 3.5 years. While markets have deemed energy inflation shocks to only imply increased interest rates in the future with no increased recession risk, core inflation shocks might have been interpreted as an indicator for a higher recession risk either due to interest rate hikes that go above the neutral level thereby causing a recession or due to the correlation between core inflation shocks and lower future real growth as suggested by Fang et al. (2022), which eventually forces the Federal Reserve Bank to lower interest rates. This could explain why longer-term treasuries were not only unaffected by higher than expected core inflation but also benefited from it when looking at the consistently positive albeit insignificant coefficients for treasuries with maturities longer than three years in response to core inflation shocks.

Another supporting argument for this hypothesis is the fact that unexpected core inflation has led to a price decrease of 3-year treasuries amounting to roughly 0.27 percent for each percent of unexpected inflation, while 10-year treasuries appreciated by 1.19 percent in response to an unexpected inflation shock, which effectively means that the yield curve either approaches inversion or further inverts. As an inversion of the yield curve is commonly known to be a robust recession predictor (Cooper et al., 2020), the sign of the coefficients therefore strengthens our hypothesis when neglecting the lack of statistical significance the two coefficients exhibit. The increased recession risk due to unexpected core inflation is also consistent with the negative exposure corporate bonds exhibit since increased recession risk tends to coincide with a widening of credit spreads as argued by Hollander and Liu (2016).

Consistent with the assumption that core inflation risk is associated with US consumption growth risk and the fact that manufacturing is a highly cyclical industry (Klier, 2000), we find the manufacturing sector to exhibit the highest exposure to unexpected core inflation. A similar explanation could also apply to the industrial metal portfolio, which exhibits a highly negative and statistically significant coefficient in response to core inflation. Remarkably, the healthcare sector had a very low but statistically significant positive coefficient for unexpected core inflation, indicating that healthcare stocks proved resistant against core inflation shocks over the last 3.5 years, albeit the magnitude of the coefficient suggests that it can not serve as an effective hedge in practice. Furthermore, the energy portfolio displays a coefficient of 2.18 in response to energy inflation shocks, suggesting unexpected price increases on traded energy commodities are not immediately passed to consumers where it would be captured by the US consumer price index.

For alternative assets and trading strategies, we find most portfolios to have a positive albeit insignificant coefficient in response to energy inflation shocks and negative, predominantly significant, coefficients for core inflation shocks. Given the lack of statistical significance for the hedging properties in response to energy and headline inflation shocks, this analysis thus neither contradicts nor supports the findings that some active trading strategies exhibit hedging properties against inflation shocks as presented by Neville et al. (2021). Contrastingly, for core inflation shocks, these findings are directly contradicted, with the underlying reasons for this inability to hedge remaining vastly underexplored in academia.

For the performance of hedge funds in response to headline inflation, however, a report by Stack et al. (2023) from Goldman Sachs Asset Management helps to explain as to why hedge funds have, although lacking significance, positive exposure to headline inflation, offering several explanations for this behaviour. These include high levels of cash in hedge funds, increased benefits from interest earned on the proceeds of shorting stocks, and the added value of security selection. Additionally, trend following and directional macro portfolios have benefited from the coordinated rise in interest rates in 2022 (Stack et al., 2023).

With regards to alternative assets, the hedging properties of TIPS are particularly intriguing as their purpose is to hedge against inflation (D'Amico et al., 2018). Since TIPS were only introduced in 1997, the inflation episode starting in 2021 represents the first time where the effectiveness of TIPS in times of high inflation could be assessed. However, as Table 21 in the Appendix shows TIPS fail to hedge against any type of inflation, with the longer-term TIPS index exhibiting a particularly high negative exposure, providing evidence that TIPS indexes can not fulfill their purpose.

In our analysis, we consider Fama-French risk factors among active trading strategies, given they imply dynamic portfolio sorting and their replication, by traders, requires active rebalancing. Remarkably, the Fama-French risk factor RMW, representing the performance difference between the companies with the highest and lowest operating profitability, behaves in the opposite direction to most of the other portfolios. While it exhibits a negative exposure to energy inflation, it was positively correlated to unexpected core inflation, with the coefficients approaching the five percent significance level. Similar to the widening of credit spreads in times of recessions, this finding could imply, in light of the core inflation risk debate, that investors prefer profitable and thus relatively safe companies in times of economic uncertainty associated with consumption growth risk.

When we use the expanded asset universe to define the effect on the price of risk, we observe a sizeable impact for all inflation types as Table 5 shows. Given that alternative assets and trading strategies carry a negative inflation risk premium for all inflation measures, including them leads to a substantially higher price of risk for all inflation shock types. In fact, the price increases to 0.35 percent for headline shocks, while the price of hedging against core and energy inflation goes up to 2.14 and 4.26 percent, respectively. This suggests that investors would be worse off in terms of inflation hedging costs when all assets under consideration are included in a portfolio.

However, Table 22 in the Appendix further dissects alternative assets and trading strategies into alternative assets, active funds and Fama-French risk factors, showing the substantial differences within alternative assets and trading strategies. When isolating active funds from alternative investments and Fama-French risk factors, we find active funds to yield a positive price of risk for all types of inflation shocks, with the price for headline inflation risk being highly significant. This means investors are rewarded to load on headline inflation risk in a scenario where we only consider actively managed funds. While we can not find a significant coefficient for the price of core inflation risk, the positive sign suggests that including actively managed funds could reduce the overall price of risk. However, rather than this being caused by active funds exhibiting hedging properties against unexpected core inflation, it appears that the positive, albeit insignificant, coefficient may be due to the fact that some active funds exhibit a negative exposure to core inflation shocks and simultaneously yield a negative return, which ultimately implies that shorting these specific funds leads to a positive core inflation risk premium. Also interestingly, the explanatory power of headline shock exposures is almost as high as when dissecting it into core and inflation shock exposures, indicating that the performance of active funds is relatively better explained by headline inflation innovations than conventional assets are. Similar to active funds, Fama-French risk factors exhibit an insignificant positive core inflation coefficient, however carrying a significant negative coefficient for headline inflation risk.

Overall, we conclude that expanding the asset universe beyond the eight assets we used initially does not significantly improve the hedging opportunities in the last 3.5 years.

However, evidence suggests that the price of risk to hedge against core inflation can be reduced if distorting assets such as Bitcoin are excluded and active trading strategies, in our case active funds and Fama-French risk factors, are included, and investors in fact demand a risk premium for headline inflation risk when only active funds are considered.

Table 5. Fama-MacBeth Regression Results with the Expanded Asset Universe

	Conventional Assets		Alternatives		Combined Asset Universe	
Headline λ	0.96		-4.05		0.35	
t-stat	0.99		-0.66		0.36	
Core λ		-1.60		-2.32		-2.14
t-stat		-2.51		-0.89		-1.51
Energy λ		-0.41		-8.61		-4.26
t-stat		-0.05		-0.31		-0.42
R^2	0.34	0.59	0.19	0.88	0.01	0.82

Note: This table presents the price of risk estimated from 35 conventional assets, alternatives and both conventional assets as well as alternatives combined, using the standard Fama-MacBeth approach with the following specification; $E(r_{i,t}) = \alpha_i + \lambda\beta_i + u_{i,t}$, where $E(r_{i,t})$ represents the average annualized excess return of an asset, β_i is the asset's inflation shock beta and λ is the price of risk. The regression is run separately for headline and jointly for core and energy inflation shocks. The t-statistics in the table are adjusted in accordance with White's approach.

4.2.5 Price of Risk Using an Out-of-Sample Forecast

The preceding analysis and standard approach for empirical research of hedging properties with a VAR involves in-sample errors ε_t. Although the literature provides support for in-sample test significance in VAR analysis (Stock and Watson, 2001), we consider an alternative methodology, using out-of-sample forecasting errors as inflation shocks. This provides a more realistic approach given investors only experience a true inflation surprise when the inflation forecast for a given future time period differs from the value reported by respective authorities. Furthermore, we find it economically interesting to consider the implied price of inflation risk from out-of-sample optimized window inflation forecasts and compare it to the results from expanding window and in-sample analysis.

We first optimize the VAR window for each inflation indicator (see Section 3.1.3 for methodology) to minimize the forecasting error. Notably, the optimal window is the shortest for energy inflation, for which the errors are minimized when the VAR captures data from the past 7 quarters. This figure is vastly different for core with an optimal window of 69 quarters and headline with 73. These results are rather intuitive if we consider that, as shown in Section 4.1.1, energy inflation is characterized by a much lower persistence, which means past results carry little information useful for forecasting.

Table 6 presents the mean percentage forecasting errors for each inflation indicator with expanding and optimized windows. It can be seen that optimizing, as expected, always leads to more accurate forecasts. This effect is seen, in particular, for core inflation where the forecast is, on average, wrong by only 7.08 percent of the inflation value in a given period, while the errors from expanding window estimates are much higher. However, optimizing does not seem to make an equally significant difference for headline and energy inflation. This supports our previous suggestion that headline inflation is more difficult to forecast than its persistent core component, while energy inflation is extremely challenging to predict and may require much more sophisticated predictive models. Although the forecasting approach employed in this section is rather simplistic, it provides interesting economic intuition with regards to the role that the accuracy of a forecast plays in the perceived price of risk by an investor, which we explore in the subsequent paragraph.

Table 6. Percentage Forecasting Errors for Optimized and Expanding Window VAR Forecasts

	Core	Energy	Headline
Optimized Window	7.08	86.59	14.02
Expanding Window	11.79	86.62	15.89

Note: This table presents mean percentage forecasting errors obtained from the following equation $\frac{\varepsilon}{\pi}$, where ε is the mean forecasting error and π is the mean core, energy or headline inflation accordingly. To permit the optimal forecasting window, the data used to construct this table spans from Q3 in 1986 to Q2 in 2023, which applies to all inflation components.

For this purpose, we then run the first and second step regressions using forecasting errors rather than VAR in-sample errors to calculate asset hedging properties as well as the price of inflation risk and compare it to the standard approach. To enhance comparability, we adjust the in-sample Fama-MacBeth to span from 1986 to 2023 specifically for this section. Notably, our results confirm the findings of Fang et al. (2022), showing that no asset class has statistically significant hedging properties against core inflation shocks (see Table 23 in the Appendix) and that the core inflation risk premium is negative, with both of these findings holding for optimized and expanding window forecasting errors. Interestingly, the price of core inflation risk falls when we use forecasting errors from the optimized window as opposed to the expanding one (see Table 7). This result provides interesting economic intuition. It appears that investors who are better informed, given the more accurate inflation forecasts, are willing to pay less to hedge themselves against core inflation risk. Interestingly, when we use optimized forecasting errors for energy inflation as opposed to expanding window ones, the coefficient of the price of energy inflation risk becomes much higher. The headline coefficients remain vastly the same and close to zero regardless of the method employed, yet notably exhibit statistical significance within this specific timeframe.

Table 7. Fama-MacBeth Regression Results with Optimized and Expanding Window Forecasting Errors

	Optimized Window		Expanding Window		In-Sample	
Headline λ	0.34		0.33		0.36	
t-stat	3.70		3.27		3.72	
Core λ		-1.02		-1.24		-1.21
t-stat		-3.19		-1.89		-3.48
Energy λ		3.79		1.08		1.45
t-stat		1.18		0.61		2.22
R^2	0.09	0.55	0.09	0.38	0.11	0.49

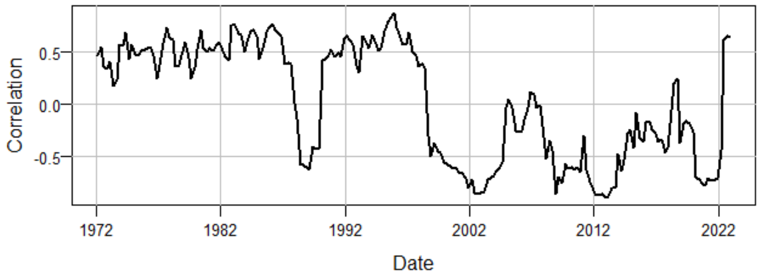
Note: This table presents the price of risk estimated from 35 asset portfolios using optimized window, expanding window and in-sample inflation shocks in the first step. The second step regression follows a standard Fama-MacBeth approach with the following specification; $E(r_{i,t}) = \alpha_i + \lambda\beta_i + u_{i,t}$, where $E(r_{i,t})$ represents the average annualized excess return of an asset, β_i is the asset's inflation shock beta and λ is the price of risk. The regression is run separately for headline and jointly for core and energy inflation shocks. The t-statistics in the table are adjusted in accordance with White's approach.

4.2.6 Time-varying Bond-Stock Correlation

As hinted in the literature review, the hedging properties of bonds and stocks against components of inflation can serve to explain, in part, the correlation of the two asset classes. The below graph depicts the correlation between market proxies for treasuries and the stock market estimated using a rolling 8 quarter window, allowing to observe key properties of that relationship.

Firstly, our analysis confirms prior findings regarding the time variation of the bond-stock correlation (Ilmanen, 2003). Although the short-term variation in the relationship is very sensitive to the window chosen to determine correlation, clear long-term trends are observable in the data. It appears that the bond-stock correlation has, predominantly, been positive between 1970 and 2000, then switched sign to negative in early 2000s and has recently become positive again. Secondly, our analysis shows that the relationship can change drastically within a short space of time. Such changes could be observed in the late 1980s, late 1990s and around 2022. Lastly, although the correlation varies with time, it also tends to exhibit long-term trends which can last for decades.

Figure 2. Bond-Stock Correlation Over Time



Note: This figure plots a simple bond-stock correlation over time using a 8 quarter window. Treasury market returns are used as bond returns, while the MSCI US is a proxy for the stock market.

In order to draw a link between the bond-stock correlation and inflation shocks, we calculate the percentage of the covariance explained by core and energy inflation as well as the mean absolute core inflation shocks and mean inflation level in the periods considered. The results suggest that in the time periods when bond-stock correlation is predominantly positive, namely 1970-2000 and the recent period after 2020, core and energy shocks explain a more significant part of the variation in the relationship, amounting to 37.81 and 59.34 percent respectively. On the contrary, when the bond-stock correlation sign is negative, core and energy shocks explain less of the correlation, amounting to a more modest 19.72 percent. Furthermore, the periods of positive correlation are also periods when core inflation is less predictable, as shown by the mean absolute core inflation shocks, and more volatile (see Tables 1 and 15). We allude to those key findings below when discussing how inflation can serve to explain the bond-stock correlation.

From Table 8, we observe a pattern that leads us to conclusions similar to those presented by Fang et al. (2022). Given bonds and stocks have the same sign of their core inflation shock betas, when core inflation is a key driver of the bond-stock correlation, its sign tends to be positive, as the prices of the two asset classes move together in response to core inflation shocks. Those periods appear to be characterised by high and relatively unpredictable core inflation. On the contrary, during phases of stable core inflation, other factors are at play, causing the sign of the relationship to become negative. Although, in such instances, core and energy inflation shocks might only explain a relatively modest percentage of the bond-stock correlation (corresponding to approximately 19.72 percent between 2000-2019), we contend that understanding inflation hedging properties remains valuable. In fact, during such periods energy inflation shocks appear to gain importance relative to core shocks as headline volatility drivers (see Table 16 in the Appendix) and bonds and stocks exhibit contrary signs to energy shocks. Therefore, we argue that in times characterised by low and stable core inflation, energy shock exposure contributes to a shift towards a negative correlation.

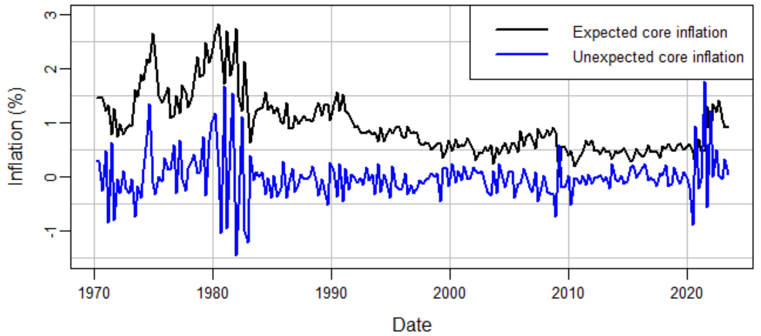
Table 8. Percentage of Bond-Stock Correlation Explained by Core and Energy Shocks

	1970-1999	2000-2019	2020-2022
% Explained	37.81	19.72	59.34
Mean Absolute Core Shocks	0.33	0.15	0.53
Mean Inflation	5.14	2.16	4.97

Note: This table shows the percentage of the bond-stock covariance explained by core and energy shocks from the following equation $Cov_{S,B}^{expl.} = Cov_{S,B}^{fitted} / Cov_{S,B}^{sample}$ (see Section 3.1.2), the mean absolute core inflation shocks from the VAR specified in Equation 3.1 (see Section 3.1.1) and the mean level inflation.

However, to counter this argument, one may rightfully point out that, as opposed to the 1970-1999 and 2020-2022 periods where core and energy inflation explain almost 40 percent and 60 percent of the bond-stock correlation respectively, this proportion is much lower between 2000 and 2019. This suggests that in such periods there may be other factors at play, besides energy inflation, that significantly explain the bond-stock correlation. Recently published papers argue one of those factors may be growth uncertainty (Wu et al., 2021; Brixton et al., 2023), towards which bond and stock returns have opposing signs. Although this may have be true, we do not test this empirically in our thesis, and hence suggest for further research to explore this hypothesis.

Figure 3. Expected vs Unexpected Core Inflation Over Time



Note: This figure plots expected and unexpected inflation. Expected inflation is defined as the fitted values from the VAR in Equation 3.1, whereas unexpected inflation represents core inflation shocks from the same equation.

4.2.7 Discount Rate vs Cash Flow News

In Section 4.2.1, we show that stocks, both US domestic and international, have a consistently negative exposure to core inflation shocks. In this section, we conduct the standard Campbell (1991) decomposition of stock returns into the cash flow and discount rate components and regress them on core and energy inflation shocks with the objective to shed further light on what drives the negative correlation. This section further contributes to the discussion of the impact of inflation shocks on expected cash flows and discount rates.

Table 9 presents the results of our regressions, showing that cash flow news of different assets exhibits consistently negative and statistically significant exposures to core inflation shocks across the analysed portfolios. The betas tend to have the highest magnitude, being the most negative, for portfolios with more cash flows expected into the future, such as high tech or growth stocks. On the other hand, coefficients closer to zero are seen for value stocks. Energy shock betas are predominantly positive but very close to zero.

In contrast, regressions using discount rate news present much less conclusive results. Core shock betas vary significantly across stock portfolios with changing signs. We observe high positive betas for value stocks and high negative ones for growth and high tech, while there does not seem to be much variation across geographies where we see marginally negative values. Consistent with cash flow news, energy shock betas are predominantly close to zero.

Our results regarding cash flow news are in line with the research in this area, conducted for instance by Fang et al. (2022) or Ammer (1994), indicating that positive unexpected inflation shocks are detrimental to future dividends and corporate profits. The impact appears more prominent on stocks with cash flows further into the future, such as growth or high tech portfolios. Being a rather intuitive conclusion, it is also a very well researched and documented concept, with notable papers exploring different avenues in which unexpected and expected inflation may impact businesses and the society (Fischer and Modigliani, 1978). The results from regressions using discount rate news are less straightforward to interpret. Intuitively, one would expect an upward inflation shock to cause an increase in future expected stock returns, and hence a strictly and consistently positive correlation, which are precisely the results reported by Fang et al. (2022). In the contrary, an earlier study of the subject conducted by Ammer (1994) also yields negative coefficients, which the author explained with various tax-related hypotheses. Although puzzling, this discussion is beyond the scope of this thesis and could be explored in further academic publications.

Table 9. Regression Results of Cash Flow and Discount Rate News on Core and Energy Inflation Shocks

	Cash Flow News				Discount Rate News			
Asset	Core β	t-stat	Energy β	t-stat	Core β	t-stat	Energy β	t-stat
Stock Market	-3.95	-2.29	0.17	0.94	-0.19	-2.29	0.01	0.94
World	-4.27	-3.46	0.21	1.10	-0.09	-3.46	0.00	1.10
North America	-3.84	-2.30	0.20	1.12	-0.18	-2.30	0.01	1.12
Europe	-4.51	-3.05	0.18	0.86	-0.26	-3.05	0.01	0.86
Far East	-4.52	-3.35	0.17	0.99	-0.35	-3.35	0.01	0.99
Consumer	-3.70	-3.12	-0.17	-2.05	0.90	1.22	-0.20	-1.71
Manufacturing	-3.76	-3.26	0.26	2.80	-0.47	-1.02	-0.10	-1.52
High Tech	-6.96	-4.03	-0.17	-2.14	-2.62	-2.39	-0.36	-2.34
Healthcare	-3.95	-2.29	0.17	0.94	-0.19	-2.29	0.01	0.94
Other	-4.16	-3.27	0.15	1.13	1.26	1.63	-0.03	-0.27
BM1 Growth	-6.15	-3.95	-0.13	-1.55	-1.45	-1.89	-0.27	-2.25
BM2	-3.57	-3.15	0.01	0.17	0.18	0.29	-0.13	-1.28
BM3	-3.37	-3.27	0.10	1.11	-0.21	-0.37	-0.14	-1.47
BM4	-1.77	-1.72	0.33	1.95	2.03	3.71	0.05	0.68
BM5 Value	-2.52	-2.44	0.34	2.86	2.27	3.03	0.01	0.09

Note: This table reports the regression results of the following specification; $CF/DR^{e}_{i,t} = \alpha_i + \beta^{i}_{\pi}\varepsilon_t + u_{i,t}$, where $CF/DR^{e}_{i,t}$ are cash flow or discount rate news backed out of stock returns and $\varepsilon_{i,t}$ is the error term from the VAR (see equation 3.1). We run the regressions for core and energy inflation jointly. The t-statistics we report are adjusted in accordance with the Newey-West methodology.

Considering the results of our regressions, we conclude that it is predominantly cash flow news driving the negative core inflation shock betas of stocks. Although the cash flow effect seems to prevail for some portfolios, it is slightly contained by the negative coefficients on discount rate news.

4.3 Robustness Checks

4.3.1 Macroeconomic Control Variables

As outlined in the literature review, some research, particularly early work on the subject such as Fama's (1981) paper, draw a link between inflation hedging properties of assets and macroeconomic factors. Hence, in order to test the robustness of the negative core risk premium we have previously identified, we replicate our prior Fama-MacBeth methodology including macroeconomic variables in the regressions. We follow the choice of variables made by Fang et al. (2022), which represent macroeconomic variables commonly used in the asset pricing literature due to their high explanatory power. Namely, we consider: PCEDG - personal consumption expenditures, PCE - percentage change in personal consumption expenditures, INDPRO - industrial production total index, PAYEMS - total number of employees excluding farm workers and some other employee classifications, and finally UNRATE - the unemployment rate.

Table 10 presents the results of the Fama-MacBeth regressions. As can be observed, the negative core inflation shock risk premium remains robust in the presence of common macroeconomic factors. The energy inflation risk premium proves unstable and insignificant, which adds to the discussion regarding the unpredictable nature of this inflation component. For completeness, we further compute the price of risk of the macroeconomic variables we consider. However, given it is not directly linked to our thesis, we do not explore it further in this analysis.

Table 10. Fama-MacBeth Regression Results Including Macroeconomic Control Variables

	PCEDG	PCE	INDPRO	PAYEMS	UNRATE
Core λ	-1.25	-1.12	-1.33	-1.27	-1.32
t-stat	-5.45	-4.57	-4.56	-7.41	-7.55
Energy λ	-2.11	-3.01	-0.03	0.17	0.37
t-stat	-0.81	-0.70	-0.01	0.07	0.16
Macro λ	3.79	0.14	-0.96	-1.08	9.92
t-stat	1.73	0.24	-0.41	-1.38	0.62
R^2	0.62	0.58	0.57	0.60	0.60

Note: This table presents the price of risk estimated from 35 asset portfolios with added macroeconomic variables, using the standard Fama-MacBeth approach with the following specification; $E(r_{i,t}) = \alpha_i + \lambda\beta_i + u_{i,t}$, where $E(r_{i,t})$ represents the average annualized excess returns of an asset, β_i is the asset's exposure to the corresponding risk factor and λ is the price of risk. The regression is run jointly for core and energy inflation shocks as well as each respective macroeconomic factor. The t-statistics in the table are adjusted in accordance with White's approach.

4.3.2 Expected vs Unexpected Inflation Hedging

Much of the early research on inflation hedging properties of asset classes was done using expected inflation (Miller et al., 1976; Solnik, 1983). Although future expected inflation should already be priced into liquid assets in efficient markets (Bekaert and Wang, 2010), one could argue that investors are only concerned with hedging their portfolios against the actual reported level inflation which is easily observable, rather than worrying about its unexpected component. Therefore, in order to test the robustness of our results, we consider the hedging properties of asset classes against level inflation as well as its expected and unexpected components. The results of this analysis are displayed in Tables 11 and 12, which we discuss below.

Firstly, we see that when we decompose inflation into expected and unexpected components and run the regressions jointly, the coefficients we obtain for inflation surprises are similar to the previously presented results and bear the same conclusion, namely that no conventional asset class can hedge investors against core inflation shocks. This suggests the hedging properties we previously discussed in the thesis are robust whether or not we consider expected inflation.

Secondly, we see that, in general, betas on the expected components of core and headline inflation are negative, with some of the coefficients being statistically significant. This proves interesting in light of an argument presented by Fang et al. (2022), according to which a beta of zero on expected inflation indicates that an asset hedges against expected inflation as well as a risk-free rate. This would imply that most asset classes provide a worse hedge against expected inflation levels than the risk free rate, in theory, should.

Lastly, the findings affirm the varying betas for level, expected, and unexpected inflation, giving proof that hedging inflation shocks poses peculiar challenges to investors, hence substantiating our approach of isolating inflation shocks. Nevertheless, regardless of whether we consider level, expected or unexpected core inflation, the key conclusion remains the same, namely that no asset can hedge investors against this persistent inflation component.

Table 11. Hedging Properties of Asset Classes Against Level, Expected and Unexpected Headline Inflation

Asset	Headline	*t*-stat	Headline Exp.	*t*-stat	Headline Shock	*t*-stat
Stock	-1.34	-1.23	-1.82	-1.67	-0.96	-0.58
Treasury	-1.55	-6.02	-0.50	-1.80	-2.40	-6.85
Agency	-1.12	-6.95	-1.80	-3.24	-1.06	-4.90
Corporate	-1.02	-2.11	-4.46	-7.20	-0.69	-2.69
Currency	0.69	1.68	-1.72	-1.86	0.82	2.64
Commodity	4.74	2.63	0.42	0.35	8.19	4.98
REIT	1.71	0.56	-5.06	-1.52	2.67	1.00
Int. Stock	-0.94	-0.86	-1.44	-1.25	-0.54	-0.32

Note: This table reports the regression results for level, expected and unexpected headline inflation (see Equations 3.9 and 3.10 for methodology). The *t*-statistics we report are adjusted in accordance with the Newey-West methodology.

Table 12. Hedging Properties of Asset Classes Against Level, Expected and Unexpected Core and Energy Inflation

Asset	Core	*t*-stat	Energy	*t*-stat	Core Exp.	*t*-stat	Core Shock	*t*-stat	Energy Shock	*t*-stat
Stock	-2.43	-2.54	0.12	0.70	-1.37	-1.29	-4.10	-2.56	0.17	0.99
Treasury	-0.73	-2.53	-0.22	-4.20	-0.36	-1.09	-1.92	-2.36	-0.21	-3.98
Agency	-0.88	-1.37	-0.10	-3.89	-2.40	-2.70	-0.48	-1.20	-0.11	-4.31
Corporate	-2.40	-1.54	-0.04	-0.95	-1.83	-0.49	-0.90	-1.20	-0.75	-0.70
Currency	-0.37	-0.43	0.11	2.25	-1.65	-1.34	-0.63	-0.71	0.12	2.42
Commodity	-1.03	-0.98	1.14	6.25	0.12	0.10	-0.41	-0.21	1.15	6.11
REIT	-4.05	-1.38	0.35	1.19	-4.95	-1.34	-2.68	-0.69	0.35	1.07
Int. Stock	-2.38	-2.55	0.15	0.80	-1.04	-0.90	-4.48	-3.68	0.21	1.12

Note: This table reports the regression results for level, expected and unexpected core and energy inflation run jointly (see Equations 3.9 and 3.10 for methodology). We do not include expected energy inflation given the high volatility of that component, making it extremely difficult to determine its expected levels. The *t*-statistics we report are adjusted in accordance with the Newey-West methodology.

4.3.3 Survey of Professional Forecasters

In order to further test the robustness of our results, we replicate our prior regressions using an alternative measure of inflation, the Survey of Professional Forecasters (SPF), a measure compiled by the Philadelphia FED with the intention to provide reliable macroeconomic forecasts. Although the time period covered by this data differs from our main analysis, as the time period spans from 1981 to 2023, it nevertheless leads to the same key conclusions.

Firstly, considering the hedging properties of different asset classes against core inflation shocks, none of the market portfolios considered can provide a hedge against core innovations, as they either yield negative coefficients or exhibit positive ones, which lack statistical significance.

Table 13. Hedging Properties of Asset Classes Using Inflation Forecasts from the Survey of Professional Forecasters

Asset Class	Mean	S.D.	Headline β	t-stat	Core β	t-stat	Energy β	t-stat
Stock	9.07	16.48	0.86	0.90	-0.00	-0.00	0.15	0.83
Treasury	3.27	7.18	-1.66	-5.67	-0.89	-1.80	-0.21	-4.43
Agency	1.93	3.45	-0.60	-2.82	0.05	0.18	-0.11	-4.03
Corporate	3.19	5.93	0.06	0.29	0.80	1.57	-0.07	-1.62
Currency	1.53	6.88	0.83	3.64	0.51	1.32	0.11	2.16
Commodity	3.13	23.38	6.75	6.66	0.58	0.55	1.28	7.47
REIT	6.62	19.74	1.62	1.15	-0.84	-0.56	0.34	1.03
Int Stock	6.39	18.87	0.94	0.82	0.11	0.10	0.18	0.87

Note: This table reports the regression results of the following specification; $r^e_{i,t} = \alpha_i + \beta^i_\pi \varepsilon_t + u_{i,t}$, where $r^e_{i,t}$ are excess asset returns and $\varepsilon_{i,t}$ is the error term from the SPF (see Section 3.1.4 for methodology). We run a univariate regression for headline shocks, while for core and energy inflation shocks we run the regression jointly. The t-statistics we report are adjusted in accordance with the Newey-West methodology. All mean returns and standard deviations reported are annualized.

Additionally, we run a Fama-MacBeth regression using the data from the survey to determine whether the price of core inflation risk remains negative. As seen in Table 14, the negative core inflation risk premium remains robust when we use shocks derived from survey data. Moreover, both the price of headline and energy inflation risk remain positive, with energy showing a λ of a higher magnitude. Furthermore, the R^2 of the regression is substantially lower than when we consider VAR errors, indicating that deriving the price of inflation risk via the SPF provides a relatively worse fit. Nevertheless, the results confirm the main findings of our thesis regarding both the hedging properties of asset classes against core inflation shocks and the price of core inflation risk.

Table 14. Fama-MacBeth Results Using Inflation Forecasts from the Survery of Professional Forecasters

35 Asset Portfolios		
Headline	0.24	
t-stat	0.85	
Core		-2.11
t-stat		-3.26
Energy		3.34
t-stat		1.59
R^2	0.02	0.27

Note: This table presents the price of risk estimated from 35 asset portfolios, using the standard Fama-MacBeth approach with the following specification; $E(r_{i,t}) = \alpha_i + \lambda\beta_i + u_{i,t}$, where $E(r_{i,t})$ represents the average annualized return of an asset, β_i is the asset's survey inflation shock beta and λ is the price of risk. The regression is run separately for headline and jointly for core and energy inflation shocks. The t-statistics in the table are adjusted in accordance with White's's approach.

4.4 Limitations

Although our intention in this analysis is to make it as consistent and inclusive as possible, there are some compromises we make with regards to data availability and methodology we use. First of all, to measure the true price of inflation risks it would be necessary to include all relevant and non-traded assets and value-weight them according to their market value. Our selection of securities includes a broad range of assets and trading strategies, however excludes some assets due to the lack of availability, and we do not value-weight them. Additionally, some indexes we use might not capture the underlying assets or trading strategies to the full extent and may also involve fees, potentially distorting the inflation exposures and prices of risk to some degree. Secondly, the availability of the assets under consideration varies, which might, particularly in the first subsample period, lead to some biases in the inflation betas since asset's exposures to inflation shocks are not constant over time as shown in our analysis.

Thirdly, for the latest subsample period we use a relatively short window and therefore employ a VAR on a monthly basis to derive inflation innovations and lag core inflation shocks by one month as previously outlined. Hence, the methodology differs to some degree when comparing it to the methodology we use for the whole sample period and the first two subsample periods. Although we show the consistency of the results when comparing quarterly with monthly VAR for price of inflation risk over the full sample period, this might nevertheless lead to small discrepancies in the results for the 2020-2023 period.

Furthermore, while using a commonly recognized approach to forecast inflation, this approach may not reflect the true, unobservable, inflation expectations of the market, possibly causing a bias to the inflation shocks in our analysis. Also, even though we show that core inflation risk is still prevalent when optimizing an out-of-sample forecasting model, there are more sophisticated inflation forecasting models, which could further reduce the price of inflation risk.

Finally, the most recent subsample presents a very particular inflation environment, with an energy demand shock and quantitative easing in the beginning, supply-chain disruptions as well as fiscal stimulus in the middle, and an energy supply shock and quantitative tightening in the end. This means we can not conclude decisively whether this has marked a structural shift as it was at the turn of the millenium, and the findings for the latest subsample may not be directly transferable to future periods with high inflation.

While all our limitations offer room for further research in the respective area, we see potential for such particularly with regards to active trading strategies as there is little evidence to explain why some of them can outperform others in inflationary environments. Overall, there is also limited research on the causality between inflation shocks and asset returns as well as about the economic drivers of different inflation hedging properties.

5. Conclusion

This thesis adds to the discussion on hedging properties of different asset classes against inflation shocks and provides novel insights from the recent inflation surge. We show that no asset class can provide a statistically significant hedge against core inflation shocks throughout any sample period examined individually or the entire timeframe. Furthermore, core inflation risk carries a negative risk premium, consistent across time periods, referred to in this thesis as the price of inflation risk. Intuitively, these findings suggest investors are willing to pay to hedge themselves against inflation risk derived from its persistent core component. With regards to energy and headline inflation, we find that they follow a similar pattern carrying insignificant risk premia, with some assets, namely currencies and commodities, displaying hedging properties against inflation innovations.

When examining alternative assets, we come to a similar conclusion, namely that no alternative asset can provide a statistically significant hedge against core inflation innovations in the time period spanning from 2020 to 2023. However, although alternative assets as a whole, consistent with conventional assets, show a negative core risk premium, when we isolate active funds and Fama-French risk factors we find that the price of risk turns positive. This leads us to the conclusion that the inclusion of some active trading strategies into portfolios of conventional assets may lead to the reduction of the price of core inflation risk.

In a subsequent analysis, we find that the price of core inflation risk remains consistent even when we consider an alternative approach to compiling the risk premium, using observable forecast errors as shocks rather than VAR residuals. This analysis also shows an interesting dynamic indicating that better informed investors, equipped with a more accurate forecast, would be willing to pay less to hedge themselves from core inflation risk.

Lastly, our analysis of the bond-stock correlation confirms its time-varying characteristics and shows that the relationship has recently become positive again. When we then consider this vital relationship through the lens of inflation, we find that core and energy inflation shocks can explain a significant portion of the correlation, particularly in the recent inflationary period.

References

Adolfsen, J. F., Kuik, F., Schuler, T., and Lis, E. (2022). The impact of the war in ukraine on euro area energy markets. *Economic Bulletin Boxes*, 4.

Ammer, J. (1994). Inflation, inflation risk, and stock returns.

Andrews, S., Colacito, R., Croce, M. M. M., and Gavazzoni, F. (2020). Concealed carry. *Available at SSRN 3743205*.

Baffes, J. and Kabundi, A. (2023). Commodity price shocks: Order within chaos? *Resources Policy*, 83:103640.

Bauer, M. (2011). What moves the interest rate term structure? *FRBSF Economic Letter*, 2011:34.

Bekaert, G., Cho, S., and Moreno, A. (2005). New-keynesian macroeconomics and the term structure. Working Paper 11340, National Bureau of Economic Research.

Bekaert, G. and Wang, X. (2010). Inflation risk and the inflation risk premium. *Economic policy*, 25(64):755–806.

Bodie, Z. (1976). Common stocks as a hedge against inflation. *The Journal of Finance*, 31(2):459–470.

Boons, M., Duarte, F., de Roon, F., and Szymanowska, M. (2020). Time-varying inflation risk and stock returns. *Journal of Financial Economics*, 136(2):444–470.

Bordo, M. D. and Duca, J. V. (2021). An overview of the fed's new credit policy tools and their cushioning effect on the covid-19 recession. *Journal of Government and Economics*, 3:100013.

Boyd, J. H., Hu, J., and Jagannathan, R. (2005). The stock market's reaction to unemployment news: Why bad news is usually good for stocks. *The Journal of Finance*, 60(2):649–672.

Breeden, D. T. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics*, 7(3):265–296.

Brixton, A., Brooks, J., Hecht, P., Ilmanen, A., Maloney, T., and McQuinn, N. (2023). A changing stock–bond correlation: Drivers and implications. *Journal of portfolio management*, 49(4):64–80.

Buraschi, A. and Jiltsov, A. (2005). Inflation risk premia and the expectations hypothesis. *Journal of Financial Economics*, 75(2):429–490.

Campbell, J. Y. (1991). A variance decomposition for stock returns. *The Economic Journal*, 101(405):157–179.

Campbell, J. Y., Sunderam, A., and Viceira, L. M. (2009). Inflation bets or deflation hedges? the changing risks of nominal bonds. Working Paper 14701, National Bureau of Economic Research.

Campbell, J. Y. and Vuolteenaho, T. (2003). *Bad Beta, Good Beta*. NBER working paper series no. w9509. National Bureau of Economic Research, Cambridge, Mass.

Case, B. and Wachter, S. M. (2011). Inflation and real estate investments. *U of Penn, Inst for Law & Econ Research Paper*, (11-33).

Chen, L. and Zhao, X. (2009). Return decomposition. *The Review of Financial Studies*, 22(12):5213–5249.

Chen, N.-F., Roll, R., and Ross, S. A. (1986). Economic forces and the stock market. *The Journal of business (Chicago, Ill.)*, 59(3):383–403.

Choi, S. and Shin, J. (2022). Bitcoin: An inflation hedge but not a safe haven. *Finance Research Letters*, 46:102379.

Cologni, A. and Manera, M. (2008). Oil prices, inflation and interest rates in a structural cointegrated VAR model for the G-7 countries. *Energy Economics*, 30(3):856–888.

Cooper, D., Fuhrer, J. C., and Olivei, G. (2020). Predicting recessions using the yield curve: The role of the stance of monetary policy. *Federal Reserve Bank of Boston Research Paper Series Current Policy Perspectives Paper*, (87522).

D'Amico, S., Kim, D. H., and Wei, M. (2018). Tips from tips: The informational content of treasury inflation-protected security prices. *Journal of Financial and Quantitative Analysis*, 53(1):395–436.

Evans, M. D. D. (1998). Real rates, expected inflation, and inflation risk premia. *The Journal of Finance*, 53(1):187–218.

Fama, E. F. (1981). Stock returns, real activity, inflation, and money. *The American Economic Review*, 71(4):545–565.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636.

Fama, E. F. and Schwert, G. (1977). Asset returns and inflation. *Journal of Financial Economics*, 5(2):115–146.

Fang, X., Liu, Y., and Roussanov, N. (2022). Getting to the core: Inflation risks within and across asset classes. Working Paper 30169, National Bureau of Economic Research.

Fischer, S. and Modigliani, F. (1978). Towards an understanding of the real effects and costs of inflation. *Review of World Economics*, 114(4):810–833.

Fisher, I. (1930). The theory of interest. *Macmillan*.

Gorton, G. and Rouwenhorst, K. G. (2004). Facts and fantasies about commodity futures. Working Paper 10595, National Bureau of Economic Research.

Grishchenko, O. V. and Huang, J.-Z. (2013). The inflation risk premium: Evidence from the tips market. *The Journal of fixed income*, 22(4):5–30.

Hardin, W. G., Jiang, X., and Wu, Z. (2012). Reit stock prices with inflation hedging and illusion. *The Journal of Real Estate Finance and Economics*, 45:262–287.

Hartzell, D., Hekman, J. S., and Miles, M. E. (1987). Real estate returns and inflation. *Real Estate Economics*, 15(1):617–637.

Hernandez, R. (2023). What caused inflation to spike after 2020? https://www.bls.gov/opub/mlr/2023/beyond-bls/what-caused-inflation-to-spike-after-2020.html.

Hollander, H. and Liu, G. (2016). Credit spread variability in the u.s. business cycle: The great moderation versus the great recession. *Journal of Banking Finance*, 67:37–52.

Hollifield, B. and Yaron, A. (2001). The foreign exchange risk premium: Real and nominal factors. *IDEAS Working Paper Series from RePEc*.

Hou, A. J., Platanakis, E., Ye, X., and Zhou, G. (2023). Commodity inflation risk premium and stock market returns.

Huberman, G. and Kandel, S. (1987). Mean-variance spanning. *The Journal of Finance*, 42(4):873–888.

Ilmanen, A. (2003). Stock-bond correlations. *The Journal of Fixed Income*, 13:55–66.

James, C., Koreisha, S., and Partch, M. (1985). A varma analysis of the causal relations among stock returns, real output, and nominal interest rates. *The Journal of Finance*, 40(5):1375–1384.

Kang, J. and Pflueger, C. E. (2015). Inflation risk in corporate bonds. *The Journal of finance (New York)*, 70(1):115–162.

Katz, M., Lustig, H., and Nielsen, L. (2016). Are Stocks Real Assets? Sticky Discount Rates in Stock Markets. *The Review of Financial Studies*, 30(2):539–587.

Kleibergen, F. and Zhan, Z. (2014). Mimicking portfolios of macroeconomic factors. Technical report, Technical report, Brown University Working Paper.

Klier, T. (2000). Structural change and cyclicality of the auto industry. *Chicago Fed Letter*, (159).

Kozlowski, J. and Jordan-Wood, S. (2023). What did the fed do in response to the covid-19 crisis?

Lee, B.-S. (1992). Causal relations among stock returns, interest rates, real activity, and inflation. *The Journal of Finance*, 47(4):1591–1603.

Lustig, H., Roussanov, N., and Verdelhan, A. (2011). Common Risk Factors in Currency Markets. *The Review of Financial Studies*, 24(11):3731–3777.

Lustig, H., Roussanov, N., and Verdelhan, A. (2014). Countercyclical currency risk premia. *Journal of Financial Economics*, 111(3):527–553.

Miller, K. D., Jeffrey, F. J., and Mandelker, G. (1976). The "fisher effect" for risky assets: An empirical investigation. *The Journal of Finance*, 31(2):447–458.

Milstein, E. and Wessel, D. (2021). What did the fed do in response to the covid-19 crisis?

Neville, H., Draaisma, T., Funnell, B., Harvey, C. R., and Van Hemert, O. (2021). The best strategies for inflationary times. *The Journal of Portfolio Management*, 47(8):8–37.

Newey, W. K. and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708.

Pukthuanthong, K., Roll, R., Wang, J., and Zhang, T. (2019). A toolkit for factor-mimicking portfolios. *SSRN Electronic Journal*.

Ready, R., Roussanov, N., and Ward, C. (2013). *Commodity Trade and the Carry Trade: a Tale of Two Countries*. NBER working paper series no. w19371. National Bureau of Economic Research, Cambridge, Mass.

Ready, R. C. (2017). Oil Prices and the Stock Market*. *Review of Finance*, 22(1):155–176.

Rubens, J. H., Bond, M. T., and Webb, J. R. (1989). The inflation-hedging effectiveness of real estate. *The Journal of real estate research*, 4(2):45–55.

Sahm, C. (2023). Real-time sahm rule recession indicator. https://fred.stlouisfed.org/series/SAHMREALTIME.

Shiller, R. J. and Beltratti, A. E. (1992). Stock prices and bond yields: Can their comovements be explained in terms of present value models? *Journal of Monetary Economics*, 30(1):25–46.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, 48(1):1–48.

Solnik, B. (1983). The relation between stock prices and inflationary expectations: The international evidence. *The Journal of Finance*, 38(1):35–48.

Spierdijk, L. and Umar, Z. (2015). Stocks, bonds, t-bills and inflation hedging: From great moderation to great recession. *Journal of economics and business*, 79:1–37.

Stack, J., Perrina, G., Steven, Q., and Hillman, M. (2023). Adapting to change: how hedge funds may benefit in a new volatility regime.

Stock, J. H. and Watson, M. W. (2001). Vector autoregressions. *Journal of Economic Perspectives*, 15(4):101–115.

Swanson, N. R. (1998). Money and output viewed through a rolling window. *Journal of Monetary Economics*, 41(3):455–474.

United States Treasury Fiscal Data (2023). Understanding the national debt. https://fiscaldata.treasury.gov/americas-finance-guide/national-debt/. Accessed: 2023-11-27.

Vuolteenaho, T. (2002). What drives firm-level stock returns? *The Journal of Finance*, 57(1):233–264.

Wu, B. D., Beatrice Yeo, C., DiCiurcio, K. J., and Wang, Q. (2021). The stock/bond correlation: Increasing amid inflation, but not a regime change.

Yang, J., Zhou, Y., and Wang, Z. (2009). The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence. *Journal of Banking Finance*, 33(4):670–680.

Appendix

Table 15. Additional Inflation Summary Statistics

	1968-1999				2000-2019			
A. Summary Statistics								
	Mean	SD	Autocorr		Mean	SD	Autocorr	
Headline	5.15	1.64	0.75		2.16	1.33	-0.04	
Core	5.20	1.45	0.71		2.01	0.33	0.35	
Food	4.96	2.22	0.43		2.28	0.91	0.46	
Energy	5.23	6.86	0.36		4.37	13.50	-0.10	
B. Headline Composition								
	β	s.e.			β	s.e.		
Core	0.70	0.02			0.92	0.07		
Food	0.22	0.01			0.15	0.03		
Energy	0.09	0.00			0.09	0.00		
C. Correlation Matrix								
	Headline	Core	Food	Energy	Headline	Core	Food	Energy
Headline	1.00				1.00			
Core	0.88	1.00			0.33	1.00		
Food	0.64	0.40	1.00		0.19	0.10	1.00	
Energy	0.68	0.39	0.28	1.00	0.95	0.10	0.08	1.00

Note: This table provides summary statistics for headline, core, food end energy inflation components. Panel A presents summary statistics for each inflation component, including their mean, standard deviation and autocorrelation. All the values are annualized. Panel B reports the regression results of headline inflation on core, food and energy inflation. Panel C reports the correlation matrix.

Table 16. Headline Inflation Shock Decomposition for All Periods

A. Full Sample					
Energy coefficient	0.10			0.10	0.09
Food coefficient		0.31		0.27	0.20
Core coefficient			0.96		0.72
R^2	0.64	0.16	0.40	0.75	0.96
B. 1968-1999					
Energy coefficient	0.11			0.10	0.09
Food coefficient		0.30		0.27	0.21
Core coefficient			0.87		0.70
R^2	0.37	0.28	0.57	0.60	0.95
C. 2000-2019					
Energy coefficient	0.10			0.10	0.09
Food coefficient		0.52		0.18	0.19
Core coefficient			1.61		0.89
R^2	0.91	0.08	0.21	0.92	0.98
D. 2020-2023					
Energy coefficient	0.10			0.10	0.08
Food coefficient		0.13		0.12	0.16
Core coefficient			1.06		0.79
R^2	0.67	0.01	0.66	0.68	1.00

Note: This table decomposes headline inflation shocks into core, energy, and food inflation shocks, using regression models with varying combinations of explanatory variables. We do this for the full sample period, a period from 1968-1999, one from 2000-2019, as well as one from 2020-2023.

Table 17. Asset Return Exposure to Monthly Inflation Shocks Using Varying Lags

	Headline β	t-stat	Core β	t-stat	Energy β	t-stat
A. All Inflation Shocks Lagged						
Stock	-1.06	-1.75	-3.40	-2.50	-0.07	-1.10
Treasury	-0.81	-2.04	-0.68	-1.19	-0.07	-1.68
Agency	-0.47	-1.42	-0.32	-0.69	-0.03	-1.00
Corporate	-0.71	-2.61	-0.98	-0.97	-0.05	-1.64
Currency	-0.17	-0.55	1.10	1.44	-0.05	-2.00
Commodity	0.68	0.53	1.18	0.75	0.01	0.03
REIT	-1.23	-1.30	-2.17	-0.94	-0.09	-0.85
Int Stock	-2.04	-3.21	-3.04	-2.40	-0.19	-2.99
B. Core Inflation Shocks Lagged						
Stock	-0.73	-0.73	-3.45	-2.71	0.07	0.87
Treasury	-1.63	-3.94	-0.71	-1.29	-0.17	-4.07
Agency	-0.77	-3.46	-0.25	-0.59	-0.06	-3.10
Corporate	-0.33	-0.94	-1.01	-0.95	-0.03	-0.94
Currency	0.99	2.28	0.95	1.18	0.11	3.15
Commodity	5.24	3.28	1.13	0.69	0.75	4.99
REIT	1.49	0.82	-2.45	-1.27	0.15	1.16
Int Stock	0.38	0.36	-3.17	-2.53	0.17	1.68
C. No Inflation Shocks Lagged						
Stock	-0.73	-0.73	-1.88	-2.19	0.08	0.92
Treasury	-1.63	-3.94	-1.11	-2.21	-0.17	-3.96
Agency	-0.77	-3.46	-0.70	-1.39	-0.06	-3.04
Corporate	-0.33	-0.94	-0.55	-0.43	-0.03	-1.09
Currency	0.99	2.28	-0.53	-0.69	0.11	3.21
Commodity	5.24	3.28	-0.25	-0.17	0.75	4.99
REIT	1.49	0.82	-0.68	-0.25	0.15	1.12
Int Stock	0.38	0.36	-1.55	-1.52	0.17	1.69

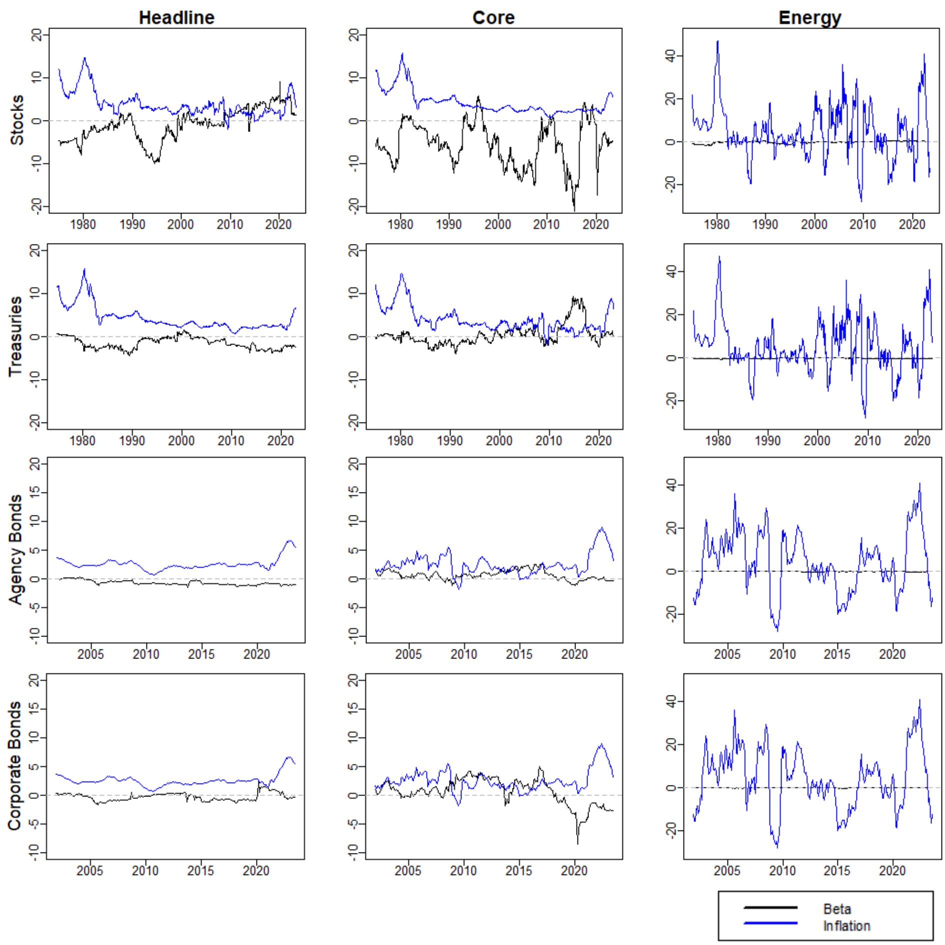
Note: This table reports the regression results of the following specification; $r^e_{i,t} = \alpha_i + \beta^i_\pi \varepsilon_t + u_{i,t}$, where $r^e_{i,t}$ are excess asset returns and $\varepsilon_{i,t}$ is the error term from the VAR (see Equation 3.1). We run a univariate regression for headline shocks, while for core and energy inflation shocks we run the regression jointly. The t-statistics we report are adjusted in accordance with the Newey-West methodology. All mean returns and standard deviations reported are annualized. We report the results for the full sample period differentiating between all inflation shocks lagged, only core inflation shocks lagged and no inflation shocks lagged.

Table 18. Monthly Fama-MacBeth Regression Results Using Varying Lags

	All Lagged		Core Lagged		None Lagged	
Headline λ	-1.03		0.14		0.14	
t-stat	-2.24		0.51		0.51	
Core λ		-1.05		-1.09		-0.97
t-stat		-3.07		-5.39		-1.90
Energy λ		6.38		3.68		6.42
t-stat		0.89		3.74		2.90
R^2	0.09	0.37	0.02	0.52	0.02	0.21

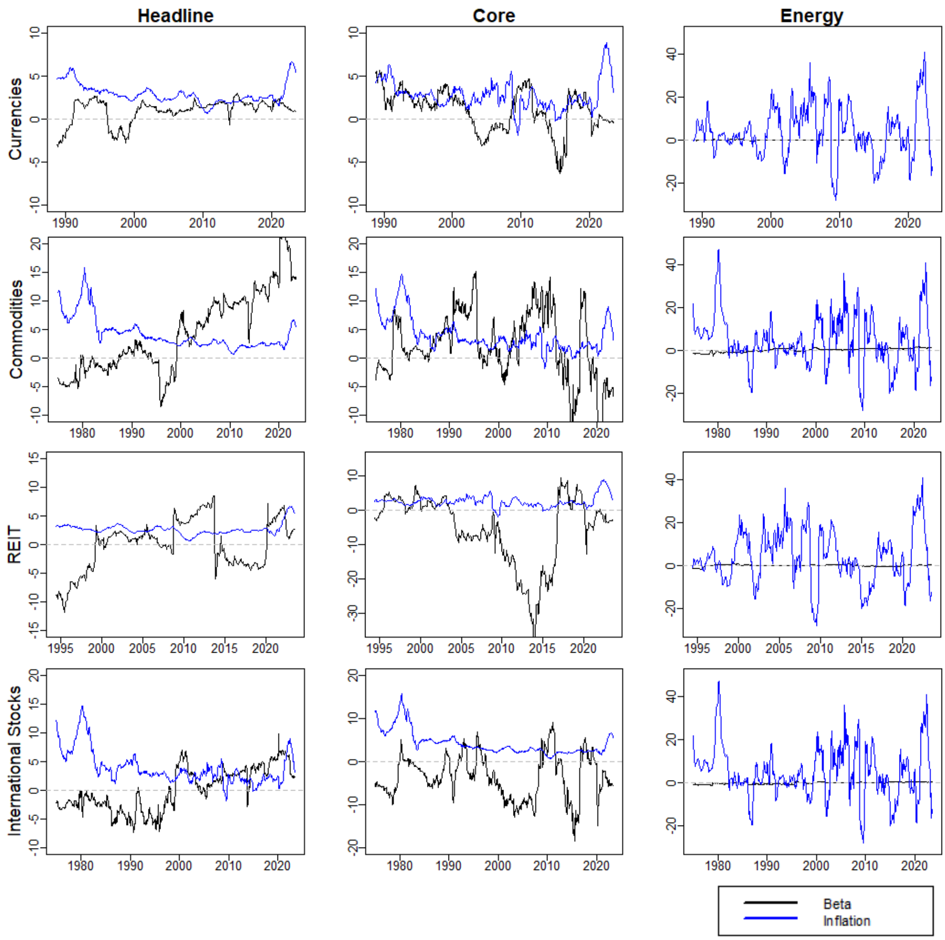
Note: This table presents the price of risk estimated from the 35 test assets, using the standard Fama-MacBeth approach with the following specification; $E(r_{i,t}) = \alpha_i + \lambda\beta_i + u_{i,t}$, where $E(r_{i,t})$ represents the average annualized return of an asset, β_i is the asset's inflation shock beta and λ is the price of risk. The regression is run separately for headline and jointly for core and energy inflation shocks on a monthly basis for the full sample period. This table compares the regression results when lagging all inflation shocks by one month vs when lagging core inflation by one month vs when not lagging it for the full sample period. The t-statistics in the table are adjusted in accordance with White's approach.

Figure 4. Betas vs Inflation Levels Over Time



Note: These graphs depict the time series of betas and headline, core and energy level inflation over time. The betas are compiled using a rolling 5 year estimation window.

Figure 5. Betas vs Inflation Levels Over Time - Continued



Note: These graphs depict the time series of betas and headline, core and energy level inflation over time. The betas are compiled using a rolling 5 year estimation window.

Table 19. Sensitivities of Inflation Shock Betas to the Level and Volatility of Inflation

	Headline	t-stat	Core	t-stat	Energy	t-stat
A. Sensitivity of Betas to Changes in Inflation Level						
Stocks	-0.00	-0.15	-0.00	-0.53	-0.00	-0.58
Treasuries	-0.00	-1.06	0.00	0.76	-0.00	-0.55
Agency Bonds	0.01	0.92	-0.06	-1.57	0.00	2.78
Corporate Bonds	-0.02	-1.75	0.22	1.11	0.00	0.67
Currencies	-0.00	-0.06	0.07	1.33	-0.00	-6.36
Commodities	0.00	1.50	-0.00	-0.03	0.00	0.31
REITs	-0.23	-3.40	-0.00	-0.02	-0.00	-4.49
International Stocks	-0.00	-1.93	0.00	0.53	-0.00	-2.74
B. Sensitivity of Betas to Changes in Inflation Volatility						
Stocks	1.39	0.47	-7.62	-0.82	0.00	0.03
Treasuries	-1.68	-2.95	1.38	0.66	-0.03	-3.76
Agency Bonds	-1.07	-8.04	2.13	3.43	-0.01	-7.27
Corporate Bonds	-1.53	-3.48	-8.30	-1.06	-0.01	-3.65
Currencies	0.74	0.82	-5.37	-1.30	0.00	0.57
Commodities	3.51	1.78	-3.23	-0.42	0.07	1.86
REITs	8.91	1.79	-11.54	-0.72	0.07	1.33
International Stocks	-0.72	-0.24	-7.11	-0.88	-0.04	-0.86

Note: This table presents the sensitivities of betas to changes in the level and volatility of inflation, with both sensitivities and changes being derived from the rolling-window regressions as described in Section 3.1.2. Respective betas are run on changes in the level and volatility of inflation jointly.

Table 20. Full Set of Conventional Assets - Return Exposure to Inflation Risks

	Mean	S.D.	Headline β	t-stat	Core β	t-stat	Energy β	t-stat
Consumer	13.91	21.96	-0.29	-0.06	-4.44	-1.34	0.12	0.32
Manufacturing	11.73	22.44	2.85	0.66	-7.68	-2.76	0.45	1.11
High Tech	18.10	23.12	-0.23	-0.06	-5.61	-1.54	0.15	0.59
Health	7.55	16.47	0.00	1.10	0.00	2.89	-0.00	-0.05
Others	9.80	23.59	-0.03	-0.88	-0.01	-0.89	-0.00	-0.89
Treasury 1-year	-0.44	0.87	-0.29	-2.20	-0.12	-1.39	-0.02	-1.87
Treasury 3-year	-1.00	1.87	-0.65	-3.23	-0.27	-1.46	-0.05	-2.19
Treasury 5-year	-2.38	4.89	-1.63	-3.68	0.27	0.41	-0.14	-3.85
Treasury 7-year	-2.83	6.60	-2.04	-3.38	0.82	0.81	-0.19	-3.63
Treasury 10-year	-4.06	8.33	-2.33	-2.82	1.19	0.81	-0.23	-2.99
Treasury 20-year	-6.95	12.95	-3.23	-2.29	1.21	0.57	-0.34	-2.43
Treasury 30-year	-8.11	17.46	-3.74	-1.82	2.36	0.84	-0.44	-2.08
Agency 1-5 years	-1.61	2.24	-0.58	-5.25	-0.24	-1.34	-0.04	-4.23
Agency 5-10 years	-2.64	5.73	-1.40	-3.36	0.32	0.47	-0.13	-5.44
Agency 10-15 years	-3.72	8.51	-1.67	-2.48	0.15	0.09	-0.15	-2.82
Agency >15	-5.17	11.70	-1.72	-2.00	1.04	0.46	-0.18	-2.97
Corporate 1-3 year	-0.61	2.93	-0.15	-1.25	-1.35	-2.81	-0.01	-0.22
Corporate 3-5 year	-0.91	5.61	-0.25	-0.28	-2.03	-2.44	-0.01	-0.13
Corporate 10-15 year	-1.79	8.89	-0.26	-0.20	-2.32	-1.90	-0.00	-0.02
Carry-1	-0.91	4.02	0.66	1.59	0.03	0.04	0.03	0.77
Carry-2	-1.43	5.71	1.60	2.28	0.51	0.73	0.10	1.79
Carry-3	-0.24	4.74	1.18	1.87	-0.34	-0.71	0.10	1.46
Carry-4	-1.11	3.90	0.97	2.13	-0.76	-1.21	0.09	1.84
Carry-5	-0.49	3.87	0.82	1.73	-0.95	-0.90	0.05	1.03
Carry-6	-0.22	5.24	1.97	2.08	-0.94	-0.74	0.18	1.97
Dollar-Carry	0.74	4.04	-0.02	-0.21	-0.18	-1.17	0.00	0.17
Livestock	-0.87	15.19	2.39	0.67	1.05	0.53	0.37	1.19
Agriculture	14.03	16.60	3.50	1.31	-2.30	-0.69	0.29	1.14
Industrial Metal	8.85	21.43	4.27	1.25	-6.51	-2.06	0.46	1.79
Precious Metal	5.44	14.11	0.20	0.16	-0.05	-0.05	-0.05	-1.98
Energy	18.53	46.61	23.00	2.02	-14.93	-1.62	2.18	2.17
North America	12.73	20.34	1.41	0.38	-5.28	-1.74	0.29	1.06
Europe	7.33	21.11	2.99	0.81	-5.50	-1.79	0.43	1.41
Far East	3.02	16.38	-0.37	-0.17	-6.64	-2.84	0.19	1.17

Note: This table reports the regression results of the following specification; $r^e_{i,t} = \alpha_i + \beta^i_\pi \varepsilon_t + u_{i,t}$, where $r^e_{i,t}$ are excess asset returns and $\varepsilon_{i,t}$ is the error term from the VAR (see Equation 3.1). The time period considered spans from the beginning of 2020 to mid-2023. We run a univariate regression for headline shocks, while for core and energy inflation shocks we run the regression jointly. The t-statistics we report are adjusted in accordance with the Newey-West methodology. All mean returns and standard deviations reported are annualized.

Table 21. Expanded Asset Universe - Return Exposure to Inflation Risks

	Mean	S.D.	Headline β	t-stat	Core β	t-stat	Energy β	t-stat
Equity L/S	3.99	10.66	1.90	1.04	-4.94	-2.58	0.27	1.64
Equity Hedge	4.38	12.37	2.09	0.97	-5.35	-2.43	0.30	1.59
Equity Hedge Multi	-0.35	11.52	1.68	0.71	-4.12	-2.19	0.26	1.22
Equity Long Biased	6.54	16.58	2.55	0.91	-6.48	-2.25	0.37	1.55
Equity Long Only	9.01	18.43	2.28	0.69	-6.98	-2.25	0.38	1.33
PE index	11.85	30.35	4.16	0.67	-10.00	-2.11	0.59	1.18
Bitcoin	89.61	75.64	-4.17	-0.31	-40.12	-2.98	1.09	0.74
IQ Mrkt NTRL Beta	-3.18	5.56	-0.76	-0.50	-1.86	-1.47	-0.01	-0.11
IQ MA	-2.77	6.71	0.18	0.16	-1.23	-1.72	0.01	0.11
Blackrock Event driven	-0.79	5.54	0.76	0.99	-2.38	-2.06	0.09	1.19
PIMCO 1-5	-2.21	4.47	-0.37	-0.48	-0.74	-0.99	0.00	0.03
PIMCO +15	-5.53	16.46	-3.89	-1.54	0.07	0.02	-0.29	-2.19
CTAs	6.36	4.83	1.33	1.45	-0.49	-0.66	0.13	1.70
SMB	-2.77	10.75	1.68	1.25	-5.60	-3.53	0.31	2.15
HML	-1.78	17.76	4.18	2.04	-0.18	-0.04	0.36	1.42
RMW	7.16	7.74	-0.74	-1.09	3.50	1.84	-0.10	-1.93
CMA	5.19	12.32	2.06	1.54	1.32	0.56	0.17	1.11
MOM	3.25	13.76	0.66	0.32	1.76	0.76	-0.08	-0.39

Note: This table reports the regression results of the following specification; $r^e_{i,t} = \alpha_i + \beta^i_\pi \varepsilon_t + u_{i,t}$, where $r^e_{i,t}$ are excess asset returns and $\varepsilon_{i,t}$ is the error term from the VAR (see Equation 3.1). The time period considered spans from the beginning of 2020 to mid-2023. We run a univariate regression for headline shocks, while for core and energy inflation shocks we run the regression jointly. The t-statistics we report are adjusted in accordance with the Newey-West methodology. All mean returns and standard deviations reported are annualized.

Table 22. Fama-MacBeth Regression Results for Alternative Assets, Active Funds and Fama-French Risk Factors

	Alternative Assets		Active Funds		Fama-French Risk Factors	
Headline λ	-13.50		3.36		-1.65	
t-stat	-0.04		8.04		-2.84	
Core λ		-2.18		1.31		0.68
t-stat				0.34		0.31
Energy λ		5.35		43.55		-8.64
t-stat				0.80		-0.39
R^2	0.28	1.00	0.79	0.82	0.48	0.82

Note: This table presents the price of risk estimated from alternative portolios and Fama-French risk factors, using the standard Fama-MacBeth approach with the following specification; $E(r_{i,t}) = \alpha_i + \lambda\beta_i + u_{i,t}$, where $E(r_{i,t})$ represents the average annualized return of an asset, β_i is the asset's inflation shock beta from Tables 20 and 21 and λ is the price of risk. The regression is run separately for headline and jointly for core and energy inflation shocks. The t-statistics in the table are adjusted in accordance with White's approach.

Table 23. Asset Return Exposure to Inflation Shocks Using Out-of-Sample Forecasting

	Mean	S.D.	Headline β	t-stat	Core β	t-stat	Energy β	t-stat
A. Optimized Window								
Stock	8.87	16.53	-0.45	-0.14	-2.50	-0.87	0.23	1.31
Treasury	2.50	6.59	-1.83	-4.62	-0.54	-0.55	-0.22	-4.01
Agency	1.93	3.45	-0.96	-4.60	-0.49	-0.83	-0.11	-4.01
Corporate	3.19	5.93	-0.72	-1.68	-1.75	-1.13	-0.04	-0.85
Currency	1.49	6.58	0.81	2.37	-0.71	-0.99	0.14	2.88
Commodity	4.20	24.53	10.87	8.93	2.63	0.76	1.34	7.82
REIT	6.62	19.74	2.41	0.81	-3.00	-0.86	0.34	1.13
Int Stock	5.48	18.54	0.82	0.43	-4.53	-2.05	0.27	1.38
B. Expanding Window								
Stock	8.87	16.53	1.11	0.66	-1.83	-0.81	0.18	1.00
Treasury	2.50	6.59	-1.97	-4.62	-0.07	-0.11	-0.22	-4.06
Agency	1.93	3.45	-0.96	-4.35	0.09	0.32	-0.11	-3.67
Corporate	3.19	5.93	-0.56	-1.84	-0.28	-0.32	-0.05	-1.13
Currency	1.49	6.58	0.88	2.63	-0.73	-1.01	0.13	2.69
Commodity	4.20	24.53	11.24	8.95	-1.10	-0.39	1.34	7.24
REIT	6.62	19.74	2.74	1.15	-1.67	-0.57	0.35	1.13
Int Stock	5.48	18.54	1.21	0.70	-3.40	-1.64	0.26	1.38

Note: This table reports the regression results of the following specification; $r^e_{i,t} = \alpha_i + \beta^i_\pi \varepsilon_t + u_{i,t}$, where $r^e_{i,t}$ are excess asset returns and $\varepsilon_{i,t}$ is the forecasting error. We run a univariate regression for headline shocks, while for core and energy inflation shocks we run the regression jointly. The time period considered for this analysis spans from 1986 until 2023. The t-statistics we report are adjusted in accordance with the Newey-West methodology. All mean returns and standard deviations reported are annualized.