What Drives Crypto Asset Prices?

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Abstract

We investigate the factors influencing cryptocurrency returns using a structural vector auto-regressive model. The model uses asset price co-movements to identify the impact of monetary policy and risk sentiment in conventional markets on crypto asset prices, with minimal reverse spillover. Specifically, we decompose daily Bitcoin returns into components reflecting conventional risk premia, monetary policy, and crypto-specific shocks. We further decompose the crypto-specific shocks into changes in crypto risk premia and levels of crypto adoption by exploiting the co-movement of Bitcoin with stablecoin market capitalization.

Our analysis shows that crypto asset prices are significantly impacted by conventional risk and monetary policy factors. Notably, contractionary monetary policy accounted for over two-thirds of Bitcoin's sharp decline in 2022. In contrast, since 2023 the compression of crypto risk premia has been the predominant driver of crypto returns, independent of the buoyant equity market backdrop. Our findings highlight the importance of identifying drivers of crypto returns and understanding crypto's evolving relationship with traditional financial markets.

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1 Introduction

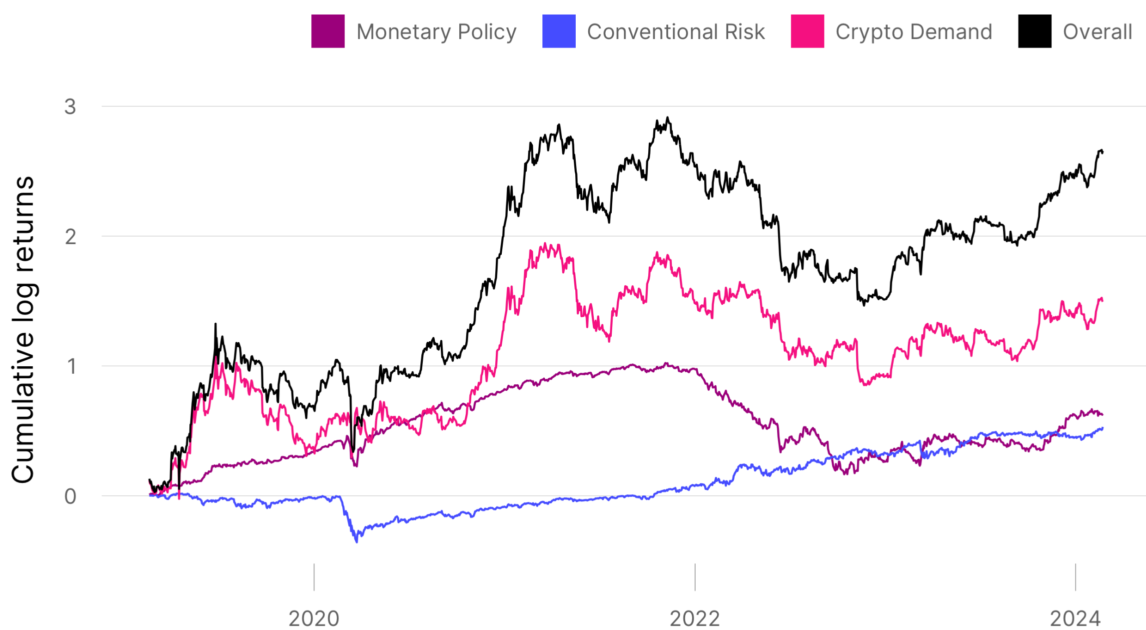
Understanding the drivers of cryptocurrency prices and their relationship with conventional financial markets is an important yet challenging task for economists, policymakers, and investors. As cryptocurrencies gain popularity and mainstream acceptance, their potential impact on the broader financial system increases. However, the factors influencing cryptocurrency price movements and crypto's interconnectedness with traditional asset classes are not yet fully understood.

This paper aims to shed light on the drivers of crypto assets through the lens of a sign-restricted vector auto-regressive (VAR) model. Figure 1 illustrates our approach's usefulness in decomposing Bitcoin returns into three structural shocks: conventional monetary policy shocks, conventional risk premium shocks, and crypto-specific demand shocks. The figure shows the decomposition both cumulatively from 2019 to 2024 (Panel A) and year-by-year (Panel B).

The model suggests that conventional shocks can significantly influence the returns of a new asset class. For instance, monetary policy shocks contributed 50 percentage points to Bitcoin's increase in 2020, but contributed more than −50 percentage points to Bitcoin's decrease in 2022. Said differently, the model suggests that if the Fed had not unexpectedly tightened its monetary policy stance over the course of 2022, Bitcoin returns would have been more than 50 percentage points larger. The model even suggests that, in 2022, monetary policy was more influential in driving crypto returns than crypto-specific demand shocks. Conventional risk premium shocks ("risk-off" shocks) generally contributed positively to crypto asset returns over our sample period—suggesting declining conventional risk premia—except for a brief period during the March 2020 COVID-19 sell-off. Finally, while conventional shocks can have large lower-frequency impacts on crypto prices, most day-to-day movements in Bitcoin prices are left unexplained by conventional shocks.

Figure 1: Bitcoin returns decomposed into structural shocks

Panel A: Decomposition of Bitcoin cumulative (log) returns



Panel B: Bitcoin (log) returns decomposition by year

The figure shows Bitcoin returns decomposed into three structural shocks: monetary policy shocks, conventional risk premium shocks, and crypto demand shocks. The decomposition uses the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions.

Our approach draws on a long-established literature in macroeconomics. Sims (1980) introduced the concept of VARs to study macroeconomics dynamics. Sign-restricted VARs were developed later on to impose structure to identify structural shocks (Faust, 1998; Canova and De Nicol'o, 2002; Uhlig, 2005). For instance, a classic sign restriction in macroeconomics is the assumption that a contractionary monetary policy shock raises the federal funds rate, whereas real GDP, prices, and reserves decline. This approach of assigning reasonable sign restrictions in order to identify structural shocks has been deemed as an "agnostic" method that lets the data speak (Uhlig, 2005). Our paper adapts this "agnostic" approach to study the rise of a new asset class—cryptocurrencies.

Specifically, we ask how much of the price fluctuations in a new asset class are coming from spillovers from traditional financial markets versus idiosyncratic risks inherent in the asset itself. To do so, we examine the daily return series of three assets— Bitcoin, two-year Treasury zero coupon bonds, and the S&P 500 index. By studying the daily return co-movements under reasonable assumptions of how a particular primitive shock would move all three assets, we are able to decompose the individual asset returns into those arising from three specific shocks, namely conventional risk premium shocks, monetary policy shocks, and crypto-specific shocks.

We employ sign restrictions that are intuitive and guided by theory. Specifically, we impose that positive conventional risk premium shocks (i.e., risk-off shocks) lead to lower Bitcoin prices, lower Treasury yields, and lower equity prices. Conversely, we impose that positive (contractionary) monetary policy shocks lead to lower Bitcoin prices, higher Treasury yields, and lower equity prices through a classic discount-rate channel. Finally, we impose that crypto-specific demand shocks raise Bitcoin prices, but leave their impact on conventional assets undetermined (while managing the impact of crypto shocks on conventional assets through magnitude restrictions).

Intuitively, the sign-restricted VAR attributes daily crypto returns to different shocks depending on the co-movements of assets. For example, if interest rates fall significantly and both equity prices and Bitcoin rally on the same day, the model picks up an expansionary (negative) monetary policy shock. On the other hand, if the stock market rallies, interest rates decline, and Bitcoin rises, the model attributes the positive Bitcoin return to a reduction in conventional risk premia. By aggregating Bitcoin returns on days with specific patterns in the Treasury and stock markets (adjusted for the magnitude of their returns), the model estimates the cumulative impact of each risk factor on Bitcoin's price over time.

We further analyze the crypto-specific shock and the associated asset returns by examining the contributions of crypto growth and crypto risk premia. To accomplish this, we expand the model by incorporating fluctuations in the market capitalization of stablecoins alongside the three previously mentioned assets. Stablecoins are considered a safe asset within the broader digital asset ecosystem (see, e.g., Baur and Hoang, 2021; Grobys, Junttila, Kolari, and Sapkota, 2021; Liao and Caramichael, 2022; Lyons and Viswanath-Natraj, 2023) and changes in their aggregate market cap relative to volatile crypto asset returns can help differentiate between shocks primarily driven by risk premia or adoption.[1]

Our central assumption in this extended model is that a positive crypto adoption shock raises both stablecoin market cap and bitcoin prices, while a positive crypto risk premium shock (crypto risk-off) decreases Bitcoin prices, but raises stablecoin market cap. Using this extended model, we show that crypto risk premia have compressed substantially from 2023 onwards and explain a predominant portion of the positive Bitcoin returns particularly around the introduction of the Blackrock Bitcoin ETF.

The four shocks examined in our extended model encapsulate both the internal dynamics of the crypto market and its interactions with broader financial variables. Crypto adoption shocks refer to changes in the intrinsic value and adoption rate of cryptocurrencies, reflecting innovation, regulatory changes, or shifts in adoption sentiments. Crypto risk premium shocks, on the other hand, represent variations in the risk compensation demanded by investors for holding crypto assets, which may be influenced by factors such as market liquidity and volatility. Similarly, conventional risk premium shocks are included to account

[1] We use secondary-market price-adjusted circulation that captures both changes in at par stablecoin outstanding and secondary market price movements that are more sensitive to immediate demand and supply imbalances.

for changes in the risk compensation required for holding traditional financial assets, which could indirectly impact crypto prices through shifts in investor risk appetite and portfolio rebalancing. Lastly, monetary policy shocks are considered to capture the effects of broader economic growth dynamics on the crypto market, acknowledging the interconnectedness of cryptocurrencies with broader financial markets.

We also find that while conventional monetary policy and risk premium shocks have lower-frequency impacts on Bitcoin returns, most of the variation in daily Bitcoin returns is attributed to crypto-risk premium shocks. This is unsurprising and echoes research on equities showing that risk premia plays a sizable role in explaining returns. To further validate our findings, we conduct event studies focusing on significant market events such as the COVID-19 market turmoil, the collapse of FTX, and the launch of BlackRock's spot Bitcoin exchange-traded fund (ETF). These case studies confirm and differentiate the crypto-specific factors in driving cryptocurrency prices and flows.

Related literature The study of cryptocurrency asset returns and their drivers has gained significant attention in recent years. Researchers have employed various methodologies to investigate the factors influencing cryptocurrency returns and their relationships with traditional financial assets. VAR models have been widely used to analyze the dynamics of time serial variables since their introduction by Sims (1980) with a more recent application to financial asset prices by Cieslak and Pang (2021). Karau and Moench (2023) and Faia, Karau, Lamersdorf, and Moench (2024) study the impact of mining shocks on Bitcoin prices. In particular, Faia et al. (2024) also estimate a sign-restricted VAR and find that both Bitcoin news and mining shocks affect Bitcoin prices, but they do not consider the impact of conventional monetary policy shocks and risk premia on Bitcoin prices. The contribution of this paper to examine how much well-known conventional drivers of asset prices (i.e., monetary policy and risk premia) are relevant as drivers of a relatively new asset class.

Related to the study of crypto asset prices, Liu and Tsyvinski (2021) examine the risks and returns of cryptocurrencies and find that they have low exposures to traditional asset classes, suggesting potential diversification benefits. Baur, Hong, and Lee (2018) investigate whether Bitcoin serves as a medium of exchange or a speculative asset and conclude that it is primarily used for speculative purposes. The relationship between cryptocurrencies and traditional financial assets has been a topic of interest. Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) investigate the dynamic relationships between cryptocurrencies and other financial assets, revealing that cryptocurrencies have limited connectedness with traditional assets. Bouri, Molnár, Azzi, Roubaud, and Hagfors (2017) examine whether Bitcoin can serve as a hedge or safe haven for major world stock indices, bonds, oil, gold, the general commodity index, and the US dollar index, finding that Bitcoin has limited hedging capabilities.

Other aspects of cryptocurrency markets have also been explored. Griffin and Shams (2020) investigate whether Tether, a digital currency pegged to the US dollar, influenced Bitcoin and other cryptocurrency prices during the 2017 boom, finding evidence of price manipulation. Makarov and Schoar (2020) analyze trading and arbitrage in cryptocurrency markets, documenting large arbitrage opportunities across exchanges and shedding light on the behavior of market participants. In a related study, Makarov and Schoar (2022) analyze the trading volume in cryptocurrency markets and estimate that wash trading, a form of market manipulation, accounts for a significant portion of trading activity.

Relative to these studies, our core contribution is to provide a decomposition of returns on a high growth and volatile asset class using a methodology with theoretical underpinning and minimum added assumptions. We document the one-way spillover of risk that has so far dominated the relationships between cryptocurrencies and traditional asset classes, and we investigate the role of monetary policy, systemic and idiosyncratic risk factors on the new asset class. Furthermore, we explore the differential pricing dynamic between stablecoins and volatile crypto assets and use the relationship to dissect crypto adoption versus risk premia factors in relation to notable events.

The paper proceeds as follows. Section 2 explains the methodology and details the sign restriction assumptions. Section 3 discusses the data and estimation procedure. Section 4 presents our main results on the drivers of Bitcoin returns, while Section 5 extends the analysis to include stablecoin flows. Section 6 provides event studies to further validate our findings. Finally, Section 7 concludes.

2 Methodology: Sign-restricted VAR

2.1 VAR model

We assume that N asset prices, summarized in a $N \times 1$ vector Y_t, follow a VAR. For simplicity, we assume that this VAR is of first order:[2]

$$Y_t = A_1 Y_{t-1} + e_t. \tag{1}$$

Equation (1) is often referred to as a reduced form, and so the e_t are reduced-form shocks. The model is referred to as a reduced form model since it is a statistical model and the shocks e_t do not necessarily have an interpretation in terms of any underlying economic shocks. For instance, one could imagine that Y_t consists of inflation and output, and interpret the shocks as shocks to inflation and output. However, the true shocks generating inflation might as well be aggregate demand or supply shocks, which influence both inflation and output simultaneously.

To provide an interpretation of the statistical model in Equation (1), we assume a structural model and identify the model using sign restrictions:

$$B_0 Y_t = B_1 Y_{t-1} + \epsilon_t, \tag{2}$$

where ϵ_t are shocks with zero mean, constant variances, and no time-serial correlation. Comparing (1) and (2) yields $B_0 e_t = \epsilon_t$. That is, the structural shocks are a linear combination of the reduced-form shocks. We can estimate the reduced-form shocks $\hat{e}_t$, so all that remains is to construct an appropriate set weights $\hat{B}_0$ in order to identify the structural shocks.

Rather than using a particular parametric model that ties reduced-form shocks and structural shocks together through a single matrix B_0, we impose sign restrictions on the responses

[2]It is well known that the first-order matrix representation can represent VARs with more lags.

of asset prices to structural shocks ϵ_t. This approach leads to a set as opposed to point identification of B_0 (i.e., model multiplicity), but it also tends to lead to more robust estimates.

2.2 Sign restrictions

We first consider three asset prices and three structural shocks in estimating a baseline model. The three asset prices examined are the dividend-adjusted price series of the S&P 500 index, the two-year Treasury expressed as zero-coupon bond yields, and the price of Bitcoin. The three structural shocks are conventional risk premium, monetary policy shocks, and crypto demand shocks. Subsequently we extend this baseline model to decompose the crypto shocks into those that reflect crypto adoption and crypto risk premium. We explain the nature of these shocks and our assumptions on their impacts on asset prices as follows.

Crypto demand shocks. Crypto demand shocks are adoption shocks that raise bitcoin prices. We leave the impact of crypto demand shock on conventional assets undetermined. That is, by assumption, there are no meaningful spillovers from crypto markets to conventional markets, which we believe is a reasonable assumption over our sample period. As bitcoin supply is entirely deterministic, there are no bitcoin supply shocks.

Conventional monetary policy shocks. The second type of shocks we consider are conventional monetary policy shocks. Conventional monetary policy shocks are exogenous shocks to short-term risk-free rates or their expected paths that are orthogonal to other state variables driving the short rate. Their impact on asset prices reflects a discount rate effect: all else being equal, asset prices are worth less when discount rates increase, simply because the opportunity cost of holding theses assets increases. In contrast to the crypto demand shock, we assume that conventional shocks can affect both conventional risk assets and crypto assets. Consequently, we assume that a positive monetary policy shock leads to higher yields (i.e., lower bond prices), lower S&P 500 prices, and lower bitcoin prices.

Conventional risk premium shocks. The third type of shocks we consider are conventional risk premium shocks. These are classic "flight-to-safey" shocks across asset classes. Consequently, we assume that increases in conventional risk premium lead to declines in risky asset prices and increases in safe asset prices. That is, a positive conventional risk premium shock decreases bitcoin prices, stock prices, and yields.

We summarize the sign restrictions in Table 1.

Table 1: Sign restrictions

Asset/Shock	Conv. Risk Premium	Monetary Policy	Crypto Demand
BTC Returns	-	-	+
2Y ZCB Yield	-	+	?
S&P 500 Returns	-	-	?

The table summarizes the sign restrictions. Shocks are in columns, assets are in rows. The assets are Bitcoin (BTC), the 2-year zero-coupon bond Treasury yield (2Y ZCB Yield), and the S&P 500.

In an extension of the model, we further decompose the crypto demand shock into a crypto adoption shock and a crypto risk premium shock. We do so using stablecoin flows, as there is evidence that stablecoins act as a safe asset within the crypto asset space (Baur and Hoang, 2021; Grobys et al., 2021; Liao and Caramichael, 2022). We compute stablecoin flows as changes in market cap:

In this extension, we assume that a crypto adoption shock raises both Bitcoin prices and the market capitalization of stablecoins and, thus, we interpret such a shock as an adoption shock to the broader crypto eco-system. Conversely, we assume that a crypto risk premium shock reflects a flight-to-safety shock within the crypto eco-system, lowering bitcoin prices and increasing stablecoin market caps.

Once again, we leave the impact of crypto shocks on conventional assets undetermined, but manage their impact through magnitude restrictions such that there are no meaningful spillovers. Even though stablecoins can act as a safe haven within the cypto ecosystem, we assume that a positive conventional risk premium shock leads to stablecoin outflows. The reason is simply that US Treasuries are the ultimate safe haven and that it is challenging for privately created money to achieve this ultimate safe haven status (see, e.g., Gorton and Zhang, 2023; Ma, Zeng, and Lee Zhang, 2023). We summarize the sign restrictions of this extended model in Table 2.

Table 2: Sign restrictions (extended model)

Asset/Shock	Con. Risk Premium	Monetary Policy	Crypto Adoption	Crypto Risk Premium
Stablecoin Flows	-	-	+	+
BTC Returns	-	-	+	-
2Y ZCB Yield	-	+	?	?
S&P 500 Returns	-	-	?	?

The table summarizes the sign restrictions of the extended model with stablecoin flows. Shocks are in columns, assets are in rows. The assets are stabecloins, Bitcoin (BTC), the 2-year zero-coupon Treasury yield (2Y ZCB Yield), and the S&P 500.

3 Data and estimation

3.1 Data

We use four assets: the S&P 500, 2-year zero-coupon Treasuries, Bitcoin, and stablecoins, and consider changes/returns in these assets. We use data from 01/2019 to 02/2024.

We limit the universe of stablecoins to USDT and USDC, as these are the two main fiat-backed stablecoins representing over 90% of all stablecoin circulation and they are more likely to serve as crypto safe-haven assets due to their backing and widespread usage (see, e.g., Anadu, Azar, Cipriani, Eisenbach, Huang, Landoni, La Spada, Macchiavelli, Malfroy-Camine, and Wang, 2024; Liao and Caramichael, 2022). In contrast, alternative stablecoins such as algorithmic stablecoins have been shown to be prone to run risk (see, e.g., Adams and Ibert, 2022; Uhlig, 2022; Liu, Makarov, and Schoar, 2023).

Daily nominal 2-year Treasury yields are from Gürkaynak, Sack, and Wright (2007) and downloadable here. S&P 500 returns are from Bloomberg. We use USD prices of Bitcoin, USDC, and USDT from CoinGecko as of US market close. We provide a link to the dataset from Dune Analytics to faciliate replication of this study.[3]

We use stablecoin circulation of USDT and USDC provided by DefiLlama, a leading data provider for cryptocurrency data. DefiLlama's data covers the period from March 30, 2021, to the present. To access earlier data, we have developed a script that retrieves the total supply directly from the Ethereum blockchain. Historically, the vast majority of stablecoin circulation was on Ethereum. However, the issuance of stablecoins on other blockchains has gradually increased, and these are now issued natively on various blockchains as captured by the more recent DefiLlama data. The discrepancy between the total stablecoin circulation and that on Ethereum alone prior to 2021 is minimal for our analysis focused on daily changes.

Additionally, we calculate the market capitalization of each stablecoin by multiplying its circulation by its price in secondary markets. This approach helps us track high-frequency changes in market capitalization due to its sensitivity to price fluctuations in these markets. We use secondary market prices because they can more immediately reflect stablecoin demand at a daily level, as primary market issuance and redemption responses to price changes can be lagged due to arbitrage process.

3.2 Estimation

We obtain reduced-form shocks from a VAR(1) estimated by OLS over the entire sample. Once we have these shocks, we employ an algorithm to generate possible combinations of candidate matrices, $\hat{B}_0$, and shocks, $\hat{\epsilon}_t$. These combinations must satisfy the equation $\hat{B}_0\hat{e}_t = \hat{\epsilon}_t$, with the condition that the shocks $\hat{\epsilon}_t$ are uncorrelated. There are numerous potential combinations; however, only some will yield impulse responses that adhere to the constraints specified in Table 1. Combinations that fail to produce impulse responses meeting these criteria are discarded, and new ones are generated and tested.

[3] Dune Analytics query: https://dune.com/queries/2977622

The crucial step in designing this algorithm is to ensure that the candidate matrices are such that the structural shocks are uncorrelated. To construct a set of uncorrelated shocks, we start with the Cholesky decomposition of the variance-covariance matrix of the reduced-form shocks, $F^{-1}\hat{\Sigma}_e F'^{-1} = I_N$. The Cholesky decomposition yields a set of uncorrelated shocks $\hat{\eta}_t$ with unit variance such that $\hat{e}_t = F\hat{\eta}_t$. The shocks $\hat{\eta}_t$ are now regarded as structural shocks and a natural starting point. However, the Cholesky decomposition corresponds to estimating a recursive VAR, and shocks from a recursive VAR do not have an economic interpretation in our setting as it is difficult to defend any particular ordering of shocks in our setting.[4]

Thus, we form combinations of the $\hat{\eta}_t$ using a matrix Q, i.e., $\hat{\eta}_t^* = Q\hat{\eta}_t$. As mentioned above, the structural shocks need to be uncorrelated and so Q must be restricted. The appropriate restriction is that Q is a square matrix such that $Q'Q = QQ' = I_N$ since $\hat{e}_t = FQ'Q\hat{\eta}_t = F^*\hat{\eta}_t^*$ and $\text{cov}(\hat{\eta}_t^*\hat{\eta}_t^{*\prime}) = Q\text{cov}(\hat{\eta}_t\hat{\eta}_t')Q' = I_N$. If we can generate such a matrix Q, we have found a new set of shocks, $\hat{\eta}_t^*$, with the same covariance matrix as $\hat{\eta}_t$, but with a different impact (F^*) on the reduced-form shocks and, thus, the variables Y_t in the VAR. The ability to create a large number of candidate shocks with varying impulse responses is central to the sign restriction method.

How do we generate a large number of matrices Q with the property $Q'Q = QQ' = I_N$? We generate these rotation matrices Q_i based on the QR matrix factorization of Rubio-Ramírez, Waggoner, and Zha (2010). Whenever $F^*(Q_i) = FQ_i'$ together with $\hat{\eta}_t^*(Q_i) = Q_i\hat{\eta}_t$ and $\hat{e}_t = F^*(Q_i)\hat{\eta}_t^*(Q_i)$ satisfy the restrictions laid out in Table 1, we store the rotation matrix Q_i as a valid solution. We store $i = \{1, ..., 1000\}$ such solutions. By construction, the structural shocks $\hat{\eta}_t^*(Q_i)$ have zero mean, unit variance, and are uncorrelated. Finally, we note that, while the shocks are contemporaneously uncorrelated, we allow for correlations over time. For instance, a positive conventional risk premium shock may subsequently lead to a negative monetary policy shock (i.e. the "Fed put").

[4] See also footnote 3 in Fry and Pagan (2011).

3.3 Set identification

We only retain those shocks whose impulse responses are consistent with the sign restrictions. Still, there may be many such shocks and impulse responses. Which ones to focus on? We follow the approach in Fry and Pagan (2011) and focus on the median target (MT) solution. The MT solution's impulse responses are closest to the median impulse responses across solutions, but the MT solution ensures that the impulse responses come from the same model without mixing different solutions, thereby maintaining a structural interpretation of the shocks. Formally, we denote the vector of impulse responses as $\theta_i = \text{vec}(F^*(Q_i))$. We standardize each impulse response by subtracting the element-wise median across admissible models and divide by the standard deviation across admissible models. Finally, we choose the impulse responses and corresponding structural shocks that are closest to the median across solutions (see also Cieslak and Pang, 2021):

$$\theta^{MT} = \min_i \left(\frac{\theta_i - \text{median}(\theta_i)}{\text{std}(\theta_i)} \right)' \left(\frac{\theta_i - \text{median}(\theta_i)}{\text{std}(\theta_i)} \right). \tag{3}$$

We present most results for this MT solution. As a robustness check, we also characterize model uncertainty by reporting the distribution of estimates across all admissible models.

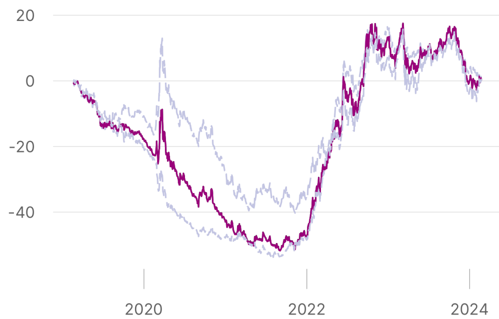
4 Drivers of Bitcoin returns

4.1 Cumulative shocks over time

Figure 2 plots the paths of cumulative shocks for the model with three structural shocks. The figure shows both the cumulative shocks for the MT solution as well as the median of cumulative shocks across all retained solutions. The median-target solution is generally close to the median of cumulative shocks across all retained solution, suggesting that the optimization in Equation (3) works well. The figure also shows the 95th and the 5th percentiles of the distribution of cumulative shocks. These are generally close to the median-target solution, suggesting that model uncertainty is not a primary concern. We note that the 95th and 5th

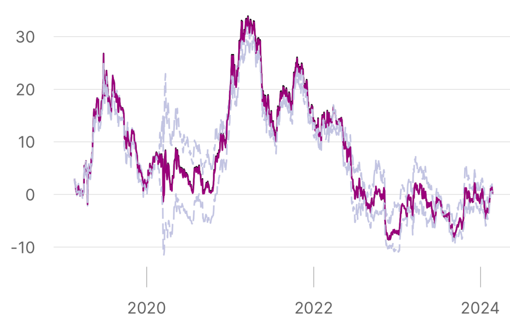
Figure 2: Cumulative de-trended shocks over time

(a) Monetary policy shocks



(b) Conventional risk premium shocks

(c) Crypto demand shocks



The figure shows cumulative shocks over time. Shocks are a monetary policy shock (positive is contractionary), a conventional risk premium shock (positive is risk-off), and a crypto (Bitcoin) demand shock. The figure shows the median-target solution (in black) of a structural vector-autoregressive model identified with sign and magnitude restrictions, as well as the median across solutions (in purple) and the 5th and 95th percentiles across solutions (in grey).

percentiles should not be interpreted as confidence intervals in the traditional sense.

The paths of cumulative shocks have intuitive appeal. The sign-restricted VAR model suggests that positive conventional risk premium shocks were responsible for the decline in risky asset prices during March 2020 amid the COVID-19 induced market turmoil. This has intuitive appeal, since many market commentators highlighted classic flight-to-safety shocks as the primary drivers of risky assets and Treasury yields during that period. Conventional risk premia subsequently declined, supporting risky asset prices. The model also suggests that monetary policy shocks were negative over 2021 and positive over 2022. This is consistent with the accommodative monetary policy in response to the economic challenges brought upon by the pandemic and the subsequent tightening of monetary policy as inflation unexpectedly rose well above target. The crypto demand shocks were positive during 2021, supporting Bitcoin prices, and negative subsequently, depressing Bitcoin prices.

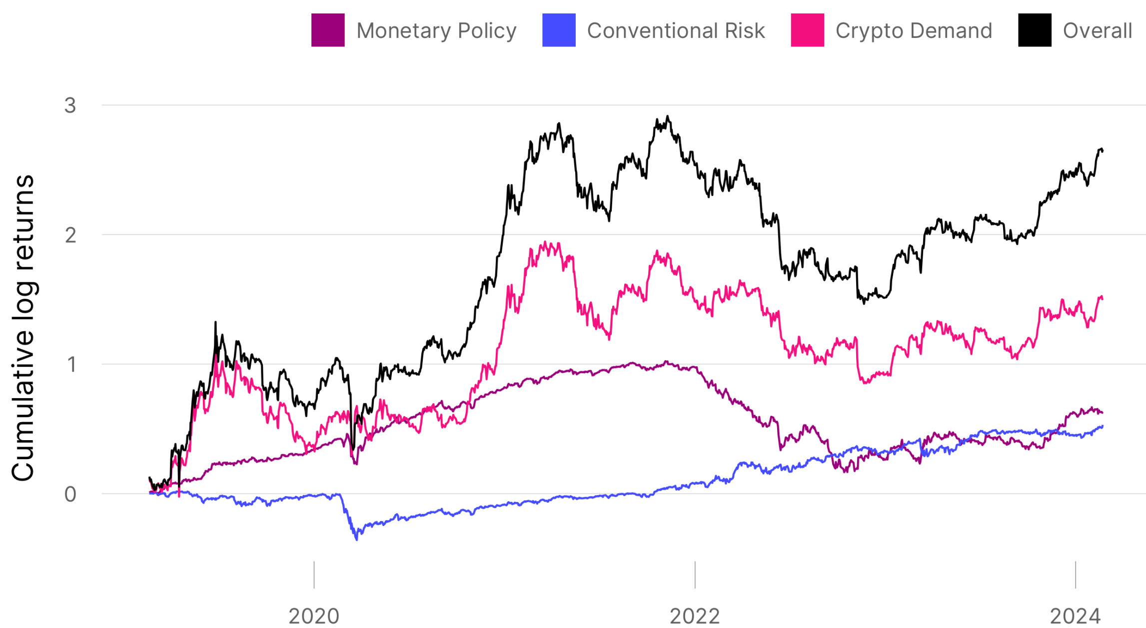
A key question we would like to answer is how much the conventional risk premium and the monetary policy shocks affect crypto assets. We examine this next.

4.2 Bitcoin return decomposition

We start by decomposing (log) Bitcoin returns into the three structural shocks: monetary policy shocks, conventional risk premium shocks, and crypto demand shocks. Figure 3 shows this decomposition over time using the MT solution. For completeness, the appendix shows similar return decompositions for the S&P 500 and 2-year Treasury yields. In these plots, adding up the cumulative shocks at a given point in time recovers the cumulative Bitcoin return until that point in time.

Figure 3 shows that, as can be expected from the paths of cumulative shocks, the decline in Bitcoin prices during March 2020 was primarily driven by conventional risk premium shocks (the blue line moves downward, showing a negative contribution to Bitcoin returns from positive conventional risk premium shocks). From March 1 to March 31, bitcoin prices declined from around \$8,600 to \$6,500—a 24.2% drop in simple returns and a 27.7% drop in log returns. The subsequent increase in Bitcoin prices over 2020 was supported by both declining conventional risk premia and accommodative monetary policy (both the Boardeaux-red line and the blue line move upwards, indicating a positive contribution to Bitcoin returns). That said, a large chunk in the increase in Bitcoin prices until early 2021 is unexplained by both conventional monetary policy and conventional risk premium shocks, and reflects significant Bitcoin demand shocks.

Figure 3: Bitcoin returns decomposed into three structural shocks



The figure shows Bitcoin returns decomposed into three structural shocks: monetary policy shocks, conventional risk premium shocks, and crypto demand shocks. The decomposition uses the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions.

Turning to 2022, the decline in Bitcoin prices over the year can be explained by a combination of negative monetary policy shocks as well as negative Bitcoin demand shocks, while declining conventional risk premia continued to support Bitcoin prices. Overall, from January 1, 2022 to January 1, 2023 Bitcoin prices declined by around -1.02 in log returns, equivalent to around 64% in simple returns. The model suggests that positive monetary shocks (tightening) led to a decline of 0.71 in log returns, crypto demand shocks led to a decline of 0.57 in log returns, and negative conventional risk premium shocks led to an increase of 0.26 in log returns to $(-0.71 - 0.57 + 0.26 = -1.02)$. Converted to simple returns, monetary policy shocks contributed around 50 percentage points to the overall decline of 64% in Bitcoin prices. Put differently, the model suggests that Bitcoin prices would have declined only 14% as opposed to 64% had there been no (positive) monetary policy shocks over 2022.

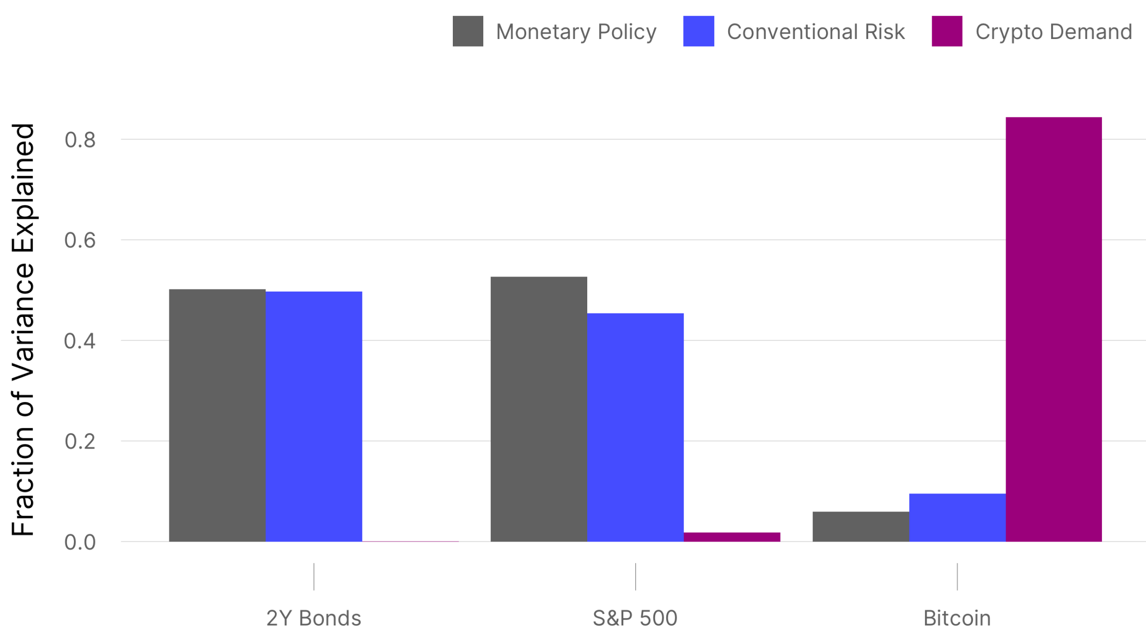
Figure 3 also suggests that, while conventional monetary policy and risk premium shocks have lower-frequency impacts on Bitcoin returns, most of the variation in *daily* Bitcoin returns is left unexplained by conventional shocks. We illustrate that most of the daily variation in Bitcoin returns is unexplained by conventional risk premium shocks and monetary policy shocks in Figure 4. The figure shows a variance decomposition of daily Bitcoin returns into the three shocks and shows that crypto demand shocks account for more than 80% of the variability in Bitcoin daily returns. This confirms the notion that Bitcoin is a volatile asset whose variability cannot be explained by shocks that drive conventional assets. The low-frequency impact of monetary policy is further highlighted in Table 3 that shows a quarterly-to-daily variance ratio of 1.8 for the monetary policy factor while less than unity for the other two factors. A variance ratio of greater than 1 indicates positive autocorrelation (Lo and MacKinlay, 1988) and possible arbitrage.[5]

[5] Daily versus weekly variance swap, for example, on a tradeable index is a direct way to express views on autocorrelation.

Table 3: Decomposed Return Volatilities

Factors	Daily Vol	Quarterly Vol	Variance Ratio (q/d)
Conventional risk	0.168	0.148	0.78
Monetary policy	0.211	0.284	1.80
Crypto-specific	0.621	0.602	0.94

Figure 4: Variance decomposition of Bitcoin returns



The figure shows the fraction of the daily variance of 2-year Treasury yields (2Y Bonds), S&P 500 returns, and Bitcoin returns explained by monetary policy, conventional risk premium, and crypto (Bitcoin) demand shocks.

To better understand the daily drivers of Bitcoin returns, we next turn to the extended model that further decomposes the crypto demand shock into a crytpo adoption shock and a risk premium shock within the crypto asset space.

5 Drivers of Bitcoin returns and stablecoin flows

5.1 Cumulative shocks over time

Figure 5 shows the cumulative shocks over time for the extended model with four shocks. The MT solution is close to the median across solutions once again and the cumulative MT monetary policy and conventional risk premium shocks are similar compared with Figure 2. That said, the 5th and 95th percentiles of across solutions are wider compared to the baseline model, suggesting that model uncertainty is larger for the extended model.

The figure shows that crypto adoption shocks (shocks that raise both stablecoin market cap and Bitcoin prices) have been positive from 2020 until mid 2021 and negative thereafter. Similarly, crypto risk premium shocks (shocks that raise stablecoin market cap and depress Bitcoin prices) have been positive from 2020 until mid 2021 and negative thereafter.

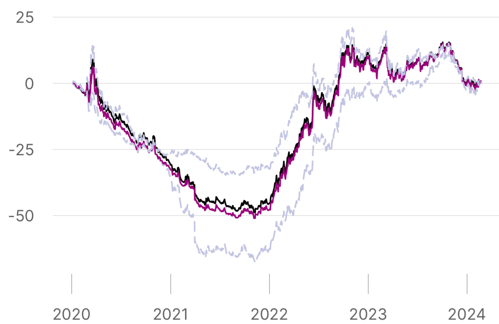
5.2 Bitcoin return and stablecoin flow decomposition

Panel A of Figure 6 shows the decomposition of bitcoin prices into structural shocks using the sign-restricted VAR model that decomposes crypto demand shocks further into crypto adoption and crypto risk premium shocks. Reassuringly, the impact of both conventional monetary and conventional risk premium shocks on bitcoin prices is similar to the impacts of these shocks in the 3 $\times$ 3 sign-restricted VAR model from the previous section. Panel B of Figure 6 shows a similar decomposition for stablecoin market cap.

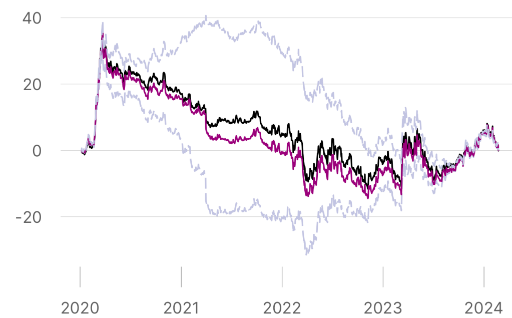
The figure shows that the model attributes most of the increase in Bitcoin prices from 2020 to mid-2021 to crypto adoption shocks. The reason is simply that both stablecoins and Bitcoin prices experienced tremendous growth over this period. Our qualification of a crypto adoption shock as indicated by the sign restrictions is that it raises both stablecoin market cap and bitcoin prices (see Table 2) and, thus, it is not surprising that the model picks up crypto adoption shocks over this period. Conversely, as the growth of stablecoins has moderated since late 2022 and, for some subperiods even reversed, the bitcoin price decomposition suggests negative crypto adoption shocks (which push both bitcoin prices and

Figure 5: Cumulative de-trended shocks over time (extended model)

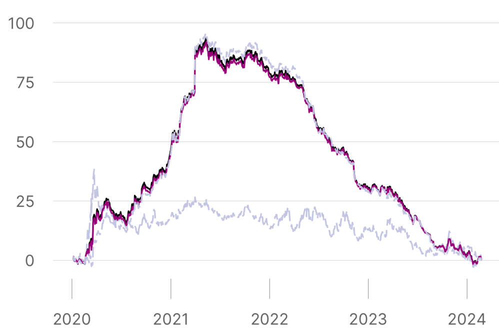
(a) Monetary policy shocks



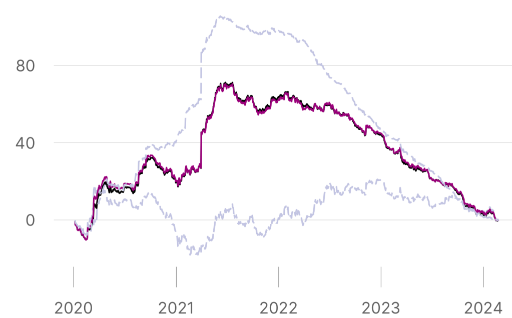
(b) Conventional risk premium shocks



(c) Crypto adoption shocks



(d) Crypto risk premium shocks



The figure shows cumulative shocks over time. Shocks are a monetary policy shock, a conventional risk premium shock, a crypto demand shock, and a crypto risk premium shock. The figure shows the median-target solution (in black) of a structural vector-autoregressive model identified with sign and magnitude restrictions, as well as the median across solutions (in purple) and the 5th and 95th percentiles across solutions (in grey).

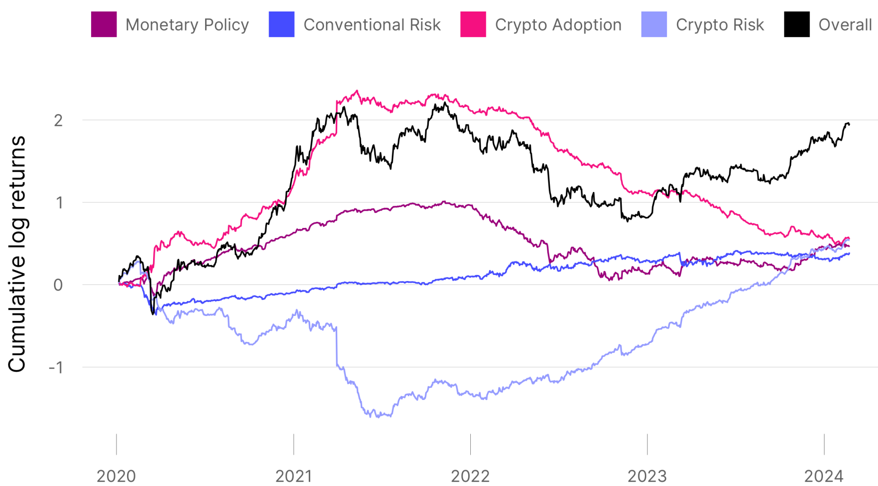
stablecoin market cap lower) and declining crypto risk premia (which raise bitcoin prices and lower stablecoin market cap).

Moreover, the analysis of stablecoins since 2020 reveals significant high-frequency fluctuations which are obscured in log-scale graphs due to the massive increase in stablecoin market cap from 2020 to 2022. Consequently, Figure 7 presents the breakdown of Bitcoin returns and stablecoin flows starting in early 2022. Panel A indicates that the decline in Bitcoin prices throughout 2022 is due to positive monetary policy shocks and negative crypto adoption shocks. Panel B suggests that the reduction in stablecoin market caps during the same period is primarily driven by negative crypto adoption shocks.

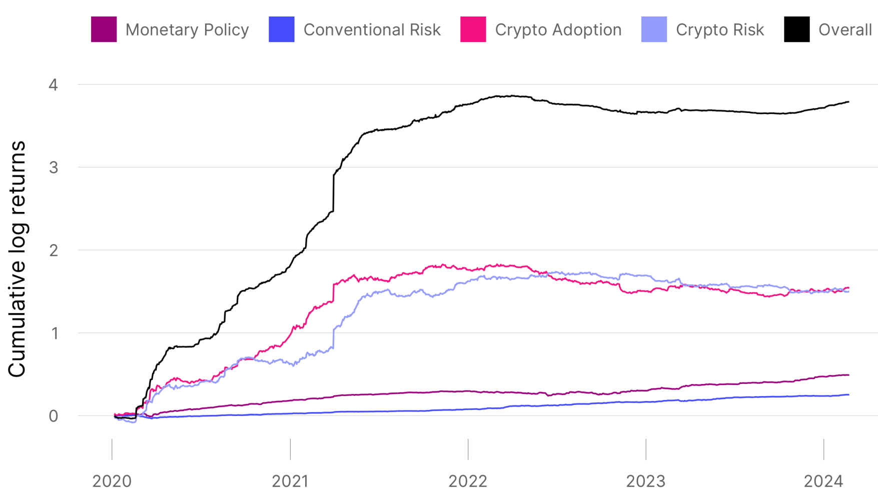
To further study the implications of the model and the drivers of crypto assets, we next turn to event studies and study crypto price movements around four events that were associated with large price movements.

Figure 6: Bitcoin return and stablecoin flow decomposition into four shocks

(a) Bitcoin return decomposition



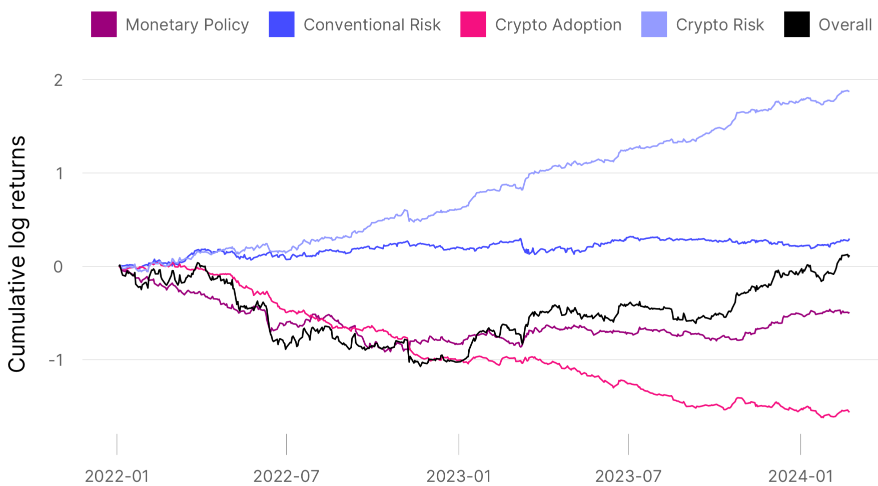
(b) Stablecoin flow decomposition



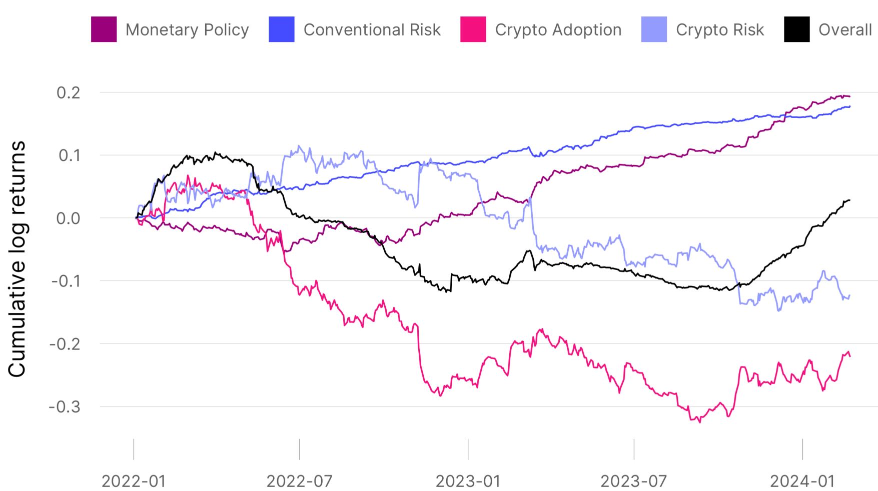
The figure shows Bitcoin returns and stablecoin flows decomposed into four structural shocks: conventional monetary policy shocks, conventional risk premium shocks, crypto adoption shocks, and crypto risk premium shocks. The decomposition uses the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions.

Figure 7: Bitcoin return and stablecoin flow decomposition since 2022

(a) Bitcoin return decomposition



(b) Stablecoin flow decomposition



The figure shows Bitcoin returns and stablecoin flows decomposed into four structural shocks: conventional monetary policy shocks, conventional risk premium shocks, crypto adoption shocks, and crypto risk premium shocks. The decomposition uses the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions.

6 Event studies

6.1 COVID-19 market turmoil

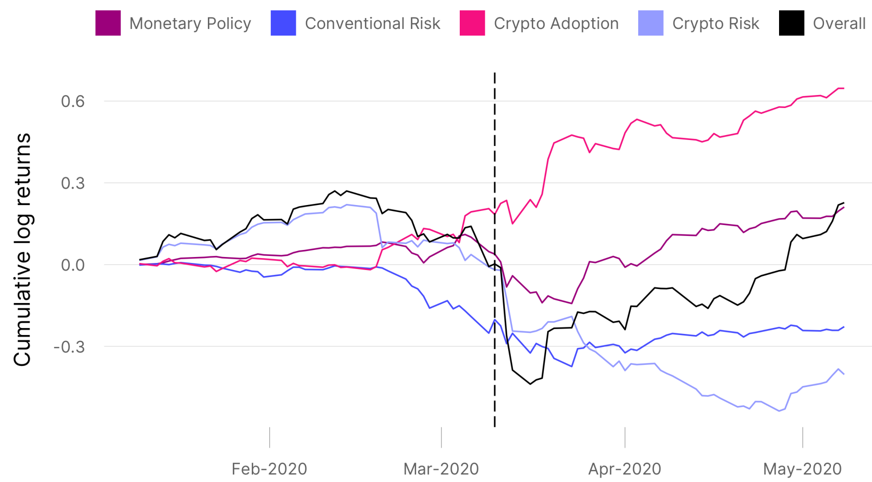
We first zoom in on the drivers of crypto assets during the COVID-19 induced market turmoil. Figure 8 shows Bitcoin returns and stablecoin flows decomposed from January 2020 to May 2020. We start with a narrative description of overall Bitcoin returns and stablecoin market caps over this period before turning to the model decomposition. Bitcoin returns declined significantly in March 2020, whereas stablecoin market caps increased significantly. The period was characterized as a "risk-off" episode with larger declines in asset prices than were be justified by the decline in fundamentals (see, e.g., Chen, Ibert, and Vazquez-Grande, 2020). The massive growth of stablecoins in this "risk-off' period suggests that, indeed, stablecoins act as a safe haven within the crypto asset space, which validates our identifying assumption laid out in Table 2.

As the period was characterized as a "risk-off" episode, we expect positive conventional risk premium shocks and crypto risk premium shocks to play a dominant role. While Treasury yields declined in the intermediate run, the immediate behavior of Treasury yields was erratic amid liquidity issues in the Treasury market. Thus, monetary policy shocks may have been mixed, as yields temporarily increased, at least during March 2020. Figure 9 plots the cumulative shocks over time. As expected, both conventional and crypto risk premium shocks were significantly positive.

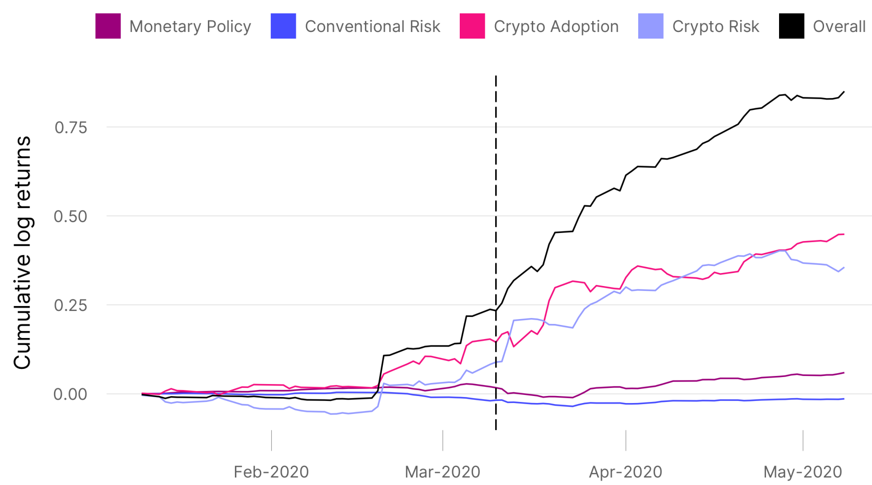
The decomposition of Bitcoin returns and stablecoin flows in Figure 8 further confirms the narrative. Panel (a) shows that, indeed, the model attributes the decline in Bitcoin prices in 2020 to a combination of positive conventional risk premium shocks and positive crypto risk premium shocks. At the same time, positive crypto adoption shocks supported Bitcoin prices. Panel (b) shows the massive growth in stablecoins over this period is due to both positive risk premium shocks (that led to safe-haven inflows into stablecoins) and positive crypto adoption shocks.

Figure 8: Crypto assets decomposition around COVID-19 market turmoil

(a) Bitcoin return decomposition



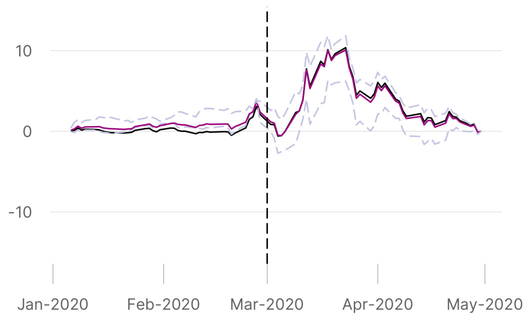
(b) Stablecoin flow decomposition



The figure shows Bitcoin returns and stablecoin flows from January 2020 to May 2020 decomposed into four structural shocks: conventional monetary policy shocks, conventional risk premium shocks, crypto adoption shocks, and crypto risk premium shocks. The decomposition uses the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions. The dashed vertical line indicates March 10th, 2020.

Figure 9: Cumulative de-trended shocks around COVID-19 market turmoil

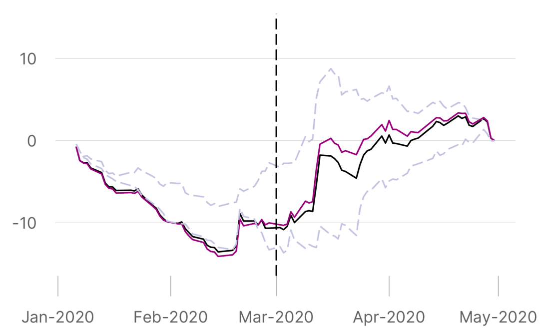
(a) Monetary policy shocks



(b) Conventional risk premium shocks

(c) Crypto adoption shocks

(d) Crypto risk premium shocks



The figure shows cumulative shocks over time. Shocks are a monetary policy shock, a conventional risk premium shock, a crypto demand shock, and a crypto risk premium shock. The figure shows the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions, as well as the median across solutions and the 5th and 95th percentiles across solutions.

6.2 FTX report

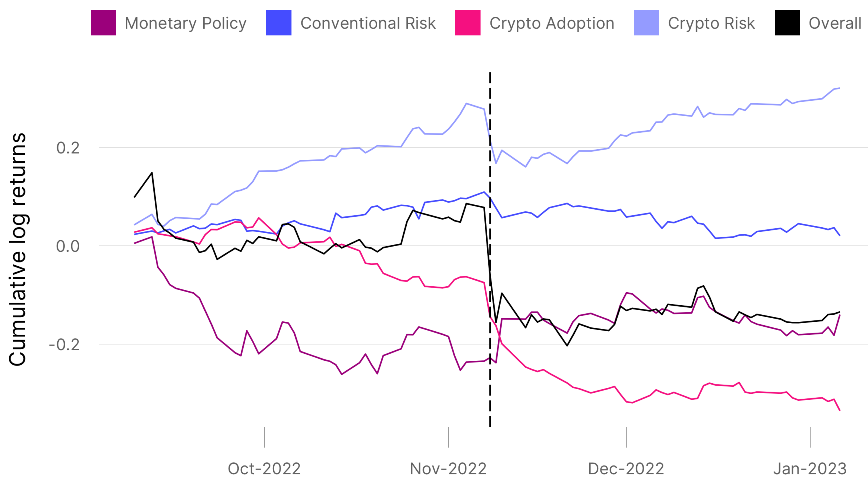
We next zoom in on the drivers of crypto assets around the collapse of FTX, beginning again with a narrative description of overall Bitcoin returns and stablecoin market caps over this period shown in the black lines of Figure 10. From September 2022 to January 2023, Bitcoin prices declined significantly, with most of the declines happening around the time of the collapse of FTX in November 2022. Meanwhile, stablecoin market caps declined modestly over the period, with a short spike around the collapse of FTX in November 2022, consistent again with a safe-hafen property of stablecoins.

The immediate period around the collapse of FTX in November 2022 was characterized by large price movements in crypto markets, but little price movements in conventional markets. Thus, around the immediate collapse of FTX, we expect crypto shocks to play a dominant role, in particular positive risk premium shocks and negative adoption shocks. We expect a smaller role for conventional shocks around the immediate collapse of FTX. Figure 11 shows the cumulative shocks and, indeed, the model picks up negative crypto adoption shocks and positive crypto risk premium shocks around the immediate collapse of FTX.

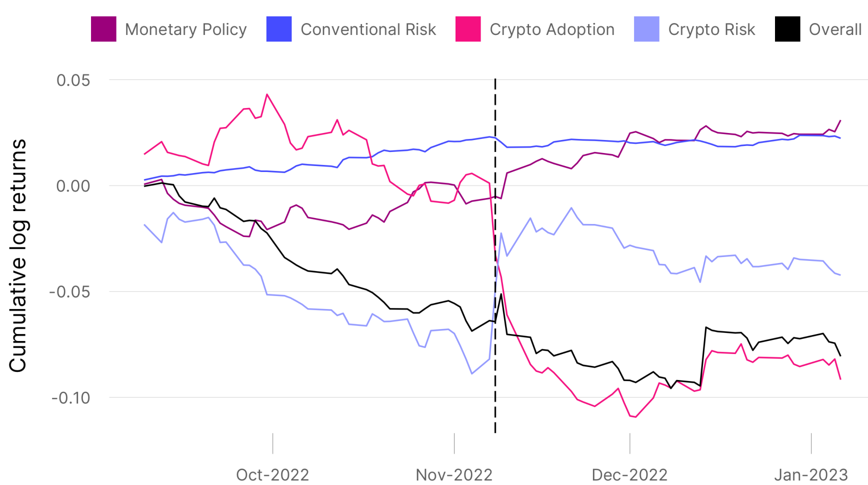
The decomposition of Bitcoin returns and stablecoin flows in Figure 10 confirms this narrative. Around the immediate collapse of FTX in November 2022, increasing crypto risk premia pushed Bitcoin prices lower and contributed to stablecoin inflows. At the same time, negative crypto adoption shocks further pushed Bitcoin prices lower and contributed negatively to stablecoin flows.

Figure 10: Crypto assets decomposition around FTX collapse

(a) Bitcoin return decomposition

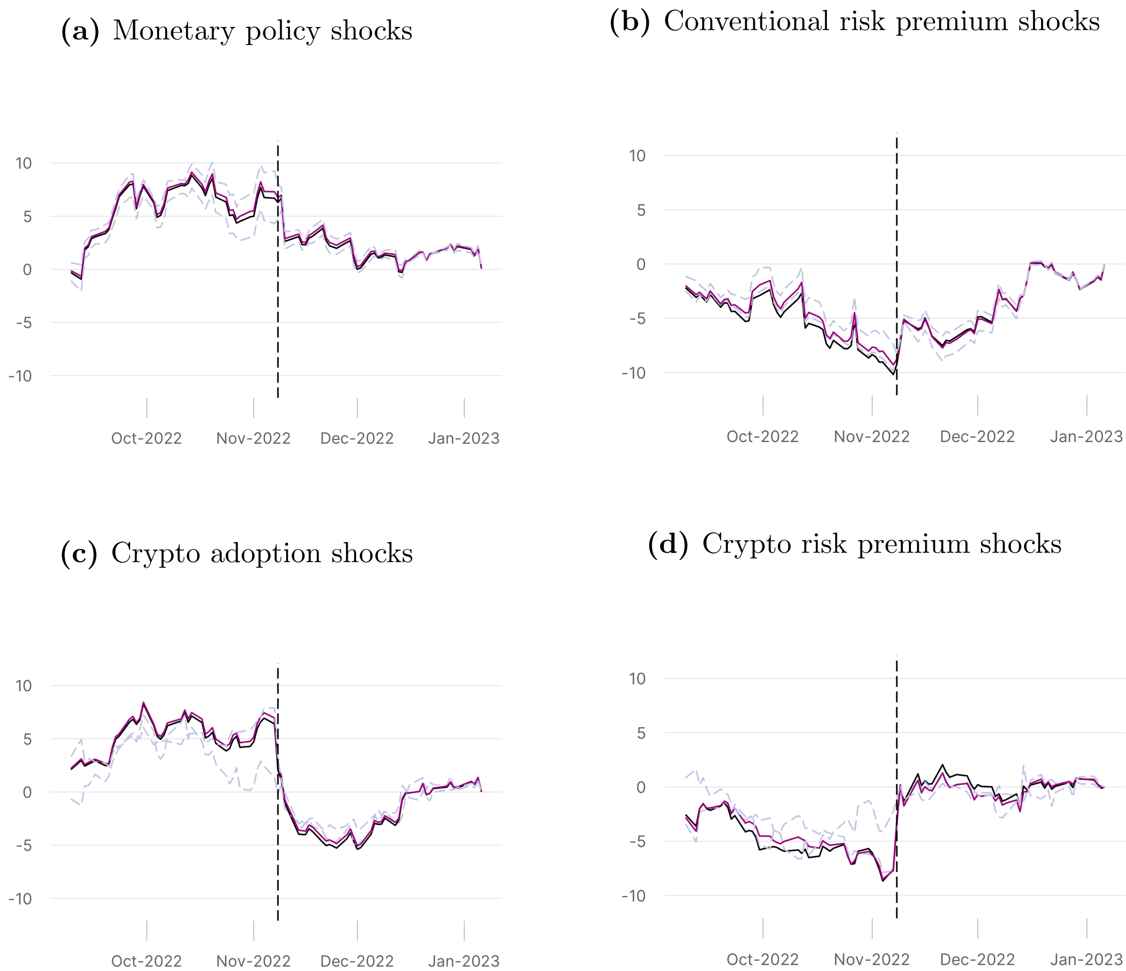


(b) Stablecoin flow decomposition



The figure shows Bitcoin returns and stablecoin flows from September 2022 to January 2023 decomposed into four structural shocks: conventional monetary policy shocks, conventional risk premium shocks, crypto adoption shocks, and crypto risk premium shocks. The decomposition uses the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions. The dashed vertical line indicates November 8th, 2022.

Figure 11: Cumulative de-trended shocks around FTX collapse



(a) Monetary policy shocks

(b) Conventional risk premium shocks

(c) Crypto adoption shocks

(d) Crypto risk premium shocks

The figure shows cumulative shocks over time. Shocks are a monetary policy shock, a conventional risk premium shock, a crypto demand shock, and a crypto risk premium shock. The figure shows the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions, as well as the median across solutions and the 5th and 95th percentiles across solutions.

6.3 Launch of BlackRock ETF

Lastly, we delve into the specific factors influencing cryptocurrency assets coinciding with the introduction of BlackRock's Bitcoin spot ETF. Figure 12 illustrates a substantial increase in Bitcoin returns following BlackRock's announcement to file for a Bitcoin spot ETF. This period marks a significant shift in investor sentiment and market dynamics within the cryptocurrency sector.

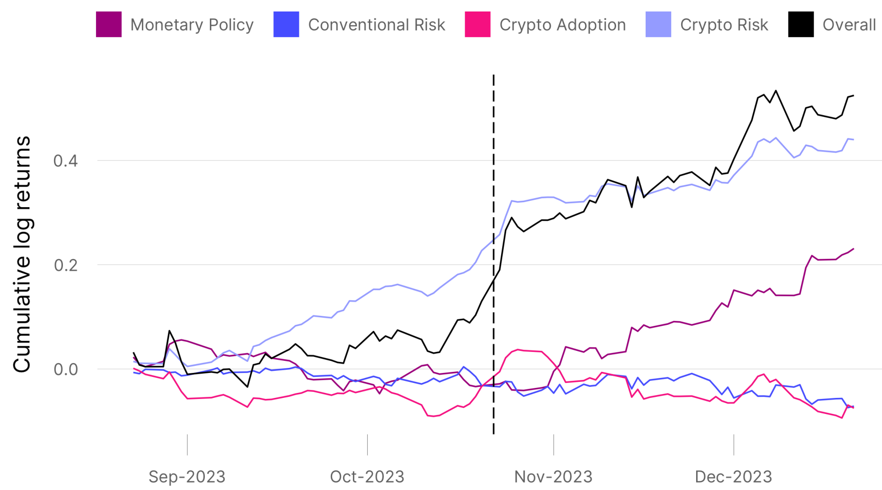
Further analysis is provided in Figure 13, which presents the cumulative shocks observed around the time of this event. The model identifies two primary influences: positive crypto adoption shocks and negative crypto risk premium shocks. The positive crypto adoption shocks likely reflect increased market acceptance and investor interest triggered by the legitimacy and entry of a major institutional player like BlackRock into the Bitcoin market.

Concurrently, the negative crypto risk premium shocks suggest a reduction in the extra return investors demand to hold Bitcoin over safer assets, indicating a perception of reduced risk associated with Bitcoin investments during this period. This combination of factors contributed significantly to the rise in Bitcoin prices. Specifically, the decomposition shown in Figure 12 attributes the majority of the Bitcoin price increase from September 2023 to December 2023 to these declining crypto risk premia.

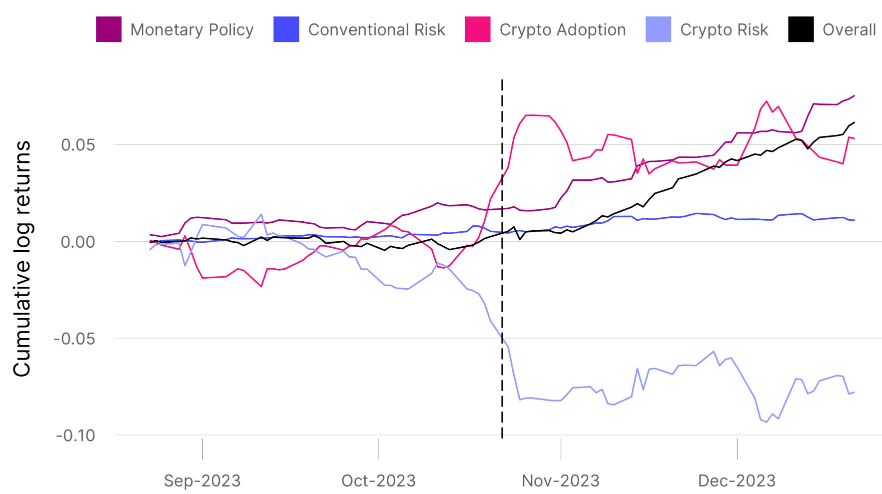
These findings underscore the impact of significant market events and the perceptions of institutional involvement on cryptocurrency markets, particularly in terms of adoption dynamics and risk valuation by investors.

Figure 12: Crypto assets decomposition around BlackRock ETF launch

(a) Bitcoin return decomposition



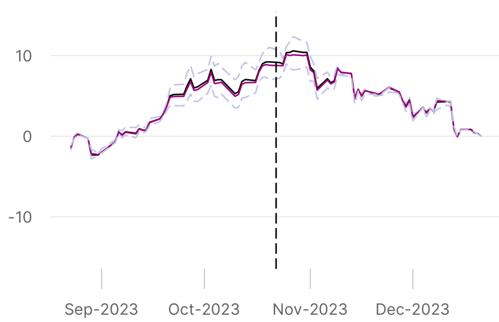
(b) Stablecoin flow decomposition



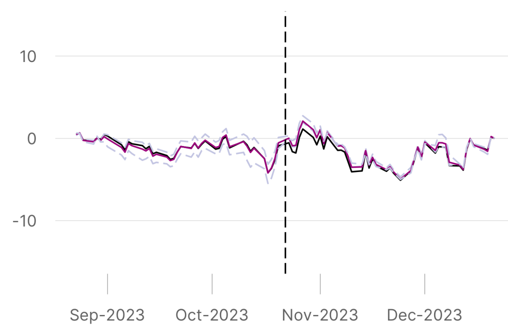
The figure shows Bitcoin returns and stablecoin flows from August 2023 to January 2024 decomposed into four structural shocks: conventional monetary policy shocks, conventional risk premium shocks, crypto adoption shocks, and crypto risk premium shocks. The decomposition uses the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions. The dashed vertical line indicates October 22nd, 2023.

Figure 13: Cumulative de-trended shocks around BlackRock ETF launch

(a) Monetary policy shocks

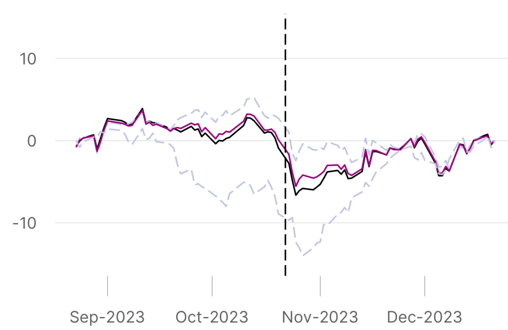


(b) Conventional risk premium shocks



(c) Crypto adoption shocks

(d) Crypto risk premium shocks



The figure shows cumulative shocks over time. Shocks are a monetary policy shock, a conventional risk premium shock, a crypto demand shock, and a crypto risk premium shock. The figure shows the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions, as well as the median across solutions and the 5th and 95th percentiles across solutions.

7 Conclusion

This paper investigates the drivers of Bitcoin returns and stablecoin flows using a structural VAR model identified with sign and magnitude restrictions. By decomposing price movements into conventional monetary policy shocks, conventional risk premium shocks, crypto adoption shocks, and crypto risk premium shocks, we provide new insights into the factors influencing cryptocurrency markets and their interconnectedness with traditional financial markets.

Our findings suggest that crypto-specific factors, namely adoption and risk premium shocks, play a dominant role in explaining the variation in daily Bitcoin returns. While conventional monetary policy and risk premium shocks have some impact on cryptocurrency prices, their influence is more pronounced at lower frequencies. Furthermore, we provide evidence supporting the safe-haven property of stablecoins within the crypto asset space, as stablecoin market capitalization tends to increase during periods of market stress.

The event studies focusing on the COVID-19 market turmoil, the collapse of FTX, and the launch of BlackRock's spot Bitcoin ETF further validate our findings. These case studies highlight the importance of crypto-specific factors in driving cryptocurrency prices and flows during significant market events. Our research has several implications for market participants and policymakers. First, investors should be aware of the distinct factors driving cryptocurrency prices and their potential diversification relative to traditional asset classes. Second, our research provide a methodology to understand the direction and magnitude of risk spillovers in new asset classes. The estimates can be used for investor hedging and prudential risk monitoring.

Future research could extend our analysis by incorporating a wider range of cryptocurrencies and exploring the impact of regulatory changes on cryptocurrency markets. Additionally, the development of more sophisticated models that capture the time-varying nature of the relationships between cryptocurrencies and traditional asset classes could provide further insights.

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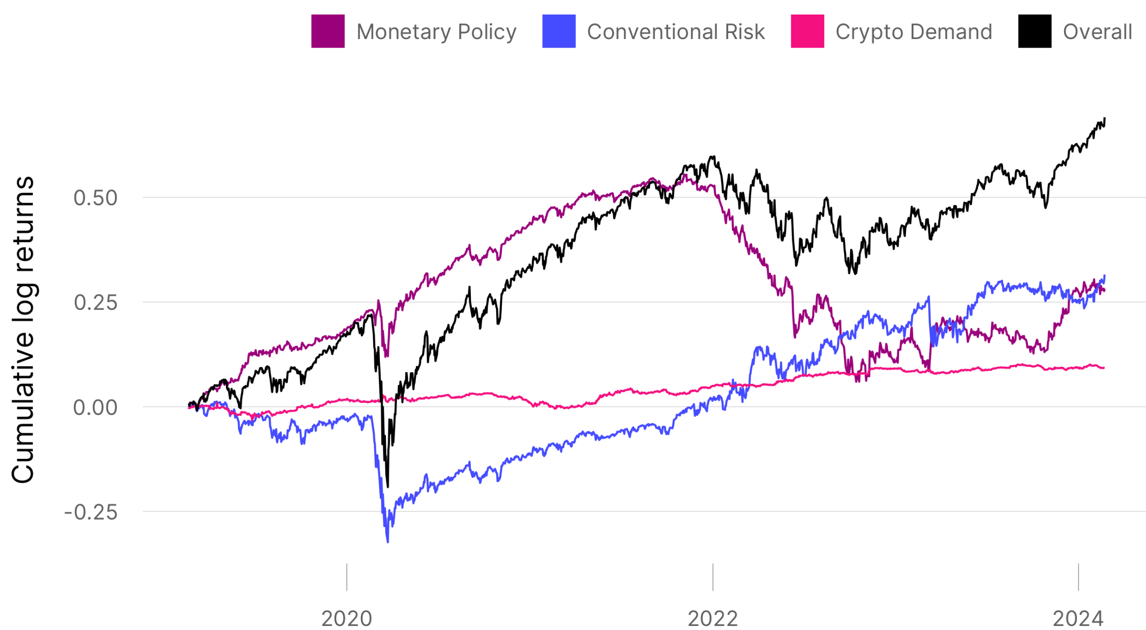
A Appendix

A.1 S&P 500 and 2-year Treasury yield decomposition

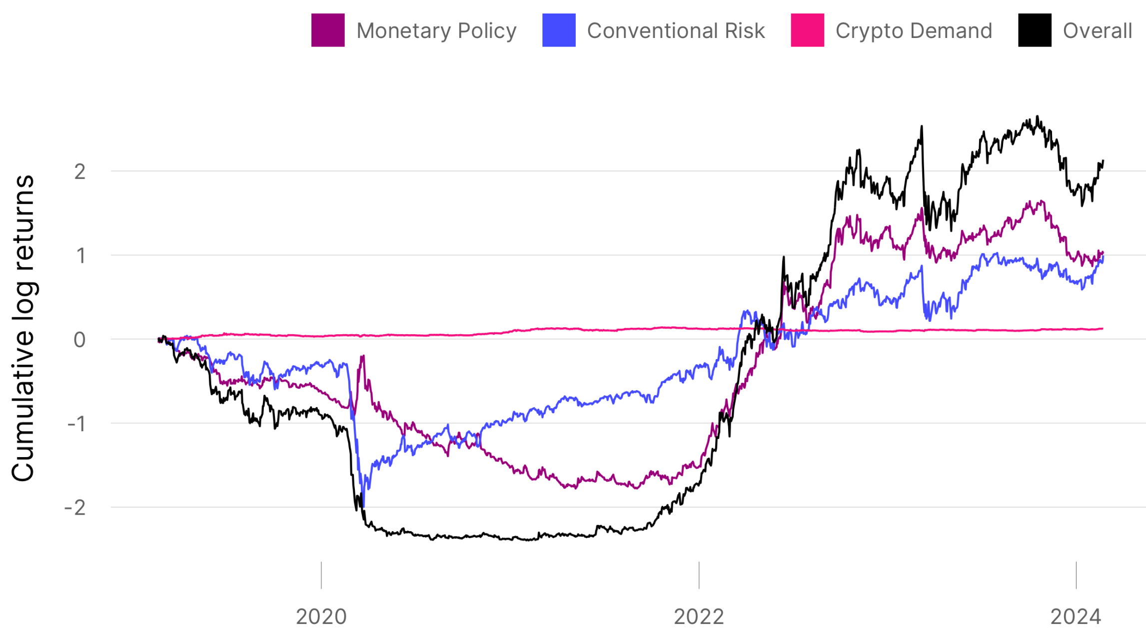
Figure A1 shows S&P 500 returns decomposed into three structural shocks. Figure A2 shows 2-year Treasury yields decomposed into three structural shocks. By assumption, there are few spillovers from crypto markets to conventional equity and bond markets.

Figure A1: S&P 500 returns decomposed into three structural shocks



The figure shows S&P 500 returns decomposed into three structural shocks: monetary policy shocks, conventional risk premium shocks, and crypto demand shocks. The decomposition uses the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions.

Figure A2: 2-Year Treasury yield changes decomposed into three structural shocks



The figure shows 2-Year Treasury yield changes decomposed into three structural shocks: monetary policy shocks, conventional risk premium shocks, and crypto demand shocks. The decomposition uses the median-target solution of a structural vector-autoregressive model identified with sign and magnitude restrictions.