Is bitcoin an inflation hedge?

Abstract

Spot bitcoin ETFs have been recently approved in the U.S., increasing retail and institutional investors' attention to the crypto space. Still, empirical evidence on whether Bitcoin is an asset that protects investors against inflation is still inconclusive. To contribute to this debate, we analyze the effect of inflation shocks on bitcoin returns through the estimation and inference of Vector Autoregressive Models (VARs). Unlike previous research on the topic, we identify inflation shocks as surprises in the US's CPI and Core PCE announcements: the difference between the announced inflation and the analysts' consensus. The results, based on monthly data between August 2010 and January 2023, indicate that bitcoin returns increase significantly after a positive inflationary shock, corroborating empirical evidence that Bitcoin can act as an inflation hedge. However, we observe that bitcoin's inflationary hedging property is sensitive to the price index – it only holds for CPI shocks – and to the period of analysis — the hedging property stems primarily from sample periods before the increasing institutional adoption of BTC ("early days"). Thus, the inflation-hedging property of Bitcoin is context-specific and is likely to be diminishing as adoption increases. This research contributes to the still under-explored strand of literature that analyzes the hedging and safe-haven properties of Bitcoin and benefits asset managers, investors, and monetary authorities.

Keywords: Bitcoin, Hedge against inflation, Unexpected inflation, surprises in CPI, surprises in PCE.

JEL classifications: E44, E31, G11.

1 Introduction

Inflation is a critical investment risk and one of the foremost challenges to conducting business in the upcoming years (World Economic Forum, 2023). Consequently, investors are urged to formulate strategies to mitigate inflation risk. A viable safeguard involves incorporating in the portfolio assets that appreciate alongside inflation (Tarbert, 1996). Such a need has gained even more importance given the recent generalized price increase in various parts of the world, including developed economies, where low interest rates and controlled inflation have coexisted for decades. But not anymore.

The recent consideration of Bitcoin as an investment instrument (Conlon et al., 2021), along with the growing interest among academics and policymakers (Phochanachan et al., 2022), has contributed to positioning the cryptocurrency as a potential inflation hedge. Commonly cited justifications for this role include its limited supply and decentralized network, conferring scarcity and resilience (Bouri et al., 2017a,b). However, existing theoretical and empirical studies have not reached a consensus on Bitcoin's ability to hedge for inflation – while Blau et al. (2021) and Choi and Shin (2021) support Bitcoin as a robust inflation hedge, most studies indicate that Bitcoin inflation hedging properties are context-specific (Conlon et al., 2021, Matkovskyy and Jalan, 2020, Phochanachan et al., 2022, Smales, 2021). This lack of consensus may be attributed to methodological differences, varying time horizons, and the specific characteristics of the economies analyzed in these studies.

One key aspect of answering this research question is whether a given inflation announcement carries *unexpected* information or not. To demonstrate this point, let us consider the following two situations. If the observed CPI matches analysts' consensus (i.e., market expectations), asset prices should not react, regardless of the level of inflation. However, if at least part of the information was a *surprise*, the announcement generates new information for financial markets, and asset prices should move accordingly. Thus, disentangling the expected and unexpected parts of inflation announcements is critical to understanding the role of inflation shocks in shaping the fluctuations in Bitcoin's price.

That is precisely how we depart from previous research on the topic – by enhancing the identification of inflation shocks in a Vector Autoregressive (VAR) system. Specifically, instead of identifying inflation shocks as the residual from a typical regression of observed (or expected) inflation on the lags of itself and of several variables (S&P 500, VIX, interest rates, etc.) (for example, as in Choi and Shin, 2021), we focus on the unexpected component of inflation releases, measured here as the difference between actual monthly inflation and the consensus forecast of market analysts. By doing that, our innovations (or shocks) consider all observed and unobserved factors that market agents consider in their projections of inflation, and not only a few covariates included in the VAR system. As Nakamura and Steinsson (2017) notes, any factors left out as covariates in the regression will be part of the "shock", even if they are anticipated by market agents. Thus, we believe that our identification strategy provides a cleaner determination of the *unexpected* portion of inflation announcements (that is, surprise inflation) and helps us understand the role of inflation in bitcoin returns.

Given this crucial conceptual issue, we contribute to this inconclusive but critical debate by estimating and analyzing, through VARs, the short-term effect of inflation shocks on Bitcoin price fluctuations. Despite the unexpected component of inflation releases mentioned above, we follow previous studies and include in the system of equations the joint effects of gold prices, the S&P500 and VIX indexes, the one-year US Treasury bill yield, and bitcoin prices. Our data is monthly and ranges from August 2010 to January 2023.

The results of the impulse response functions indicate that Bitcoin returns increase following a positive inflation shock, ceteris paribus. Compared to other assets, such a pattern is similar to the responses observed on Gold and contrasts with the one observed on the S&P 500. This finding suggests that Bitcoin acts as a hedge against unexpected fluctuations in inflation, which corroborates some of the empirical evidence. Furthermore, the variance decomposition analysis indicates that the return-inflation relationship may exhibit greater strength for gold than for Bitcoin, consistent with the findings of Smales (2021).

However, further analyses suggest that the efficacy of Bitcoin as an inflation hedge appears contingent on two aspects: the selected price index and the sample period. Regarding the former, when considering the Core PCE index instead of the CPI, the cryptocurrency return reveals a negative response to a positive inflation shock. This discrepancy can be attributed to different criteria, such as composition, weighting, and release dates. Regarding the former, we find a notable decrease in the inflation-hedging properties of Bitcoin when we exclude the initial sampling period ("early days" of Bitcoin), suggesting that such hedging property may be diminishing as adoption – and, consequently, market fluctuations – become mainstream. Thus, the inflation-hedging property of Bitcoin is likely to be diminishing as adoption increases.

This research contributes to a growing but still underexplored debate on Bitcoin hedging properties in the face of inflationary shocks (Blau et al., 2021, Choi and Shin, 2021, Conlon et al., 2021, Matkovskyy and Jalan, 2020, Phochanachan et al., 2022, Smales, 2021). Notably, our contributions are twofold. First, we identify inflation shocks through their surprising or unexpected components. This approach fundamentally differs from most previous studies that have examined Bitcoin's hedging ability based on its expected (or actual) component. Second, in contrast to studies that considered unexpected inflation in their analyses (Matkovskyy and Jalan, 2020, Smales, 2021), our empirical methodology takes into account the dynamic and temporal relationships among the variables in the model, which is especially relevant in time series analyses. At the same time, we seek to mitigate possible endogeneity problems that often arise in this type of investigation.

Furthermore, as this is a current discussion with significant practical implications for asset managers, investors, and monetary authorities, the empirical evidence presented in this study directly affects resource allocation decisions and allows for a recent analysis of the behavior of Bitcoin, gold, and other assets following inflation shocks. In particular, recent research has shown that sophisticated retail investors are attracted to cryptocurrencies for macroeconomic and portfolio reasons (Colombo and Yarovaya, 2024). Our study is also timely since the SEC approved spot Bitcoin ETFs only in 2024, bringing tremendous attention and demand for Bitcoin exposure in retail investors' portfolios.

The remainder of this paper is organized as follows: Section 2 presents the theoretical framework and methodology used in this study. Section 3 presents the data used in this work. Section 4 reports the empirical results, and Section 5 presents the conclusions.

2 Methodology

2.1 VAR model

To capture the dynamics of the variables and deal with the potential endogeneity in their relationships, we use a VAR framework (Sims, 1980), which is reliable in describing, summarizing, and forecasting macroeconomic data (Stock and Watson, 2001).

Specifically, let $y_1, y_2, \ldots, y_T$ be multivariate time series, with $y_t = (y_{1t}, y_{2t}, \ldots, y_{kt})'$. A VAR model of order p, in its basic form, can be expressed as follows:

$$y_t = v + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + u_t \quad ; \quad t = 1, 2, 3, \ldots, N \tag{1}$$

All symbols used in this representation have usual meanings, that is, $y_t = (y_{1t}, y_{2t}, \ldots, y_{kt})'$ is a random vector $(K \times 1)$ of endogenous variables; $v = (v_1, v_2, \ldots, v_k)'$ is a fixed vector of intercepts $(K \times 1)$, which allows the possibility of a non-zero mean $E(y_t)$; A_i are fixed matrices of coefficients $(K \times K)$ where $i = 1, \ldots, p$, which are interpreted as the sensitivity of a model variable about a lag of another variable; $u_t = (u_{1t}, u_{2t}, \ldots, u_{kt})'$ is a K-dimensional vector of white noise, such that $E(u) = 0$, $E(u_t u_t') = \Sigma_u$, and $E(u_t u_s') = 0$ for $s \neq t$, that is, it represents random shocks that do not correlate and are time-invariant.

Under the stability condition, the process Y_t has the MA representation defined as:

$$Y_t = \mu + \sum_{i=0}^{\infty} A^i U_{t-i} \quad (4)$$

Where Y_t is modeled as a function of the mean term μ and in terms of the past and present of the innovation vector U_t.

Furthermore, the MA representation of y_t can be found by pre-multiplying Y_t by a matrix $J = [I_K : 0 : \ldots : 0]$ of dimension $(K \times Kp)$. Here, $\mu = J\mu$, $\Phi_i = JA^iJ'$, and $u_t = JU_t$.

$$y_t = JY_t = J\mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i} = \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i} \quad (5)$$

The challenge of estimating these parameters incurs the same difficulties as obtaining the parameters of the primitive model from the reduced model. This methodology does not permit estimation in cases of underidentification, where the number of equations is fewer than the number of unknowns. To identify the system written in MA form, we estimate each equation by OLS and then compute the Cholesky factorization of the reduced form VAR covariance matrix (Lütkepohl, 2005).

2.2 Model checking

Stationarity. The formal approach to ascertain the stationarity of time series involves employing the unit root test, with the Augmented Dickey-Fuller (ADF) test serving this purpose. The null hypothesis indicates the existence of a unit root, indicative of non-stationarity. Its rejection implies that the underlying stochastic process governing the series is time-invariant. In that case, the VAR model can be estimated with the series at level. Throughout the implementation of the ADF test, the analysis considered various model specifications, including those without a constant or trend, with a constant, and with both a constant and a trend.

Serial autocorrelation. To address the threat of serial autocorrelation, which has the potential to compromise the integrity of impulse response functions, the authors employ the Ljung and Box (1978) test. The number of lags, denoted as h, is determined by the Schwert (1989) criterion. In short, the null hypothesis posits that residuals up to the h-th lag exhibit white noise characteristics. When rejected, it implies that at least one autocorrelation is statistically different from zero. In such a case, the model must be rejected, prompting a re-specification and re-estimation of the VAR (Lütkepohl, 2011).

Model stability. To appraise the temporal consistency of a VAR model, it is imperative to scrutinize its stability, denoting the absence of explosions in the time series and the predictability of behavior over time. The stability examination aims to validate whether the roots of the eigenvalues in the coefficient matrix fall within the unit circle. If the eigenvalues modulus resides within the unit circle, the model attains stability, rendering the dependent variables weakly stationary. Conversely, if the eigenvalues modulus lies outside the unit circle, the model is deemed unstable, and the dependent variables are integrated.

According to Lütkepohl (2005), the stability of the VAR model assumes paramount significance in ensuring the reliability of results, as an unstable model can engender inaccurate predictions, particularly sensitive to minor fluctuations in input data. Furthermore, as highlighted by Baum (2013), adherence to stability conditions is imperative for the accurate estimation of Impulse Response Functions and Variance Decomposition.

2.3 Model evaluation

Impulse Response Function (IRF). The IRF illustrates how a shock to a specific variable propagates to others over time, enabling the measurement of the magnitude and time horizon of the impact. In linear models with uncorrelated error terms, this process is straightforward. However, in the presence of correlated errors, identifying shocks with specific variables becomes complex and lacks clarity. This complexity arises from common components in errors affecting multiple variables. According to Farias (2008), a common approach in such cases is to arbitrarily assign the effects of these shared components to the variable that appears first in the system. The drawback of this approach is its dependency on the particular equation order within the model.

In a VAR(p) model, the derivation of IRFs involves inducing a one-period shock to an endogenous variable. Specifically, an increase in u_1 by one standard deviation at time $t = 0$ is considered, maintained for only one period, constituting a "boost". The impact of this shock permeates through the model, influencing all endogenous variables. Subsequently, a one-period shock is introduced to the next endogenous variable, for instance, an increase in u_2 by one standard deviation. This iterative process extends to all endogenous variables, allowing for a comprehensive tracking of effects across the entire model.

Forecast error variance decomposition (FEVD). A complementary approach to analyzing the results of the VAR model is through variance decomposition. This technique enables the breakdown of forecast error variances for each variable into components attributable to the variable itself and others. The outcome is a percentage-wise representation of the impact that a shock to a specific variable exerts on itself and other system variables.

According to Enders (2008), if the shocks observed in a variable, y_2t, cannot account for the variance in the forecast error of variable y_1t, the sequence y_1t is deemed exogenous; otherwise, it is considered endogenous. Lütkepohl (2005) further notes that this technique is sensitive to changes in the considered system. The forecast error variance components may undergo alterations with system expansions, including additional variables or exclusions of series from the model. Furthermore, factors such as measurement errors, seasonal adjustments, and the use of aggregated data can impact the outcomes of this approach.

3 Data

This study utilizes monthly data from August 2010 to January 2023 (150 observations). The beginning of this time frame stems from the earliest available data on Bitcoin trading prices. The variables used in this study (in stationary form) are the following: returns on S&P500 (Ret_SP500), Gold (Ret_Gold), and bitcoin (Ret_BTC); first differences of the US 1y interest rates (Dif_US_1Y) and the VIX (Dif_VIX); and surprise inflation (Surp_Inf). Table I describes and details the variables considered in this study.

Our framework for variable selection, estimation, and inference is similar to Choi and Shin (2021), but we introduce modifications to enhance the identification of inflation shocks. These adjustments are inspired by the work of Kuttner (2001), Romer and Romer (2004), and Nakamura and Steinsson (2017), and the specification proposed by Lowenkron and Garcia (2007). Particularly, as described in Table I, we include in the VAR system inflation surprises estimated as the difference between the actual (CPI_t) and the expected ($E_{t-1}(CPI_t)$) CPI MoM (also CPI YoY and Core PCE MoM in further analyses). With such refinements, we seek more assertive estimates and robust outcomes by identifying inflation through its surprising component.

One key operational concern is to homogenize each variable's measurement period to coincide with inflation announcements, in the same spirit as Kuttner (2001), Cochrane and Piazzesi (2002), and Hanson and Stein (2015).[1] Thus, we consistently use the closing quote on the day of the inflation announcement relative to the closing price of the previous day for all series. By doing that, our variables capture the impact of the inflation announcement, regardless of different trading hours across various financial markets.

Particularly, the specification of variables, excluding $Surp\_Inf$, involves calculating changes from $t-1$ to t for each announcement of the U.S. economy price index, CPI or PCE (day t). This approach aims to capture the complete market response to the announcement, operating under the implicit assumption that the entire reaction to the economy price index announcement may not be immediate. Investor uncertainty about the implications of news may lead to a gradual reaction, where beliefs are updated as others' interpretations unfold through trading volume, the pricing process, and financial media. Consistent with this idea and similar to our case, Hanson and Stein (2015) argues the full reaction to an FOMC announcement might not be instantaneous.[2]

Regarding the scale transformation applied to specific variables, this is a practice frequently adopted in this type of study. As Morettin and de Castro Toloi (2006) emphasize, working with scale-free returns rather than asset prices is recommended since the former have more advantageous statistical properties.

3.1 Descriptive analysis

As shown in Table II, the centrality measures across all series are similar and nearly zero. Regarding asymmetry values, the return series exhibit negative asymmetry, with Ret_Gold approaching a distribution closest to symmetry. Kurtosis results depart from normal standards, with most demonstrating a leptokurtic distribution. $Surp\_Inf$ is the closest to a normal pattern, with a kurtosis of 2.59. Regarding volatility, it is noteworthy that the standard deviation of Bitcoin returns significantly exceeds that of gold, consistent with findings by Choi and Shin (2021), Smales (2021) and Phochanachan et al. (2022).

Since the surprise measures of inflation are key to our analysis, we take a closer look on them. Figure A1, available in Appendix A, illustrates the frequency distribution graphs for the $Surp\_Inf$, $Surp\_Inf\_YoY$, and $Surp\_Inf\_PCE$ series. For the first two, the actual value aligned with market expectations approximately 33% of the time. This proportion is notably lower compared to the $Surp\_Inf\_PCE$ series, where 55% of the time the inflationary surprise

[1]The authors use a window of one or two days around FOMC meetings to identify the effects of changes in monetary policy on financial markets.

[2]More specifically, Fleming and Remolona (1999) explored price dynamics in the financial market following the release of crucial economic announcements, such as monetary policy decisions. Their findings indicate a gradual formation of prices in the market after such information is released, characterized by elevated levels of volume and volatility persisting for at least 90 minutes.

Table I. Data sources and description of model variables

Variable	**Calculation**	**Definition and source**
Ret_SP500	$Ln(SP500_t/SP500_{t-1})$	The log-return is derived from a theoretical portfolio comprising the 500 largest companies traded on the NYSE or NASDAQ exchanges. It is widely used to capture general financial market conditions. Source: Yahoo Finance.
Ret_Gold	$Ln(Gold_t/Gold_{t-1})$	The log-return is obtained from gold futures contracts traded on the COMEX, a division of NYMEX. It serves as a crucial benchmark for investors seeking to track the price dynamics of gold in the financial market. Source: Yahoo Finance.
Ret_BTC	$Ln(BTC_t/BTC_{t-1})$	The log-return is calculated from the real-time market price of Bitcoin, determined by global transactions. Source: Investing.com.
Dif_US_1Y	$US1Y_t - US1Y_{t-1}$	Represents the change in the par yield of U.S. Treasury securities with a one-year maturity. It is based on the closing bid prices of the most recently auctioned securities in the over-the-counter market. The rate is published daily and reflects market expectations concerning the economic trajectory and monetary policy. Source: United States Department of the Treasury.
Dif_VIX	$VIX_t - VIX_{t-1}$	Represents the change in the reference indicator measuring the expected short-term volatility of the stock market. It is based on the stock options prices comprising the S&P500 index and is updated in real-time, during trading sessions. Source: Yahoo Finance.
Surp_Inf	$CPI_t - E_{t-1}(CPI_t)$	Represents the unexpected component of inflation, calculated at the moment of the official inflation rate announcement as the difference between the actual (CPI_t) and the expected ($E_{t-1}(CPI_t)$) CPI MoM. Alternative metrics such as CPI YoY and Core PCE MoM will also be taken into account. MoM (YoY) data are (are not) seasonally adjusted. Source: U.S. Bureau of Labor Statistics, Bureau of Economic Analysis and Investing.com.

Note: The subscript t $(t-1)$ denotes, except for $Surp\_Inf$, the closing price of the asset/index on the day (previous day) of the official inflation rate announcement.

equaled zero. This discrepancy may be attributed to differing criteria, such as composition and disclosure dates (the PCE announcement occurs after the CPI release for the same period of reference; thus, market agents update beliefs following any surprise in CPI). We can see in the figures that the dispersion of surprises is larger for CPI MoM and CPI YoY than for PCE MoM. Furthermore, surprises in CPI are positively skewed – i.e., extreme values are more common in the right tail (positive ones).

Another important issue to discuss is the timing and correlation of these surprises. Figure A2 shows the actual, forecast, and surprise (actual - forecast) values for our baseline measure of inflation (CPI MoM, Panel A) and for the further analyses (CPI YoY, Panel B, and PCE MoM, Panel C). We can observe from the Figure that average surprises are close to zero; however, positive surprises started to become more frequent in the recent period, starting in the middle of 2021, following a supply-side disruption brought by COVID-19.[3] Such a pattern is more pronounced in the CPI MoM and CPI YoY, suggesting that positive surprises in CPI are incorporated in PCE forecasts, reducing the forecast error in the latter

[3]On May 12, 2021 (reporting inflation from April 2021), the actual CPI MoM came on 0.8%, while the expected inflation was 0.2%. Such a surprise of 0.6 p.p. is the largest value in our sample period. After that, market agents witnessed a sequence of positive unexpected inflation values that made the FOMC start, on March 16, 2022, eight successive increases in the policy rate.

Table II. Summary statistics

Variable	Mean	p50	SD	Asymmetry	Kurtosis	Min	Max	Obs.
Ret_SP500	-0.000	0.001	0.012	-0.680	6.759	-0.050	0.054	150
Dif_VIX	-0.123	-0.175	1.899	1.794	9.214	-5.710	11.090	150
Surp_Inf	-0.000	0.000	0.136	0.769	2.588	-0.400	0.600	150
Dif_US_1Y	0.003	0.000	0.045	2.607	13.714	-0.160	0.230	150
Ret_Gold	0.001	0.001	0.009	-0.210	1.341	-0.029	0.028	150
Ret_BTC	-0.004	0.000	0.091	-5.094	49.918	-0.849	0.288	150

Note: This table provides statistics for all series covering the period from 2010:08 to 2023:01. The Ret (Dif) prefix indicates that the series was derived from returns (differences) calculated within one-day windows around monthly CPI MoM announcements.

inflation index.

Finally, Figure A3 plots the three surprise measures and shows the correlation coefficient among them: the contemporaneous linear association is stronger for the pair CPI MoM-CPI YoY (0.63), but almost uncorrelated on the pairs CPI MoM-PCE MoM (0.12) and CPI YoY-PCE MoM (0.02). Such evidence reinforces that markets adapt expectations and reduce the forecast error for the PCE, whose announcement date always occurs later than the CPI. Finally, Figure A4 shows the cross-correlation among each surprise pair, and again shows a clear pattern for CPI MoM-CPI YoY: the correlation coefficient is a lot stronger in t0 (i.e., their contemporaneous values). On the other hand, the relationship between CPI and PCE is noisier, showing that the correlation is near zero for contemporaneous values and for other lead-lag relationships.

3.2 Model identification

Since the literature does not provide clear theoretical or empirical evidence on the causal relationships among all variables, we identify the structural shocks (i.e., the uncorrelated or orthogonal errors, not the reduced-form errors that correlate across equations) based on an economically reasonable temporal ordering criterion. This procedure represents a recursive VAR, where the error term in each regression equation is constructed to be uncorrelated with the error the the preceding equations (Stock and Watson, 2001).

Our ordering criteria for the Choleski triangular decomposition of the residuals are the following. Initially, variables representing broad measures of economic activity and market volatility are selected for their ability to assimilate new information promptly. Subsequently, series reflecting the dynamics of prices in the economy and the stance of monetary policy are incorporated. Lastly, variables theoretically presumed to be influenced by the aforementioned factors are considered: the price of a reference financial asset and the price of an emerging financial asset.

Given the relatively lower significance of Bitcoin in financial markets (Choi and Shin, 2021), as well as empirical findings suggesting its lesser efficiency compared to stock and gold markets in assimilating available information (Al-Yahyaee et al., 2018), which also indicate its responsiveness to changes in inflation, interest rates (Li and Wang, 2017), and financial market volatility (Bouri et al., 2017a), it is reasonable to treat Bitcoin as the most endogenous variable in the system.

Regarding the order of remaining variables, support for the identification assumption is drawn from the literature on the monetary VAR model, particularly highlighted by Choi and Shin (2021). Studies such as those by Christiano et al. (2005) and Coibion (2012) placed inflation before short-term interest rates in the Cholesky identification method applied in their analyses. Additionally, empirical research conducted by Beaudry and Portier (2006) and Jordà et al. (2017) provides evidence indicating that movements in financial variables, such as stock prices, may precede changes in macroeconomic variables like inflation and interest rates. The analyses by Rigobon and Sack (2003) and Kurov et al. (2022) are particularly relevant in this context, revealing the FED's responsiveness to the stock market dynamics, adjusting its monetary policy in response to changes in market conditions.

In light of the evidence provided, the baseline VAR model includes an intercept and six variables arranged in the following sequence: the log-return of the S&P500 (Ret_SP500), the variation of the VIX index (Dif_VIX), the surprise inflation ($Surp\_Inf$), the variation in the one-year US Treasury bill yield (Dif_US_1Y), the log-return of gold prices (Ret_Gold), and the log-return of Bitcoin prices (Ret_BTC).

3.3 Model checking

The model-checking outcomes, featured in Appendix B, demonstrate favorable statistical properties, enhancing the reliability of the empirical results. Particularly, Table B1 exhibits the ADF test findings, indicating that all series have no unit root and are stationary at a 0.01 significance level. Such a result is robust to several model specifications – without drift or trend, with drift, with drift and trend, and with drift and linear and quadratic trends.

Furthermore, Table B2 displays the outcomes of the portmanteau test, revealing that, at a 0.05 significance level, only the VAR(6) model residuals exhibit white noise characteristics up to the maximum lag.[4] Finally, Table B3 showcases the findings of the stability diagnosis test applied to the VAR(6) model, indicating that all eigenvalues reside inside the unit circle, affirming the dynamic stability of the model.

4 Empirical Results

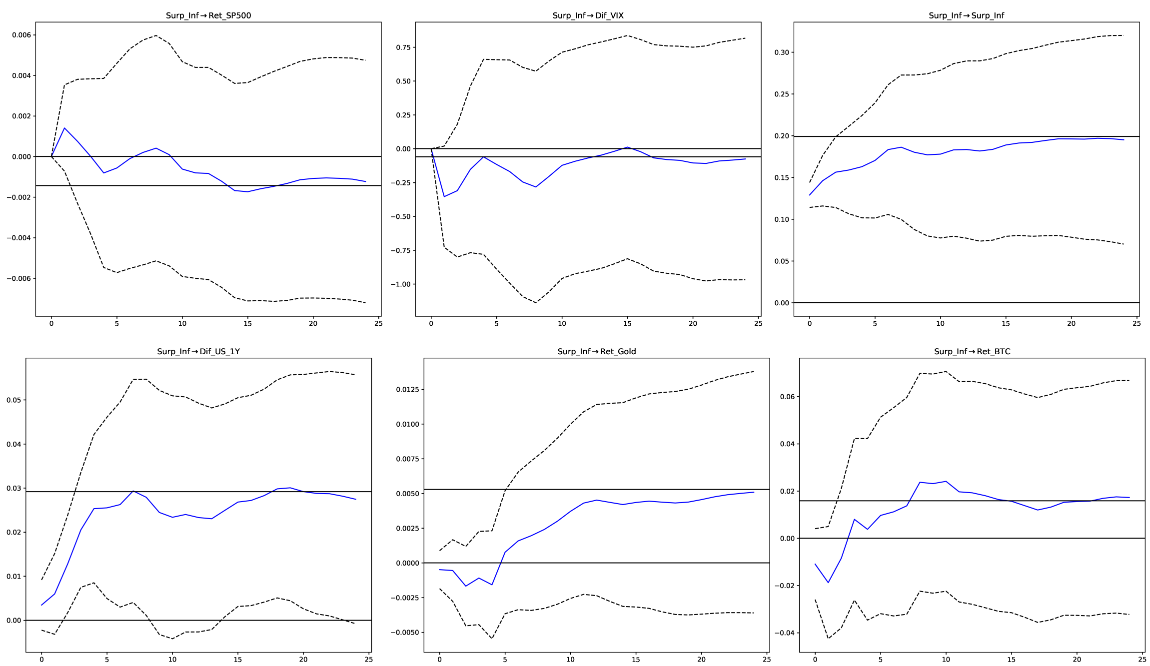
4.1 Baseline model

Figure 1 depicts the main empirical results of this study, considering the CPI MoM as the underlying index to calculate the inflation surprises. Specifically, the Figure shows the cumu-

[4]Defined by the Schwert (1989) criterion.

lative responses of each variable in the system following an impulse in the surprise component of the CPI MoM announcements.[5] Overall, we can infer that an unexpected, positive shock in CPI MoM increases Gold, BTC, and US1y interest rates, while it decreases the S&P 500 and has no effect on the VIX. While the results are statistically non-significant in most cases (the exception is the impact on interest rates in some horizons), such a pattern reveals that responses in BTC are similar to the ones of Gold and interest rates and contrast those of the S&P500.[6] Put differently, interest rates, Gold, and BTC returns increase following inflation shocks, while S&P returns diminish. Thus, the results suggest that Bitcoin could be a helpful hedge against unexpected fluctuations in inflation, an overall finding that aligns with empirical evidence supporting Bitcoin's role as an inflation hedge (Blau et al., 2021, Choi and Shin, 2021).

Figure 1. COIRF - Baseline model (CPI MoM)



Note: This figure shows cumulative orthogonal impulse response functions (COIRFs) of the six variables to the one-standard-deviation shock in inflation and their 95% confidence bands for the sample period between 2010:08 and 2023:01. The Ret (Dif) prefix indicates that the series was constructed from returns (differences) calculated in one-day windows around monthly CPI MoM announcements. The horizontal axes show the number of months after the impulse.

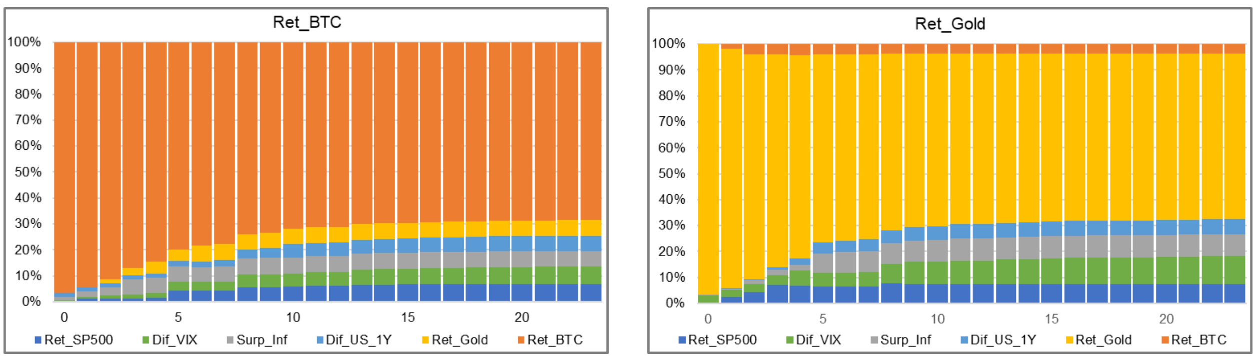
The baseline, entire period results highlight further similarities in the behavior of BTC and GOLD. Firstly, both assets exhibit an initial negative effect, with Bitcoin displaying a

[5]Figure C1 in Appendix C plots the entire set of impulse response functions for a comprehensive picture.

[6]Relative to BTC, The COIRFs suggest a similar, albeit less pronounced, response in gold returns to inflation shocks, indicating that the returns of both assets react in the same direction but with different intensities.

more significant but less enduring impact. For both assets, there is a convergence to the final cumulative effect after the tenth month. Second, the forecast error variance decomposition of Bitcoin and gold returns (as shown in Figure 2) indicates that Bitcoin (gold) return fluctuations are predominantly explained by a shock to itself, decreasing over time from 94% (92%) in the initial period to 69% (64%) in the final period. These results partially contrast with the findings of Choi and Shin (2021), who found this property only in gold. Regarding the contribution of a shock in inflation to the variance in the forecast error of the two series, gold is superior (8%) compared to Bitcoin (6%). This finding suggests that the relationship between return and inflation may be slightly more substantial for the commodity than for the cryptocurrency, aligning with the results of Smales (2021) and consistent with studies by Corbet et al. (2020) and Pyo and Lee (2020), which found that CPI announcements have a negligible impact on Bitcoin prices.

Figure 2. FEVD - Baseline model



Note: This figure shows forecast error variance decomposition (FEVD) of Bitcoin and gold for the sample period between 2010:08 and 2023:01. The Ret (Dif) prefix indicates that the series was constructed from returns (differences) calculated in one-day windows around monthly CPI MoM announcements. The horizontal axes show the number of months after the impulse.

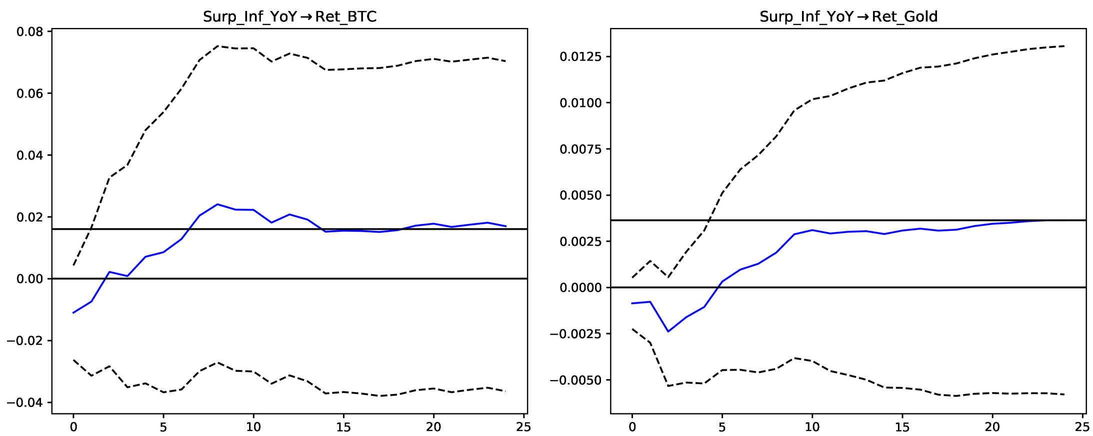
4.1.1 CPI MoM vs. CPI YoY

So far, we have considered inflation measured on a month-over-month (MoM) basis. One drawback of this approach is that short-term measures of inflation may be noisy. Thus, in this section, we replace the MoM CPI with the 12-month, year-over-year (YoY) CPI. This further analysis brings forth several potential benefits. Firstly, employing CPI YoY enables the capture of a more comprehensive perspective on price variations over time, providing a more representative view across an extended period. Additionally, it facilitates the identification of long-term inflation trends, as monthly fluctuations may be influenced by temporary factors that could distort the analysis. Hence, it is possible to obtain a more consistent view of inflationary pressures by opting for an annual inflation measurement.

Figure 3 illustrates that the results from cumulative orthogonalized impulse-response functions (COIRFs) are preserved even with the alternative specification of inflation shocks.

Relative to the previous set of results (Figure 1), the cumulative responses are very similar in terms of magnitude for both BTC and GOLD, reinforcing that they behave similarly.

Figure 3. COIRF - CPI YoY



Note: This figure shows cumulative orthogonal impulse response functions (COIRFs) of Bitcoin and gold to the one-standard-deviation shock in inflation and their 95% confidence bands for the sample period between 2010:08 and 2023:01. The Ret prefix indicates that the series was constructed from returns calculated in one-day windows around monthly CPI YoY announcements. The horizontal axes show the number of months after the impulse.

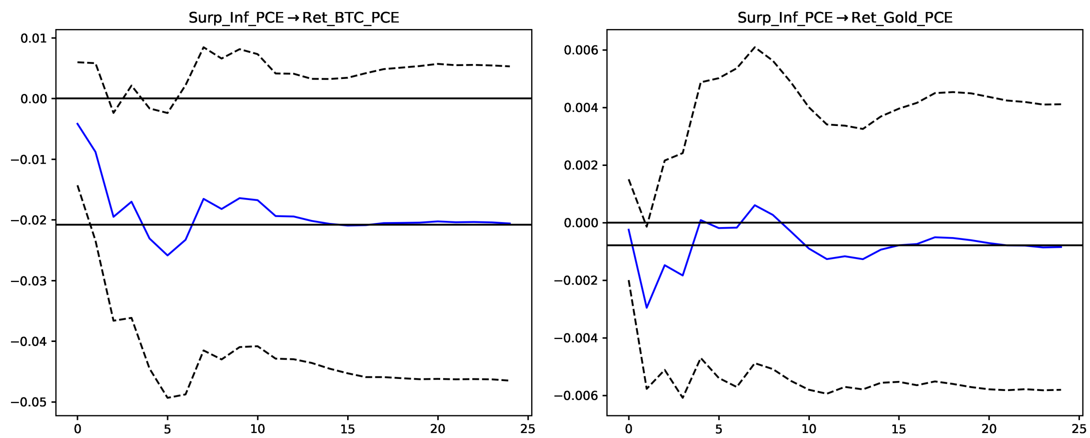
4.1.2 CPI MoM vs. Core PCE MoM

Complementing the CPI, another relevant consumer price index in the U.S. is the Personal Consumer Expenditures (PCE), released by the Bureau of Economic Analysis (BEA). Although similar in spirit, the CPI and the PCE carry distinctions in four dimensions (Bureau of Labor Statistics (BLS), 2011): formula effect (Laspeyres vs. Fisher-Ideal), weight effect (Consumer Expenditure Survey vs. business surveys), scope effects (CPI considers all urban households, while the PCE considers goods and services consumed by all households, and nonprofit institutions serving households), and other effects (e.g., seasonal-adjustment differences, price differences, etc.). Furthermore, the PCE has been the official inflation target of the FOMC since January 2012, and looking to the core inflation may eliminate temporary distortions as it excludes the volatile components of food and energy prices.

Figure 4 indicates that responses to inflation shocks measured by the PCE MoM generate partially contrasting results. While there is a shift in the response sign, BTC and Gold continue to react in the same direction. On the left graph, Bitcoin returns are observed to react with the same intensity, but negatively after a positive inflation shock. In contrast, the right graph shows that gold returns also respond negatively, although insignificantly, to the inflation shock. Furthermore, it is noteworthy that convergence to the final cumulative effect continues to occur after the tenth period.

The discrepancy in the response sign may be attributed to differing criteria, such as composition and disclosure dates, that can impact inflation surprises. Since PCE announcements occur after CPI releases, every surprise in the CPI – positive or negative – is plausibly incorporated in PCE expectations. This could explain why, as previously discussed, there is a very low contemporaneous correlation between surprise inflation in the pairs CPI MoM-PCE MoM and CPI YoY-PCE MoM.[7] Although such adjustments may explain the negative responses in BTC and Gold returns, it is imperative to note that the empirical validation of this mechanism is beyond the scope of the present study. However, this observation is suggested as a potential avenue for future research to deepen its understanding.

Figure 4. COIRF - CPI MoM vs. Core PCE MoM



Note: This figure shows cumulative orthogonal impulse response functions (COIRFs) of Bitcoin and gold to the one-standard-deviation shock in inflation and their 95% confidence bands for the sample period between 2010:08 and 2023:01. The Ret prefix indicates that the series was constructed from returns calculated in one-day windows around monthly Core PCE MoM announcements. The horizontal axes show the number of months after the impulse.

4.2 Robustness checks

4.2.1 Alternative VAR lag order

Acknowledging that estimated impulse responses may exhibit bias due to an insufficient number of lags (Enders, 2008, Lütkepohl, 2005), we perform a sensitivity analysis by reestimating the model using nine and twelve lags. Figure D1 in Appendix D illustrates the findings, highlighting that the primary results remain consistent regardless of the lag length. However, we note that with extended lag, the impact of impulses on the results intensifies.

[7] As Figure A3 shows, correlations between CPI MoM (CPI YoY) and PCE MoM surprises are 0.12 (0.12) in our sample. They are not just low, on average, but they also differ in time trends: while the CPI has shown a sequence of positive surprises in 2021 onwards (following supply-chain imbalances brought by COVID-19 and, in 2022, the Russian invasion of Ukraine), the PCE has not shown such a trend.

4.2.2 Alternative identification #1: changing order of variables in the Choleski decomposition

The model is identified based on the premise that movements in the rest of the economy are less endogenous concerning the Bitcoin market. While this assumption is reasonable, it is crucial to note that any recursive assumption can pose challenges, especially in the presence of financial variables at a low frequency (Furlanetto et al., 2019). Furthermore, unless there are special reasons for a recursive structure, the order of the variables used in the Choleski decomposition of the white noise covariance matrix is arbitrary (Lütkepohl, 2005). Because there is no trivial solution to this issue, we re-estimate the model with modifications to the identification scheme.

Firstly, recognizing the inherent complexity of the relationship between inflation and interest rates and the possibility that this connection is bidirectional and variable in different economic contexts and market conditions (Alvarez et al., 2001), the time sequence of both series was inverted. Then, it was decided to position these variables at the beginning of the system, drawing on studies such as Roley and Sellon (1998), Bomfim (2003), Rigobon and Sack (2004) and Farka (2009) that illustrate the endogenous nature of interactions between the stock market, monetary policy, and inflation. Finally, Bitcoin was chosen to remain the most endogenous variable in the system, aligning with research by Bouri et al. (2017a), Li and Wang (2017), Al-Yahyaee et al. (2018), and Choi and Shin (2021). Therefore, the Cholesky ordering of the VAR system is as follows: Dif_US_1Y, $Surp\_Inf$, Ret_SP500, Dif_VIX, Ret_Gold, and Ret_BTC.

Figure D2, available in Appendix D, confirms that the change in model identification does not affect any of the baseline findings.

4.2.3 Alternative specification #2: adding a trend term

The baseline model comprises six variables plus the intercept. To incorporate more precise information regarding the historical trajectory and potential patterns in the temporal evolution of the series, we include in this robustness check a trend term in the VAR specification.

Figure D3 in Appendix D illustrates that, although the intensity of impulse responses for both assets is reduced, the results exhibit qualitative similarity overall when incorporating a linear trend component into the model specification.

4.2.4 Changing sample period: before COVID-19

Although the COVID-19 pandemic is a unique opportunity to test Bitcoin's inflation-hedging properties, it is crucial to acknowledge potential influences from this atypical event.[8] As highlighted by Maneejuk et al. (2021), an asset's ability to hedge against inflation may be subject to the state of the economy, encompassing both stable and turbulent economic

[8]Previous research has shown that the sensitivity of performance measures to the COVID-19 period was higher for portfolios with cryptocurrency relative to otherwise identical portfolios (Colombo et al., 2021).

regimes. Taking into account this possibility, the model was re-estimated using data up to December 2019.

Figure D4, available in Appendix D, underscores that the findings are partially preserved. Despite an increased intensity in the impulse response, Bitcoin's primary results are confirmed. However, excluding the pandemic episode revealed a slight negative reaction of gold returns to inflation shocks. These findings align with empirical evidence from Phochanachan et al. (2022), suggesting that Bitcoin's reactions to inflation shocks are more significant in stable scenarios, unlike gold, which demonstrates better performance in turbulent contexts.

4.2.5 Changing sample period: after the BTC structural break

Over the last decade, perceptions of cryptocurrencies, especially Bitcoin, have undergone significant transformations, impacting the trading system and market dynamics. In the initial phase of the examined period, Bitcoin trading volumes were minimal, and the cryptocurrency was not widely recognized as an investment option. Identifying the precise moment when Bitcoin emerged as a viable investment alternative is challenging. However, for this sensitivity test, the authors adopted Choi and Shin (2021) proposition of a structural break in the Bitcoin market around 2013.

Figure D5 in Appendix D confirms that restricting the analysis to data from 2014 onward has no discernible impact on gold prices. However, the positive cumulative effect on Bitcoin prices, while still present, diminishes significantly. This outcome implies that the early years of trading significantly influenced Bitcoin's performance as a hedge against inflation.

4.2.6 Including observed inflation in the model

Including a variable representing realized inflation enhances our understanding of the formation of expectations over time and their impact on economic behavior (Armantier et al., 2011, Binder and Kamdar, 2022, Weber et al., 2022), offering a more thorough analysis of the dynamic relationships between inflation and the price of assets like Bitcoin. Moreover, this approach provides a more comprehensive assessment of market conditions by considering the cumulative effects of inflation and structural changes in the economy.

Figure D6, available in Appendix D, illustrates the key empirical findings of this examination. Firstly, actual inflation increases over time in response to a positive inflation shock. Secondly, Bitcoin returns experience a significant upswing following a positive shock to realized inflation, aligning with empirical evidence that supports Bitcoin's potential as an effective hedge against inflation (Blau et al., 2021, Choi and Shin, 2021). Lastly, gold returns display limited responsiveness to the realized inflation shock.

5 Concluding remarks

The recent consideration of Bitcoin as an investment option (Conlon et al., 2021), along with the growing interest among academics and policymakers (Phochanachan et al., 2022), has contributed to positioning the cryptocurrency as a potential inflation hedge. Commonly cited justifications for this role include its limited supply and decentralized network, conferring scarcity and resilience (Bouri et al., 2017a,b). However, like gold, existing theoretical and empirical studies have not reached a consensus regarding its hedging ability (Choi and Shin, 2021). This lack of consensus may be attributed to methodological differences, varying time horizons, and the specific characteristics of economies analyzed in these studies.

This article investigates the dynamic response of Bitcoin returns to inflation shocks, considering different inflation measures, changes in the sampling period, and various model specifications. The results suggest that Bitcoin can be a valuable hedge against unexpected fluctuations in inflation. However, the efficacy of Bitcoin as an inflation hedge appears contingent upon the selected price index (evidence is found on CPI MoM and CPI YoY, but not for the Core PCE MoM) and the analyzed sampling period. Regarding the latter, the inflation-hedging properties of Bitcoin diminish significantly when we exclude the initial sampling period ("early days" of Bitcoin), suggesting that mainstream adoption may be driving BTC returns to be closer to returns of other risky assets (like stocks). At the end of the day, bitcoin does not seem to be as reliable as Gold in protecting portfolios against unexpected, positive inflation shocks.

Our paper contributes to the still incipient literature on the role of Bitcoin as an inflation hedge (see, e.g., Blau et al., 2021, Choi and Shin, 2021, Conlon et al., 2021, Matkovskyy and Jalan, 2020, Phochanachan et al., 2022, Smales, 2021) by identifying inflation shocks based on the *unexpected* component of CPI and PCE releases – the difference between the actual data and analysts' expectations. By doing that, our innovations (or shocks) consider all observed and unobserved factors that market agents consider in their projections of inflation, and not only a few covariates included in typical VAR systems. As Nakamura and Steinsson (2017) indicates, any factors left out as covariates in the regression will be part of the "shock", even if they are anticipated by market agents. Therefore, we believe that our identification strategy provides a cleaner projection of the *unexpected* portion of inflation announcements (i.e., inflation shocks). Furthermore, this research carries direct implications for managers[9], investors, and monetary authorities, contributing to the growing but still underexplored literature about the inflation-hedging properties of Bitcoin.

While this study has unveiled numerous empirical findings, it is imperative to acknowledge certain caveats that offer valuable insights for future research. Firstly, the dynamic nature of the cryptocurrency market requires caution in interpreting results. Specifically, the employed model does not account for the potential impacts of regulatory changes or the proliferation of new cryptocurrencies on Bitcoin prices. Secondly, in comparison to prior

[9]Not only asset managers, but also corporate managers since many corporations acquired bitcoin in recent years diverse reasons (Gimenes et al., 2023).

analyses of other inflation-hedge assets, such as gold, the sampling period is confined to the cryptocurrency market's early stages. Consequently, pivotal aspects like trading volume or liquidity may undergo abrupt changes in the future, posing challenges to the drawn conclusions. Thirdly, the study's methodology relies on a linear model, potentially overlooking nonlinear relationships and structural shifts in the analyzed variables. Lastly, it is crucial to highlight that returns are calculated on a daily basis, which may lead to the loss of pertinent intraday information and impact analysis accuracy. Therefore, future studies should explore the feasibility of capturing these variations at a high frequency.

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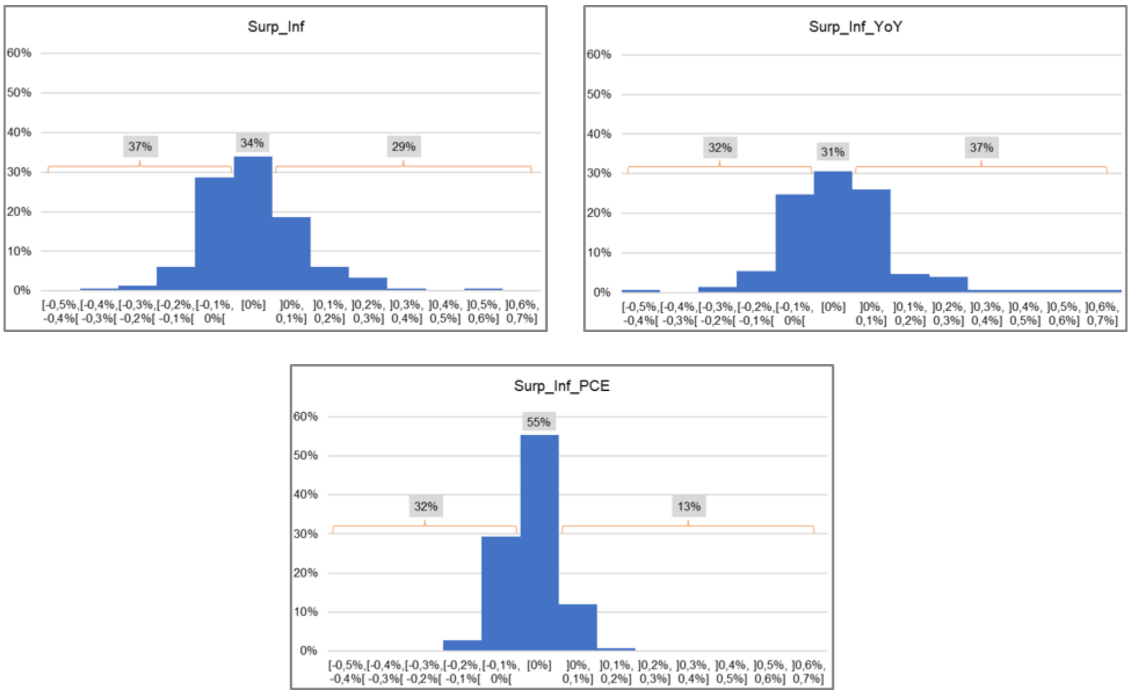
A Appendix

A Descriptive statistics - Surprise inflation measures

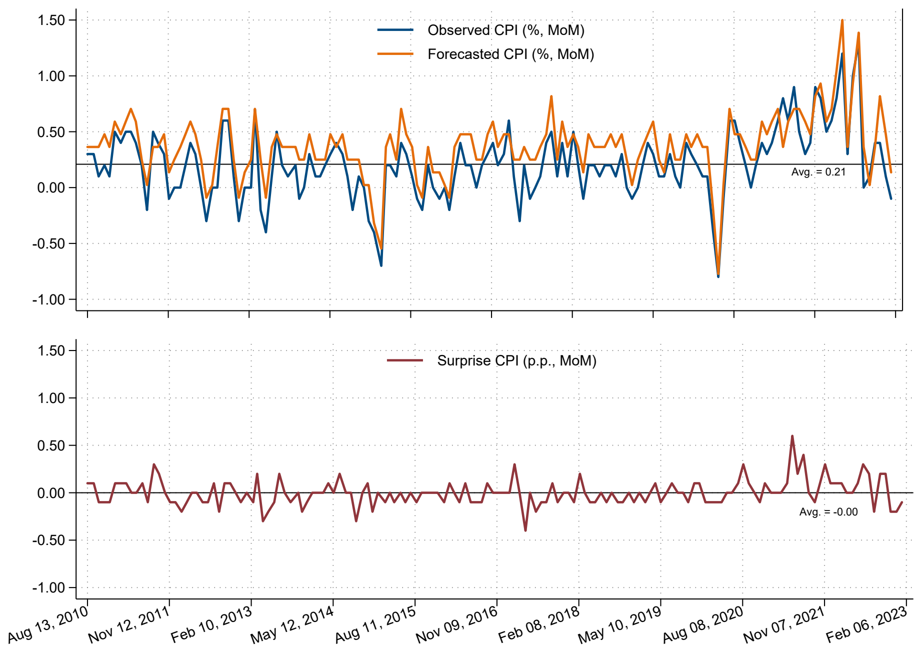
Figure A1. Frequency distribution of surprise inflation



Note: This figure shows the frequency distribution graphs of the unexpected component of inflation calculated in one-day windows around monthly CPI MoM (top left graph), CPI YoY (top right graph), and Core PCE MoM (bottom graph) announcements. The sample period covers from 2010:08 to 2023:01. The horizontal axes represent different intervals/values of surprise inflation.

Figure A2. CPI MoM, CPI YoY, and PCE MoM - Actual, Forecast, and Surprise comparisons

(a) CPI MoM – Actual, Forecast, and Surprise



(b) PCE MoM – Actual, Forecast, and Surprise

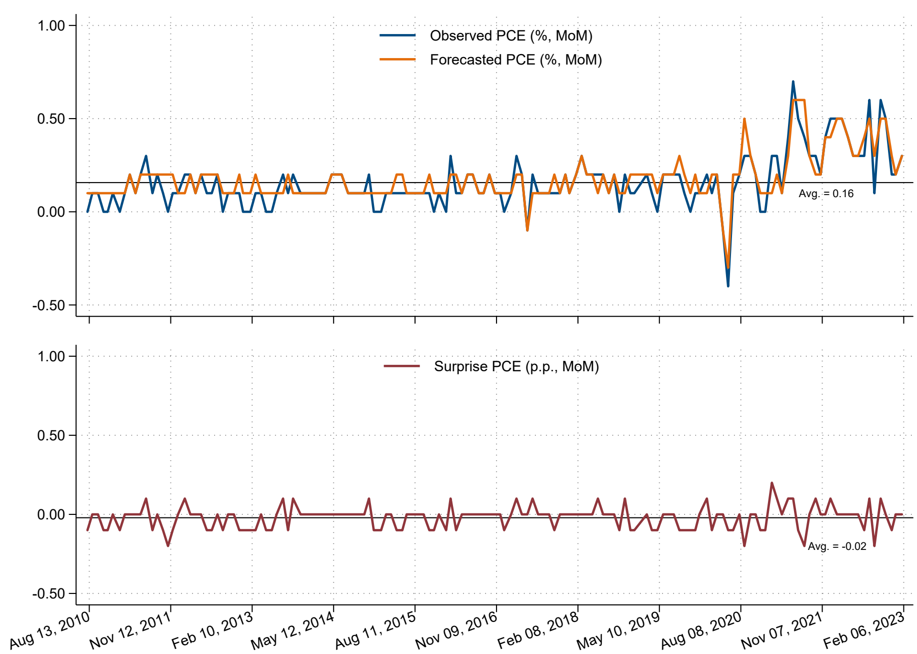
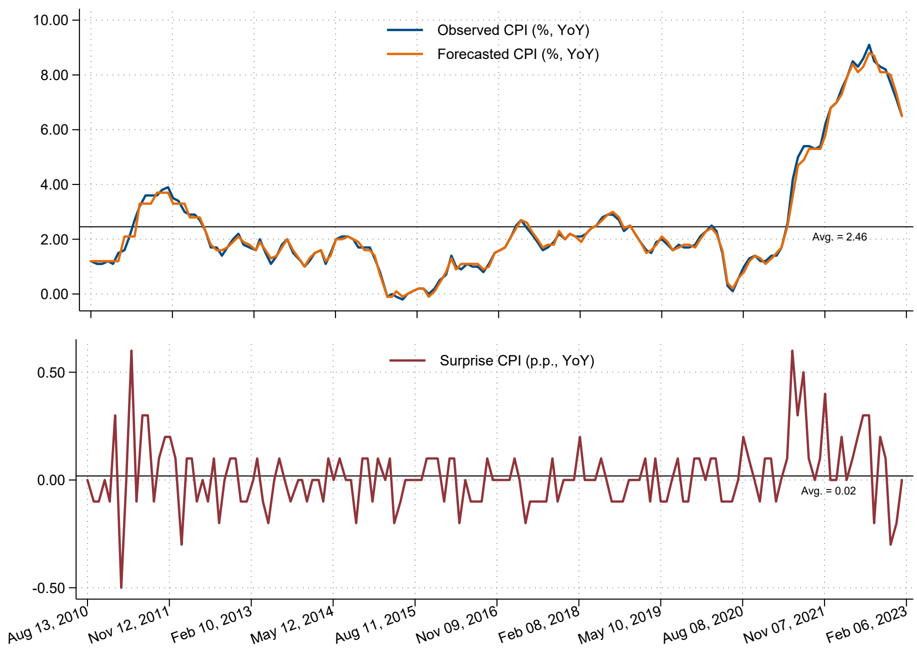


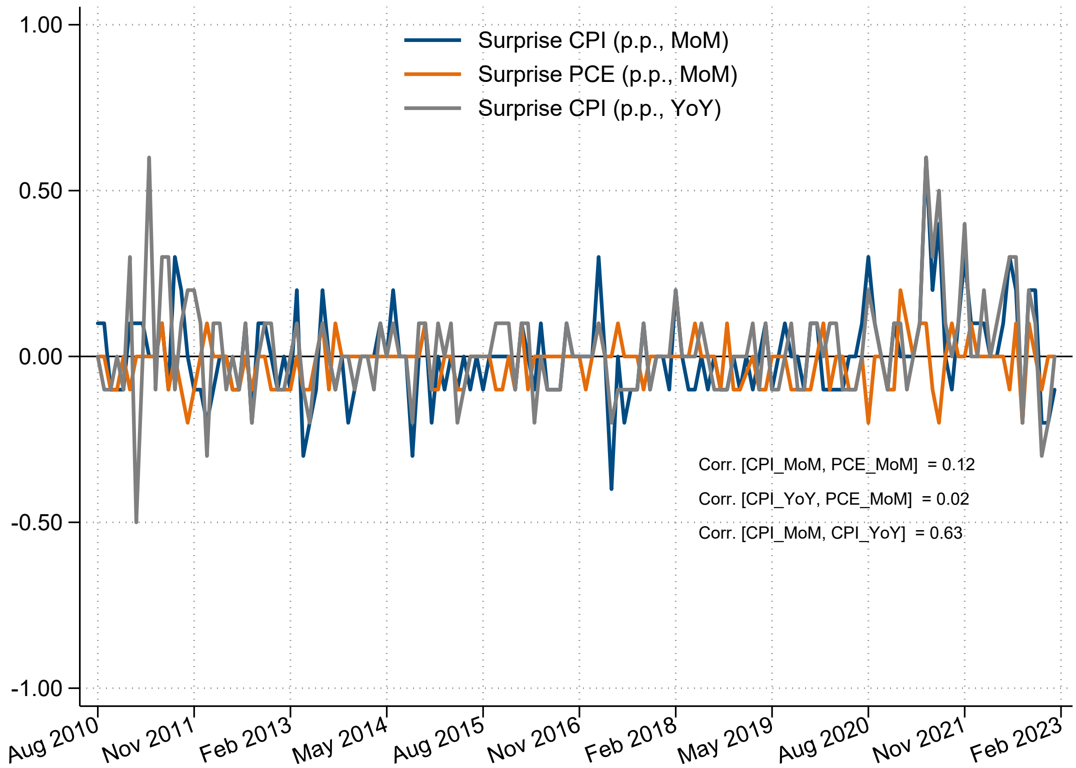
Figure A2. CPI MoM, CPI YoY, and PCE MoM - Actual, Forecast, and Surprise comparisons (cont.)

(a) CPI YoY – Actual, Forecast, and Surprise



Note: Subfigures (a), (b), and (c) show the observed and the forecasted U.S. Consumer Price Index (CPI, %, Year-over-Year) for each release of the U.S. Bureau of Labor Statistics (BLS). Actual data is seasonally adjusted for MoM comparisons (not seasonally adjusted for YoY comparisons) and comes from the BLS, and forecasts are obtained at Investing.com. The lower part of the figure shows the time series of the Surprise component (difference between the observed, actual inflation, and the analysts' forecast). Covered CPI (PCE) announcements range from August 13, 2010 (August 30, 2010), to January 12, 2023 (Jan 27, 2023).

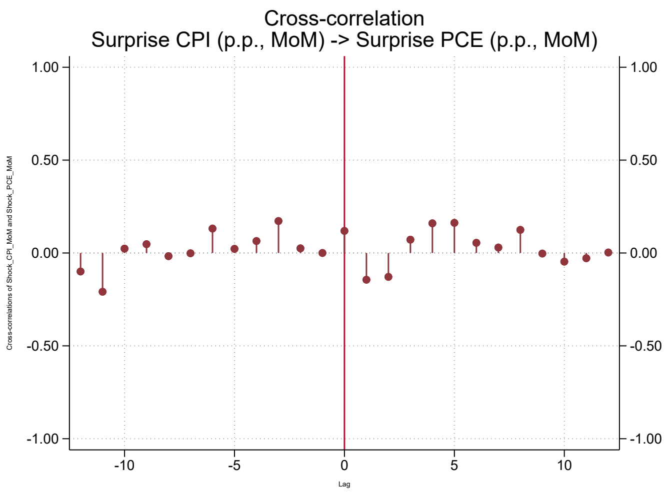
Figure A3. Time series and correlation of Surprises – CPI MoM, CPI YoY, and PCE MoM



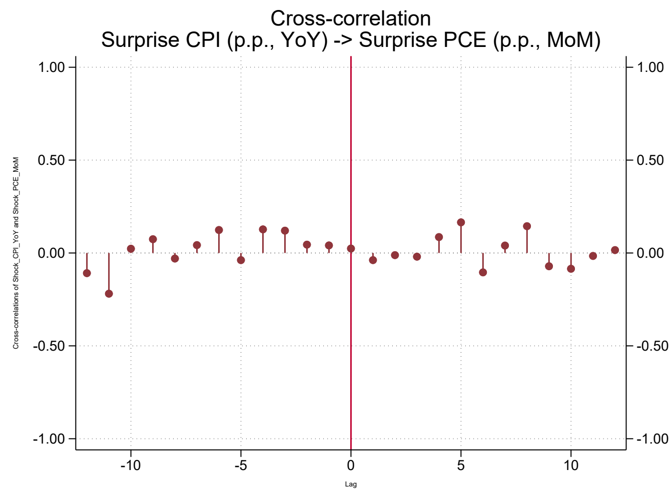
Note: The upper part of this figure shows the observed and forecasted U.S. Consumer Price Index (CPI, %, Year-over-Year) for each release of the U.S. Bureau of Labor Statistics (BLS). Actual data is seasonally adjusted for MoM comparisons (not seasonally adjusted for YoY comparisons) and comes from the BLS, and forecasts are obtained at Investing.com. The lower part of the figure shows the time series of the Surprise component (difference between the observed, actual inflation, and the analysts' forecast). Covered CPI (PCE) announcements range from August 13, 2010 (August 30, 2010), to January 12, 2023 (Jan 27, 2023).

Figure A4. Cross-correlation between surprise inflation measures: CPI MoM, PCE MoM, and CPI YoY

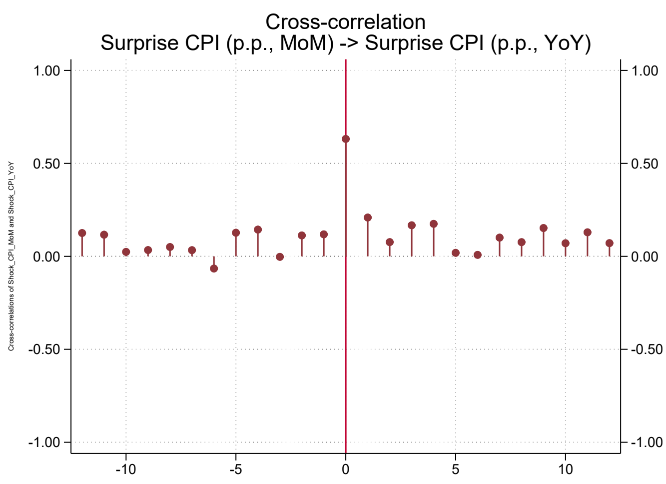
(a) CPI MoM x PCE MoM



(b) CPI YoY x PCE MoM



(c) CPI MoM x CPI YoY



Note: This Figure shows the cross-correlation among each pair of computed inflation surprise (difference between the observed, actual inflation, and the analysts' forecast): CPI MoM-PCE MoM (Panel A), CPI YoY-PCE MoM (Panel B), and CPI MoM-CPI YoY (Panel C). The Y-axis shows the linear correlation coefficient that ranges from -1 to +1. The X-axis presents the lags and leads that are symmetrical and range from one to ten. The red vertical line emphasizes the contemporaneous linear correlation coefficient (lead/lag equals zero). Covered CPI (PCE) announcements range from August 13, 2010 (August 30, 2010), to January 12, 2023 (Jan 27, 2023).

B Model Checking

Table B1. Augmented Dickey-Fuller unit root test

Variable	Order	Lags	Test stat.	p-value	Assessment
Panel A: Model with drift					
Ret_SP500	I(0)	4	-5.868 *	< 0.01	Reject H_0
Dif_VIX	I(0)	0	-13.547 *	< 0.01	Reject H_0
Surp_Inf	I(0)	0	-10.074 *	< 0.01	Reject H_0
Dif_US_1Y	I(0)	10	-4.508 *	< 0.01	Reject H_0
Ret_Gold	I(0)	0	-10.243 *	< 0.01	Reject H_0
Ret_BTC	I(0)	0	-11.729 *	< 0.01	Reject H_0
Panel B: Model without drift or trend					
Ret_SP500	I(0)	4	-5.894 *	< 0.01	Reject H_0
Dif_VIX	I(0)	0	-13.527 *	< 0.01	Reject H_0
Surp_Inf	I(0)	0	-10.108 *	< 0.01	Reject H_0
Dif_US_1Y	I(0)	10	-4.488 *	< 0.01	Reject H_0
Ret_Gold	I(0)	0	-10.075 *	< 0.01	Reject H_0
Ret_BTC	I(0)	0	-11.745 *	< 0.01	Reject H_0
Panel C: Model with drift and trend					
Ret_SP500	I(0)	4	-5.836 *	< 0.01	Reject H_0
Dif_VIX	I(0)	0	-13.554 *	< 0.01	Reject H_0
Surp_Inf	I(0)	0	-10.345 *	< 0.01	Reject H_0
Dif_US_1Y	I(0)	10	-4.872 *	< 0.01	Reject H_0
Ret_Gold	I(0)	0	-10.898 *	< 0.01	Reject H_0
Ret_BTC	I(0)	0	-11.688 *	< 0.01	Reject H_0
Panel D: Model with drift and linear and quadratic trends					
Ret_SP500	I(0)	4	-5.895 *	< 0.01	Reject H_0
Dif_VIX	I(0)	0	-13.523 *	< 0.01	Reject H_0
Surp_Inf	I(0)	0	-10.669 *	< 0.01	Reject H_0
Dif_US_1Y	I(0)	10	-5.308 *	< 0.01	Reject H_0
Ret_Gold	I(0)	0	-10.876 *	< 0.01	Reject H_0
Ret_BTC	I(0)	0	-11.801 *	< 0.01	Reject H_0

Note: This table shows the results of the Augmented Dickey-Fuller (ADF) test for the Model with different specifications. The sample period covers from 2010:08 to 2023:01. The Ret (Dif) prefix indicates that the series was constructed from returns (differences) calculated in one-day windows around monthly CPI MoM announcements. The maximum number of lags considered for implementing the test is 13 and is defined by the Schwert criterion (1989). *, **, and *** denote statistical significance at 1, 5, and 10%, respectively, and lead to the rejection of the null hypothesis indicating the non-existence of a unit root. The Lags column reports the optimal number of lags following the Akaike information criterion (AIC).

Table B2. Portmanteau residual autocorrelation test

Model	**Test stat.**	**Critical value (5%)**	**p-value**	**Degrees of freedom**	**Assessment**
VAR(6)	264.8	290.0	0.277	252	Accept H_0
VAR(7)	265.5	251.3	0.012	216	Reject H_0
VAR(8)	265.5	212.3	0.000	180	Reject H_0

Note: This table shows the results of the Ljung and Box test (1978) for the Model with different VAR orders. The sample period covers from 2010:08 to 2023:01. The maximum number of lags considered for implementing the test is 13 and is defined by the Schwert criterion (1989). Q_{LB} statistic values lower than the critical values lead to the acceptance of the null hypothesis and indicate that the residual autocorrelation up to the maximum number of lags is zero, considering a 95% confidence interval.

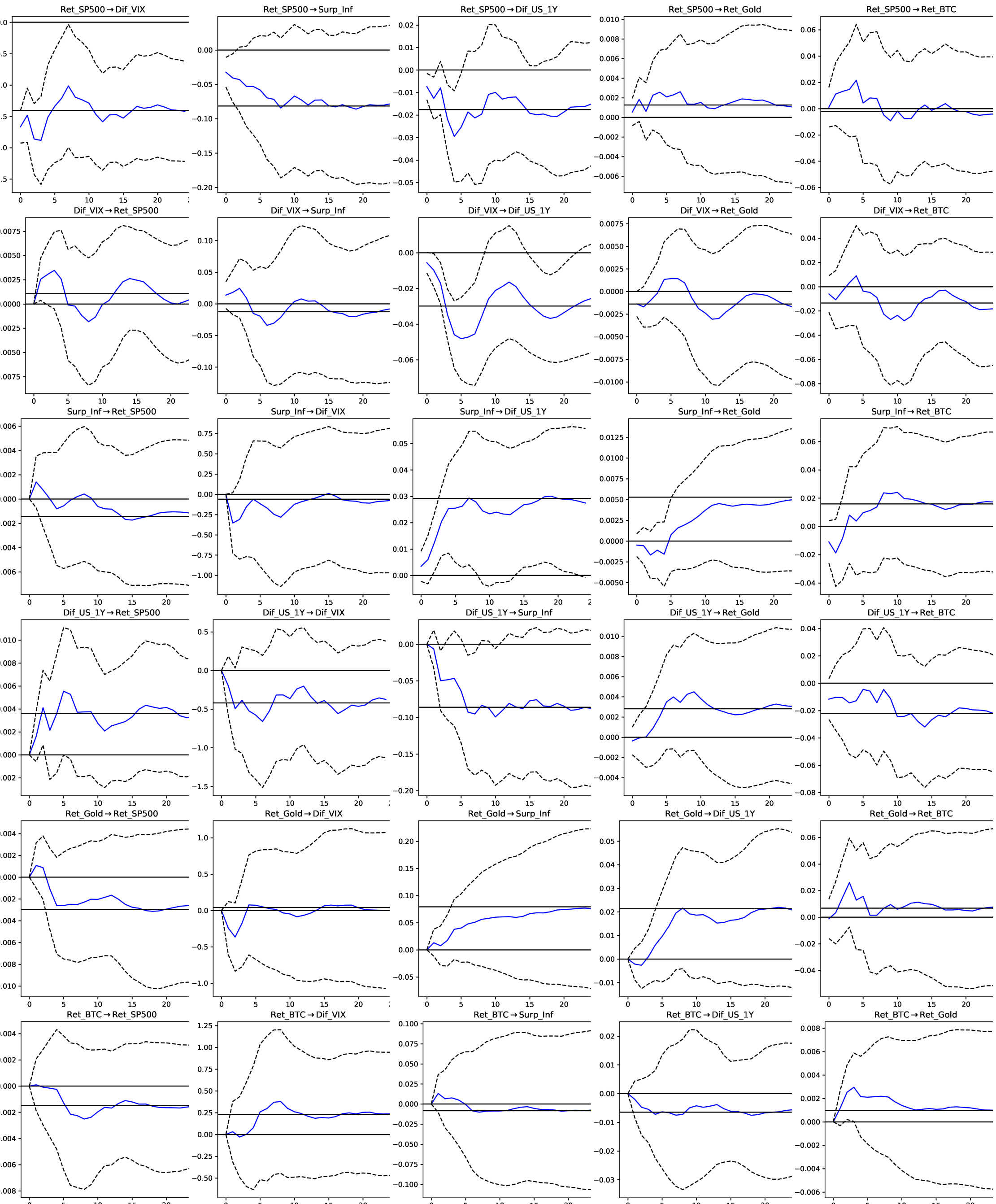
Table B3. Model stability

Lag	**Ret_SP500**	**Dif_VIX**	**Surp_Inf**	**Dif_US_1Y**	**Ret_Gold**	**Ret_BTC**
1	0.120	0.233	0.233	0.235	0.077	0.077
2	0.207	0.185	0.185	0.152	0.068	0.008
3	0.631	0.157	0.157	0.158	0.158	0.032
4	0.242	0.223	0.223	0.206	0.206	0.169
5	0.197	0.197	0.273	0.120	0.107	0.034
6	0.271	0.334	0.076	0.076	0.011	0.093

Note: This table shows the results of the stability diagnosis test applied to the VAR(6) model. The sample period covers from 2010:08 to 2023:01. The Ret (Dif) prefix indicates that the series was constructed from returns (differences) calculated in one-day windows around monthly CPI MoM announcements. The values reported correspond to the eigenvalues (in modulus) associated with each model lag. Values lower than 1 mean that they are inside the unit circle, which highlights the stability of the model.

C Full results - COIRFs of the baseline model

Figure C1. COIRF Panel - Baseline model

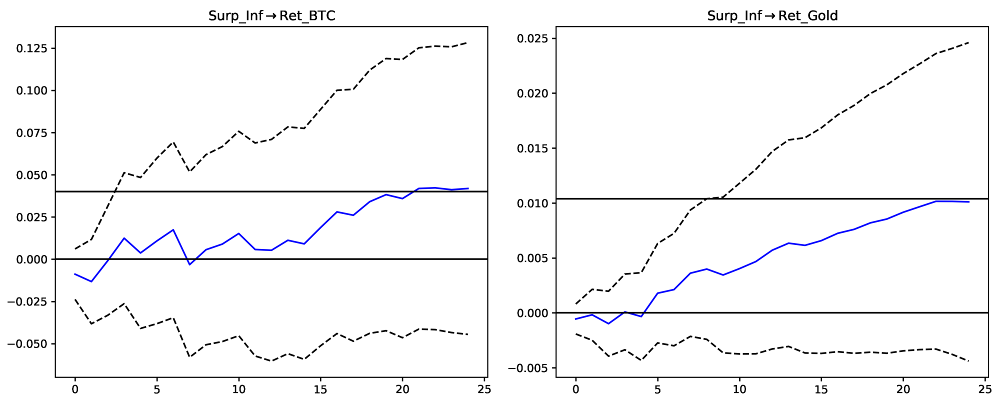


Note: This figure shows cumulative orthogonal impulse response functions (COIRFs) of the six variables and their 95% confidence bands for the sample period between 2010:08 and 2023:01. The Ret (Dif) prefix indicates that the series was constructed from returns (differences) calculated in one-day windows around monthly CPI MoM announcements. The units of the horizontal axes are months.

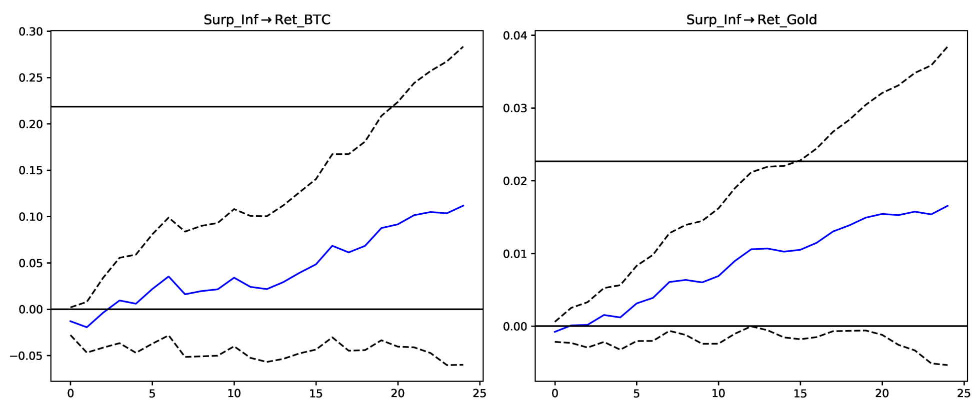
D Robustness Tests

Figure D1. RT 01 - Alternative VAR order

VAR(9)

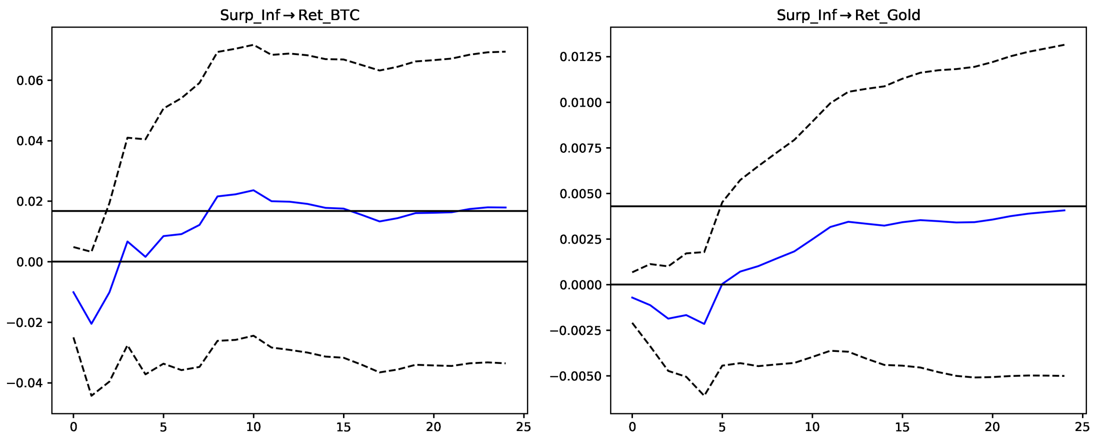


VAR(12)



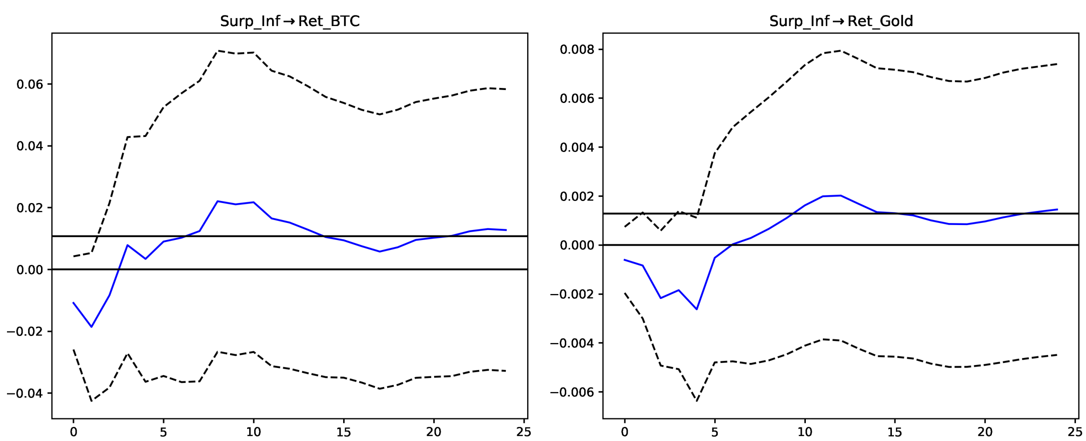
Note: This figure shows cumulative orthogonal impulse response functions (COIRFs) of Bitcoin and gold to the one-standard-deviation shock in inflation and their 95% confidence bands for the sample period between 2010:08 and 2023:01 for the Model with alternative lags. The Ret prefix indicates that the series was constructed from returns calculated in one-day windows around monthly CPI MoM announcements. The units of the horizontal axes are a month.

Figure D2. RT 02 - Alternative identification



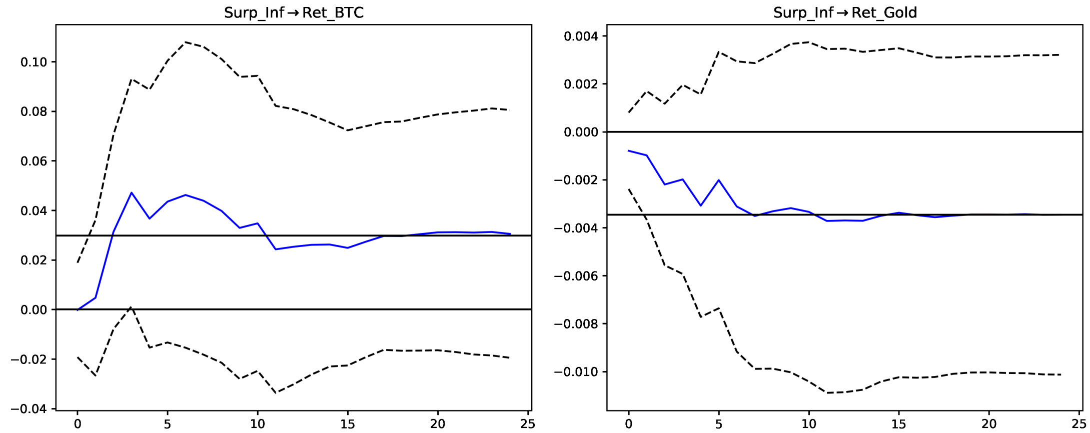
Note: This figure shows cumulative orthogonal impulse response functions (COIRFs) of Bitcoin and gold to the one-standard-deviation shock in inflation and their 95% confidence bands for the sample period between 2010:08 and 2023:01 for the Model with the following temporal ordering: Dif_US_1Y, $Surp\_Inf$, Ret_SP500, Dif_VIX, Ret_Gold and Ret_BTC. The Ret (Dif) prefix indicates that the series was constructed from returns (differences) calculated in one-day windows around monthly CPI MoM announcements. The units of the horizontal axes are a month.

Figure D3. RT 03 - Alternative specification



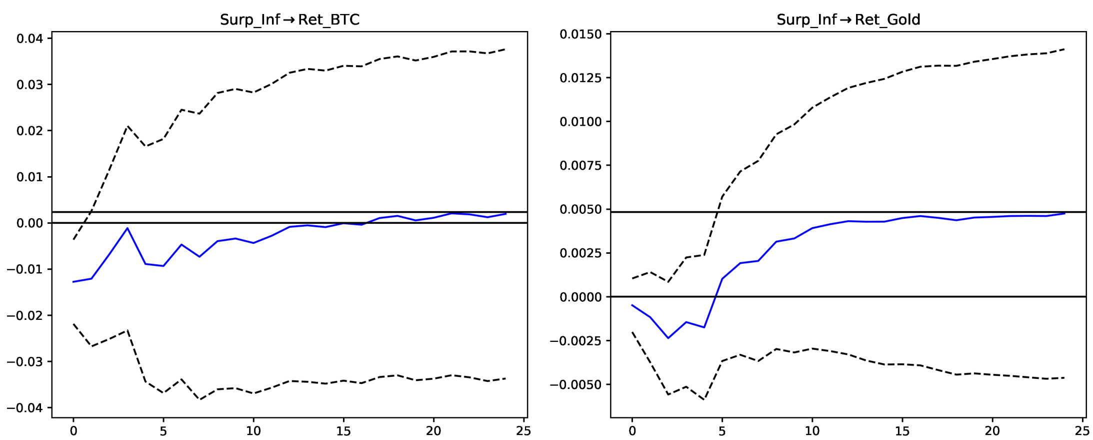
Note: This figure shows cumulative orthogonal impulse response functions (COIRFs) of Bitcoin and gold to the one-standard-deviation shock in inflation and their 95% confidence bands for the sample period between 2010:08 and 2023:01 for the Model with the addition of a linear trend component in the specification. The Ret prefix indicates that the series was constructed from returns calculated in one-day windows around monthly CPI MoM announcements. The units of the horizontal axes are a month.

Figure D4. RT 04 - Before COVID-19



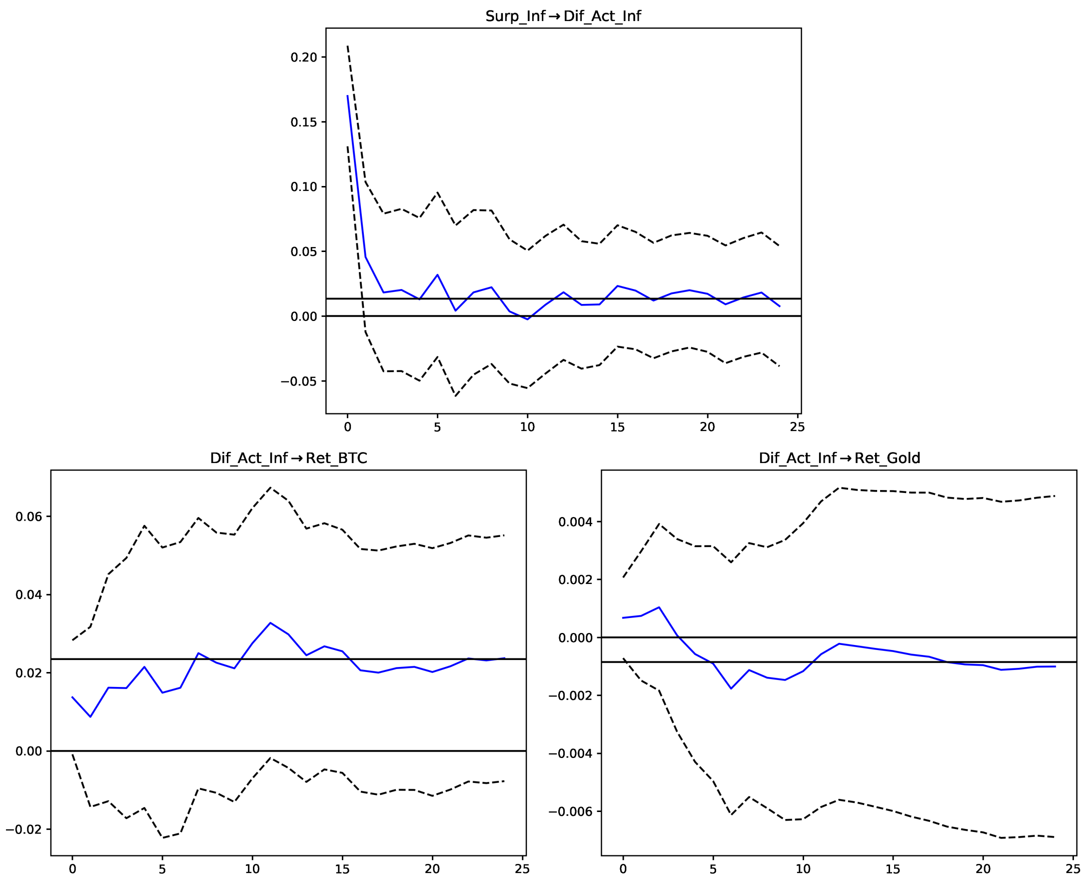
Note: This figure shows cumulative orthogonal impulse response functions (COIRFs) of Bitcoin and gold to the one-standard-deviation shock in inflation and their 95% confidence bands for the sample period between 2010:08 and 2020:01 (114 observations). The Ret prefix indicates that the series was constructed from returns calculated in one-day windows around monthly CPI MoM announcements. The units of the horizontal axes are a month.

Figure D5. RT 05 - After BTC structural break



Note: This figure shows cumulative orthogonal impulse response functions (COIRFs) of Bitcoin and gold to the one-standard-deviation shock in inflation and their 95% confidence bands for the sample period between 2014:01 and 2023:01 (109 observations). The Ret prefix indicates that the series was constructed from returns calculated in one-day windows around monthly CPI MoM announcements. The units of the horizontal axes are a month.

Figure D6. RT 06 - Including actual inflation



Note: This figure shows cumulative orthogonal impulse response functions (COIRFs) and their 95% confidence bands for the sample period between 2010:08 and 2023:01 for the Model with the inclusion of the actual inflation series (Act_Inf). The Ret (Dif) prefix indicates that the series was constructed from returns (differences) calculated in one-day windows around monthly CPI MoM announcements. The units of the vertical axes correspond to the intensity of the series' response to the one-standard-deviation shock in inflation (actual inflation). The units of the horizontal axes are a month.

Table D1. Summary statistics: Full period, Before COVID-19 and After BTC structural break

Variable	Mean	p50	SD	Asymmetry	Kurtosis	Min	Max	Obs.
Panel A: Full period (2010m8 to 2023m1)								
Ret_SP500	-0.000	0.001	0.012	-0.680	6.758	-0.050	0.054	150
Dif_VIX	-0.123	-0.175	1.900	1.794	9.214	-5.710	11.090	150
Surp_Inf	-0.000	0.000	0.136	0.769	2.588	-0.400	0.600	150
Dif_US_1Y	0.003	0.000	0.045	2.607	13.714	-0.160	0.230	150
Ret_Gold	0.001	0.001	0.009	-0.210	1.341	-0.029	0.028	150
Ret_BTC	-0.004	0.000	0.091	-5.094	49.918	-0.849	0.288	150
Panel B: Before COVID-19 (2010m8 to 2020m1)								
Ret_SP500	0.001	0.001	0.009	-1.467	6.692	-0.046	0.020	114
Dif_VIX	-0.167	-0.140	1.703	2.134	17.015	-5.710	11.090	114
Surp_Inf	-0.021	0.000	0.114	0.024	1.200	-0.400	0.300	114
Dif_US_1Y	-0.000	0.000	0.018	1.701	11.132	-0.050	0.110	114
Ret_Gold	0.001	0.000	0.009	-0.190	1.667	-0.029	0.028	114
Ret_BTC	-0.006	0.000	0.101	-4.892	43.346	-0.849	0.288	114
Panel C: After BTC structural break (2014m1 to 2023m1)								
Ret_SP500	0.000	0.001	0.012	-0.441	6.968	-0.050	0.054	109
Dif_VIX	-0.230	-0.300	1.757	0.876	3.839	-5.710	6.600	109
Surp_Inf	0.006	0.000	0.138	0.925	3.378	-0.400	0.600	109
Dif_US_1Y	0.005	0.000	0.053	2.199	9.413	-0.160	0.230	109
Ret_Gold	0.002	0.003	0.009	-0.289	1.938	-0.029	0.028	109
Ret_BTC	-0.010	-0.000	0.095	-6.607	58.196	-0.849	0.104	109

Note: This table shows statistics for all series covering different sampling periods. The Ret (Dif) prefix indicates that the series was derived from returns (differences) calculated within one-day windows around monthly CPI MoM announcements.