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The Crypto Cycle and US Monetary Policy

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ABSTRACT: We examine fluctuations in crypto markets and their relationships to global equity markets and US monetary policy. We identify a single price component—which we label the "crypto factor"—that explains 80% of variation in crypto prices, and show that its increasing correlation with equity markets coincided with the entry of institutional investors into crypto markets. We also document that, as for equities, US Fed tightening reduces the crypto factor through the risk-taking channel—in contrast to claims that crypto assets provide a hedge against market risk. Finally, we show that a stylized heterogeneous-agent model with time-varying aggregate risk aversion can explain our empirical findings, and highlights possible spillovers from crypto to equity markets if the participation of institutional investors ever became large.

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WORKING PAPERS

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1 Introduction

Crypto assets vary substantially in their design and value propositions, yet their prices have moved in common cycles.[1] Total crypto market capitalization boomed from US$20 billion in 2016 to almost US$3 trillion in November 2021, before collapsing to below US$1 trillion in the latest crypto 'winter'.[2] Periods of exponential returns have attracted retail and institutional investors alike (Benetton and Compiani, 2022; Auer and Tercero-Lucas, 2021; Auer, Farag, Lewrick, Orazem, and Zoss, 2022), while subsequent crashes have drawn increasing attention from politicians and regulators. These fluctuations in crypto markets may also be increasingly synchronized with other asset classes: prior to 2020, Bitcoin provided a partial hedge against market risk, yet it has since become increasingly correlated with the S&P500 (Adrian, Iyer, and Qureshi, 2022).

However, we know relatively little about the common drivers of crypto asset prices or the factors affecting the correlation between crypto and equity markets, including US monetary policy. This paper tries to shed light on these issues by answering the following questions. To what extent is there a common cycle across crypto assets? Are crypto markets becoming more synchronized with global equity markets? If so, why? Given that US monetary policy has been identified as a key driver of the global financial cycle (Miranda-Agrippino and Rey, 2020), does US monetary policy influence the crypto cycle to a similar extent? If so, through which channels?

We start answering these questions by using a dynamic factor model to identify a single dominant trend in crypto-asset prices. Using a panel of daily prices for seven tokens created before 2018, which together account for approximately 75% of total crypto market capitalization, we decompose their variation into asset-specific idiosyncratic disturbances and an

[1] For instance, the white papers of prominent crypto assets include aims to provide peer-to-peer electronic cash, more efficient transactions, censorship-resistant decentralized computing, and functionality within a financial services ecosystem (Nakamoto, 2008; Buterin, 2014; Ripple Labs Inc., 2014; Binance, 2017; Sun, 2018). We exclude stablecoins from our analysis, as they are intended to maintain a constant price.

[2] Source: CoinMarketCap.com.

AR(q) common component. We find that the resulting "crypto factor" explains approximately 80% of the variance in the crypto price data. This is substantially larger than the 20% figure for global equities calculated by Miranda-Agrippino and Rey (2020), which also reflects the greater concentration of market capitalization in the largest crypto assets relative to that in the largest equities. This figure is robust for various lag orders q, and we find a similarly high degree of correlation when broadening the panel to include more crypto assets.[3]

In a second step, we study the relationship of this crypto factor to a set of global equity factors, constructed using the equity indices of the largest countries by GDP (in the spirit of Rey, 2013; Miranda-Agrippino and Rey, 2020). We find a positive correlation over the entire sample, driven by a particularly strong correlation since 2020. The increasing co-movement is not limited to Bitcoin vis-a-vis the S&P500, but pertains more broadly to the crypto and global equity factors. Disaggregating across equity markets, we find that the crypto factor correlates most strongly with the global tech factor and the small-cap factor since 2020, while it is surprisingly less correlated with the global financial factor.

The increased correlation between crypto and equities coincides with the growth in the participation of institutional investors in crypto markets since 2020. Although institutions' exposure is small relative to their balance sheets, their absolute trading volume is much larger than that of retail traders. In particular, the volume of trading by institutional investors in crypto exchanges increased by more than 1700% (from roughly \$25 billion to more than \$450 billion) from 2020Q2 to 2021Q2 (Auer et al., 2022). Since institutional investors trade both stocks and crypto assets, this has led to a progressive increase in the correlation between the risk profiles of marginal equity and crypto investors, which in turn is associated with a higher correlation between the global equity and crypto factors. When decomposing factor movements following Bekaert, Hoerova, and Lo Duca (2013), we find that correlation in the

[3]Since most crypto assets have been created only in the last couple of years, a broader panel of assets also implies a shorter time dimension—hence we focus on the seven main assets in our baseline measure.

aggregate effective risk aversion of crypto and equities can explain a large share (up to 65%) of the correlation between the two factors.

Since US monetary policy affects the global financial cycle (Miranda-Agrippino and Rey, 2020), the high correlation between equities and crypto suggests a similar impact on crypto markets. We test this hypothesis using a daily VAR with the shadow federal funds rate (SFFR) by Wu and Xia (2016) to account for the important role of balance sheet policy over our sample period. Our identification of the impact of monetary policy shocks is based on a Cholesky decomposition with the following ordering: the SFFR; the Treasury 10Y2Y spread, reflecting expectations of future growth; the dollar index, oil and gold prices, as proxies for international trade, credit and commodity cycles; the VIX, reflecting expected future uncertainty; and finally the equity and crypto factors. In this setup, endogeneity is not likely to be an issue as it is implausible that the Federal Reserve adjusts its monetary policy according to crypto price movements and that it does so at the daily level.[4]

We find that US monetary policy affects the crypto cycle, as it does with the global equity cycle, contrasting starkly with claims that crypto assets provide a hedge against market risk. A one percentage point rise in the SFFR leads to a persistent 0.15 standard deviation decline in the crypto factor over the subsequent two weeks, relative to a 0.1 standard deviation decline in the equity factor.[5] Interestingly, as with the global financial cycle (Rey, 2013), we find that only the US Fed's monetary policy matters, and not that of other major central banks—likely reflecting that crypto markets are highly dollarized.[6]

We find evidence that the risk-taking channel of monetary policy is an important channel

[4]Note that our results are also robust to relaxing the aforementioned variable ordering. When we invert the order of the variables to allow the policy rate to be the *most endogenous* one, we find similar results. As expected, we also find that the policy rate does not respond to changes in the crypto factor. Thus, our findings do not depend on an arbitrary ordering of the variables. In addition, using the available Bu, Rogers, and Wu (2021) monetary policy shocks; we still find a significant negative effect of US monetary policy on the crypto cycle at the monthly level.

[5]This refers to standard deviations of variation in crypto or equities over 2018-2023, the period for which we can construct the crypto factor.

[6]For instance, the two largest stablecoins Tether and USD Coin are pegged to the dollar, while Coinbase, the largest centralized crypto exchange, is listed on the New York Stock Exchange.

driving these results, paralleling the findings of Miranda-Agrippino and Rey (2020) for global equity markets. In particular, we find that a monetary contraction leads to a reduction of the crypto factor that is accompanied by a surge in a proxy for the aggregate effective risk aversion in crypto markets. Put differently, restrictive policies render the risk positions of investors less sustainable, and thus they reduce their exposure to crypto assets. When splitting the sample in 2020, we find that the impact on risk aversion in crypto markets is significant only for the post-2020 period, consistent with the entry of institutional investors reinforcing the transmission of monetary policy to the crypto market. More formally, we find the same result when testing this hypothesis using a smooth transition VAR following Auerbach and Gorodnichenko (2012), where the transition variable is the share of institutional investors.

Next, we rationalize our results in a model with two heterogeneous agents, namely crypto and institutional investors. The former are retail investors who only invest in crypto assets, while the latter can invest in both stocks and crypto assets. Crucially, crypto investors are risk averse, while institutional investors are risk-neutral but face a value-at-risk constraint. We can rewrite the equilibrium returns on the crypto assets as a linear combination of their variance and their covariance with stocks' returns, scaled by the aggregate effective risk aversion. The latter can be interpreted as the average risk aversion of the agents, weighted by their wealth. This implies that the higher the relative wealth of institutional investors, the more similar the crypto aggregate effective risk aversion becomes to their risk appetite and the more correlated are crypto and equity markets. Since the presence of institutional investors in crypto markets decreases the aggregate effective risk aversion, we interpret the increasing reaction of crypto prices to monetary contraction as reflecting that more levered investors are more sensitive to the economic cycle (Coimbra, Kim, and Rey, 2022; Adrian and Shin, 2014). Finally, we note that spillovers from crypto to equities can arise even in our simple framework: if institutions' crypto holdings become large, a crash in crypto prices reduces equilibrium returns in equities.

Overall, our results highlight that the crypto cycle is remarkably synchronized with global equity markets and reacts similarly to monetary policy shocks. Despite the range of explanations for crypto asset values—e.g., as an inflation hedge or as a provider of more efficient payments, censorship-resistant computing or property rights—most variation in crypto markets is highly correlated with equity prices and highly influenced by Fed policies. This also suggests emerging crypto ventures that benefited from high crypto returns were concomitantly supported by the low interest-rate environment. Finally, we find that growth in institutional participation has strengthened these conclusions and increased the risk of spillovers from crypto markets to the broader economy.

Literature: This paper contributes to the burgeoning literature on crypto assets by connecting work on specific crypto prices and the composition of crypto investors to the established literature on the global financial cycle.

First, our paper builds on work assessing the drivers of the prices of specific crypto assets. The primary aim of early developers, led by Nakamoto (2008), was to provide a new form of decentralized electronic cash that people could freely access. Several scholars have studied the matter through these lenses (Biais, Bisière, Bouvard, and Casamatta, 2018; Schilling and Uhlig, 2019; Brunnermeier, James, and Landau, 2019; Cong, He, Li, and Jiang, 2021; Auer, Monnet, and Shin, 2021; Pagnotta, 2022), yet the high price volatility and the relatively low scalability of existing distributed ledger technology have led researchers to think of most crypto tokens as assets rather than currencies (see for instance Liu, Tsyvinski, and Wu, 2022; Makarov and Schoar, 2020; Scaillet, Treccani, and Trevisan, 2020).[7] Indeed, many crypto assets lack explicit fundamental value or cash-flows (Makarov and Schoar, 2020), and are subject to fragmentation, arbitrage opportunities and market manipulation (Griffin and Shams, 2020; Gandal, Hamrick, Moore, and Oberman, 2018; Foley, Karlsen, and Putnins, 2019). In this paper, we abstract from crypto-asset-specific pricing considerations, and

[7]Indeed, to address such high volatility, the industry developed stablecoins, such as Tether or USD Coin, which are pegged to another currency (most commonly the US dollar).

instead consider the common movement in the entire asset class. In doing so, we build on Iyer (2022), who provides evidence of the positive correlation between US equity markets and Bitcoin and Ether prices, and Corbet, Larkin, Lucey, Meegan, and Yarovaya (2020) who assess the impact of macroeconomic news on Bitcoin returns.

Second, we draw on an emerging empirical literature examining the composition and motivations of crypto investors, including the increased participation of institutions. Auer and Tercero-Lucas (2021) study the profile of US crypto investors and highlight that they are in general less motivated by distrust in the traditional financial system than by the prospects for high returns.[8] Auer, Farag, Lewrick, Orazem, and Zoss (2022) are the first to focus on the role of institutional investors in crypto markets, and show that traditional financial institutions, especially lightly regulated banks, are starting to hold crypto assets.[9] We use this literature to help explain the co-movement between crypto and equities, and to construct a stylized framework for investigating potential spillovers between the two.

Third, we contribute to the literature on the global financial cycle.[10] In her seminal contribution, Rey (2013) shows the existence of a single factor that explains 20% of the variation in global asset prices. In more recent works, Miranda-Agrippino and Rey (2020) and Miranda-Agrippino and Rey (2021) highlight how US monetary policy affects this global financial cycle through the risk-taking channel. A change in interest rates forces financial intermediaries to change their leverage and thus the effective risk appetite of the marginal investor. A US monetary contraction thus negatively affects global equity prices, eroding the independence of other central banks and reinforcing the dominant role of the US dollar (Passari and Rey, 2015; Farhi and Maggiori, 2018). Within this literature, we particularly focus on the risk-taking channel of monetary policy. Coimbra et al. (2022) develop a com-

[8]Similarly Hackethal, Hanspal, Lammer, and Rink (2021) and Didisheim and Somoza (2022) document the behaviour of crypto retail investors and their portfolio allocation between equity and crypto assets.

[9]Nonetheless, banks' exposure remains limited with respect to the size of their balance sheets. In addition, Cornelli, Doerr, Frost, and Gambacorta (2023) document differences in trading behaviour between small and large investors during crisis episodes.

[10]For early discussions, see: Diaz-Alejandro (1985); Calvo, Leiderman, and Reinhart (1996).

prehensive dynamic model with heterogeneous intermediaries, which features time-varying endogenous macroeconomic risk. In their framework, the variation in risk-aversion across agents determines the aggregate risk of the economy. Relatedly, Adrian and Shin (2014) highlight how the cyclicality of leverage depends on the constraints of financial intermediaries. Fostel and Geanakoplos (2008) show how leverage cycles can be explained by differences in agents' beliefs, whereas Kekre and Lenel (2018) and Gourinchas, Rey, and Govillot (2010) focus on heterogeneity in risk aversion. We contribute to this literature by incorporating analysis of the crypto cycle.

The rest of this paper proceeds as follows. Section 2 derives the crypto factor, then Section 3 investigates its relationship to equity prices and the global financial cycle. Section 4 examines the impact of US monetary policy on the crypto factor, and Section 5 rationalizes our findings in a heterogeneous-agent model. Section 6 concludes.

2 The Crypto Factor

The prices of crypto assets are highly correlated. Table 1 reports the cross-correlations among the crypto assets with the largest market capitalization. These are remarkably high, and much larger than the correlations documented across equity markets (see, for instance, Rey, 2013). For example, Bitcoin has a 52% average correlation with other crypto assets. We thus conjecture the existence of a common crypto factor that co-moves with crypto prices, in the same spirit as the global equity factor pioneered by Rey (2013).

Table 1: Correlations among crypto assets

	Bitcoin	Ethereum	Binance Coin	Ripple	Cardano	Solana	Dogecoin	Polkadot	Tron	Shiba Inu	Maker Dao	Avalanche	Uniswap	Litecoin	FTX	Chainlink	Monero	THETA
Bitcoin	1.00																	
Ethereum	0.82	1.00																
Binance Coin	0.64	0.64	1.00															
Ripple	0.62	0.67	0.52	1.00														
Cardano	0.69	0.75	0.56	0.65	1.00													
Solana	0.47	0.57	0.51	0.42	0.48	1.00												
Dogecoin	0.34	0.31	0.24	0.26	0.30	0.16	1.00											
Polkadot	0.64	0.70	0.58	0.49	0.63	0.52	0.23	1.00										
Tron	0.59	0.61	0.47	0.58	0.59	0.37	0.25	0.56	1.00									
Shiba Inu	0.49	0.47	0.46	0.41	0.42	0.34	0.51	0.43	0.34	1.00								
Maker Dao	0.38	0.45	0.32	0.33	0.38	0.43	0.15	0.54	0.27	0.32	1.00							
Avalanche	0.55	0.59	0.55	0.48	0.64	0.54	0.21	0.59	0.44	0.34	0.51	1.00						
Uniswap	0.53	0.63	0.47	0.44	0.54	0.47	0.14	0.60	0.46	0.43	0.54	0.51	1.00					
Litecoin	0.80	0.82	0.63	0.67	0.72	0.49	0.33	0.66	0.58	0.45	0.38	0.53	0.56	1.00				
FTX	0.03	0.00	0.03	0.00	-0.01	0.52	0.00	0.52	0.00	0.31	-0.01	0.48	0.45	-0.01	1.00			
Chainlink	0.59	0.66	0.51	0.53	0.58	0.53	0.27	0.70	0.52	0.42	0.33	0.59	0.59	0.60	-0.01	1.00		
Monero	0.75	0.73	0.59	0.59	0.66	0.43	0.30	0.55	0.55	0.39	0.34	0.46	0.44	0.72	0.04	0.54	1.00	
THETA	0.55	0.56	0.48	0.46	0.53	0.43	0.22	0.60	0.48	0.40	0.27	0.50	0.49	0.55	-0.01	0.48	0.53	1.00

Notes: This table shows pairwise correlations between selected crypto-asset returns. Data is from January 2018 to March 2023.

To summarize the fluctuations in crypto markets into one variable, we use dynamic factor modelling, a dimensionality reduction technique.[11] This allows us to decompose a set of prices into their idiosyncratic components and a common trend. Specifically, we start with the daily prices of the largest crypto assets that were created before January 2018 (excluding stablecoins). This leaves us with seven crypto assets, accounting for 75% of total market capitalization in June 2022.[12] We then write this panel of crypto prices p_{it} as a linear combination of an AR(q) common factor f_t and an asset-specific idiosyncratic disturbance ϵ_{it} (which in turn follows an AR(1) process):

$$
\begin{aligned}
p_{it} &= \lambda_i(L) f_t + \epsilon_{it} && && (1)\\
f_t &= A_1 f_{t-1} + ... + A_q f_{t-q} + \eta_t && \eta_t \sim \mathcal{N}(0, \Sigma) &&\\
\epsilon_{it} &= \rho_i \epsilon_{it-1} + e_{it} && e_{it} \sim \mathcal{N}(0, \sigma_{it}^2) &&
\end{aligned}
$$

where L is the lag operator and $\lambda_i(L)$ is a q-order vector of factor loadings for asset i. Estimating this system using maximum likelihood, selecting q using information criteria,

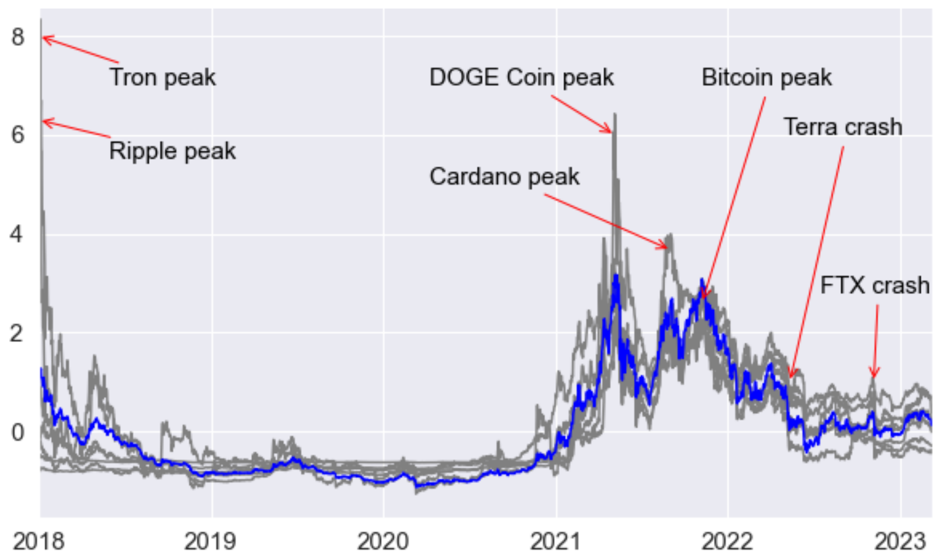
[11] For the evolution of the method, see, among others: Geweke (1977); Sargent and Sims (1977); Forni, Hallin, Lippi, and Reichlin (2000); Bai and Ng (2002); Stock and Watson (2002); Miranda-Agrippino and Rey (2020).

[12] These are: Bitcoin, Ethereum, Binance Coin, Ripple, Cardano, DogeCoin, and Tron.

produces our common factor f_t.[13] It is also possible to specify multiple factors that affect prices differently, and we use this latter specification when we consider multiple distinct sub-classes of crypto assets.

Figure 1 shows the crypto factor and the underlying price series from which we extract it. The crypto factor effectively captures the salient phases that characterized crypto markets—such as the decline at the beginning of 2018, the subsequent 'crypto winter', the latest boom with the peaks in Bitcoin and Dogecoin, and finally the slump of Terra and FTX of 2022—without being overly influenced by isolated spikes like those of Ripple and Tron.

Figure 1: The crypto factor



Notes: This figure shows the crypto factor (blue) and the standardized crypto prices from which it is constructed (grey) using a dynamic factor model.

To gauge the importance of this factor more systematically, we regress each price series in turn on the crypto factor. On average, 80% of variation in the underlying series is explained by our crypto factor.[14] This figure is above 68% for all seven assets, underscoring

[13]We use the Python package STATSMODELS/DYNAMICFACTOR. For further information about the model and algorithm, see `https://www.statsmodels.org/dev/examples/notebooks/generated/statespace_dfm_coincident.html`.

[14]See Appendix Figure A.1 for the breakdown across individual crypto assets.

the high degree of co-movement over our sample period. For comparison, the global equity factor calculated by Miranda-Agrippino and Rey (2020) explains only 20% of global equity prices, highlighting the greater co-movement and concentration of market capitalization in the crypto market. Our findings thus strongly corroborate the hypothesized existence of a single crypto factor that drives the prices of the entire crypto market.

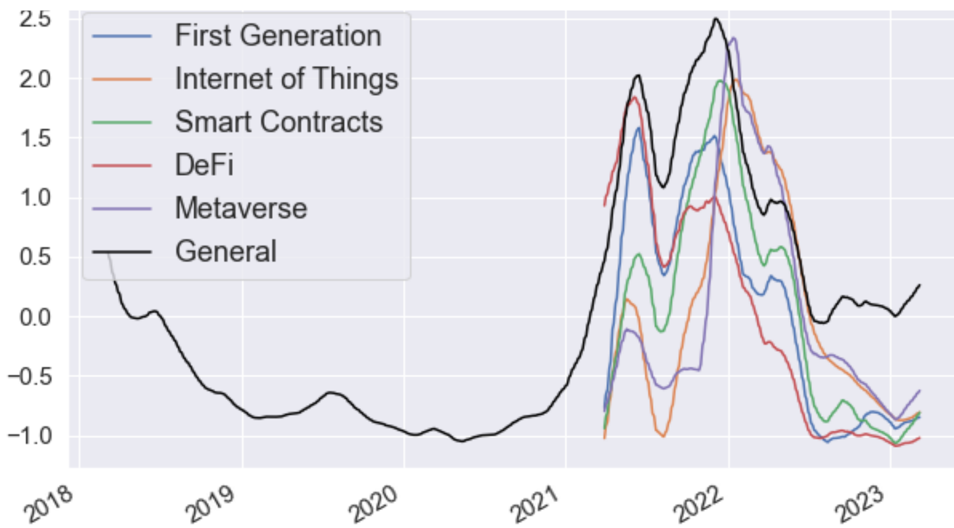
Given the limited range of assets used to calculate our factor, we also confirm that our crypto factor reflects more recent trends in newer assets.[15] To do so, we examine a broader sample of assets, grouped into five categories: First Generation tokens (Bitcoin, Ripple and Dogecoin), Smart Contracts platform tokens (Ethereum, Binance Coin, Cardano, Solana and Polkadot), DeFi tokens (Chainlink, Uniswap, Maker and Aave), Metaverse tokens (Flow, Ape Coin, the Sandbox, Decentraland and Theta Network) and Internet of Things tokens (Helium, Iota, IoTex and MXC). We then estimate a new model with five different factors, where each factor can only affect one class. The results are shown in Figure 2, along with the general crypto factor estimated above.[16] All classes are highly correlated with the general crypto cycle, validating our focus on the common trend.[17]

[15]We do not include these newer assets in the calculation of the main factor, as they would further limit the timespan of our sample.

[16]Note that the timespan for each of the new factors is substantially shorter, given that many were created only in 2021.

[17]The main exception is the jump in the Metaverse factor in late 2021, when Facebook re-branded to Meta. Outside of this idiosyncratic shock, movements in the Metaverse factor also follow the general trend.

Figure 2: Crypto sub-factors

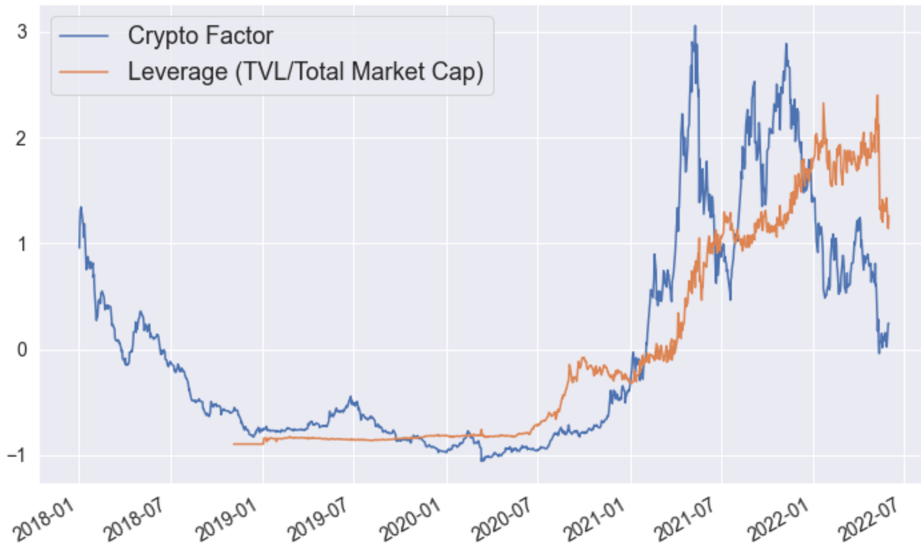


Notes: This graph shows the overall crypto factor and five crypto sub-factors, standardized and smoothed. The sub-factors are constructed from the following assets: First Generation tokens—Bitcoin, Ripple and Dogecoin; Smart Contract platform tokens—Ethereum, Binance Coin, Cardano, Solana and Polkadot; DeFi tokens—Chainlink, Uniswap, Maker and Aave; Metaverse tokens—Flow, Ape Coin, the Sandbox, Decentraland and Theta Network; and Internet of Things tokens—Helium, Iota, IoTex and MXC.

Finally, and consistent with anecdotal evidence, the crypto factor correlates with a proxy for leverage in crypto markets. Figure 3 plots the crypto factor against crypto leverage, defined using the total value locked (TVL) in decentralized finance ("DeFi") contracts normalized by total crypto market capitalization.[18] This shows that the system was relatively unlevered until the end of the 2018-2019 crypto winter, after which leverage increased substantially and the correlation with the general crypto factor increased.

[18] TVL data from `https://defillama.com/`. While this measure of leverage is incomplete, since it does not capture the indebtedness present in exchanges or due to bilateral loans, it is indicative of total leverage in the system. We normalize by total crypto market capitalization to control for the fact that a large share of DeFi lending is denominated in crypto assets, so a rise in the price of these assets increases nominal leverage, and hence would generate a mechanical correlation with our crypto factor in the absence of the normalization.

Figure 3: De-fi leverage



Notes: This graph shows the overall crypto factor and a proxy for total DeFi leverage, defined as the total value locked (TVL) in decentralized finance contracts normalized by total crypto market capitalization. The TVL data is downloaded from `https://defillama.com/`.

3 Crypto and the Global Financial Cycle

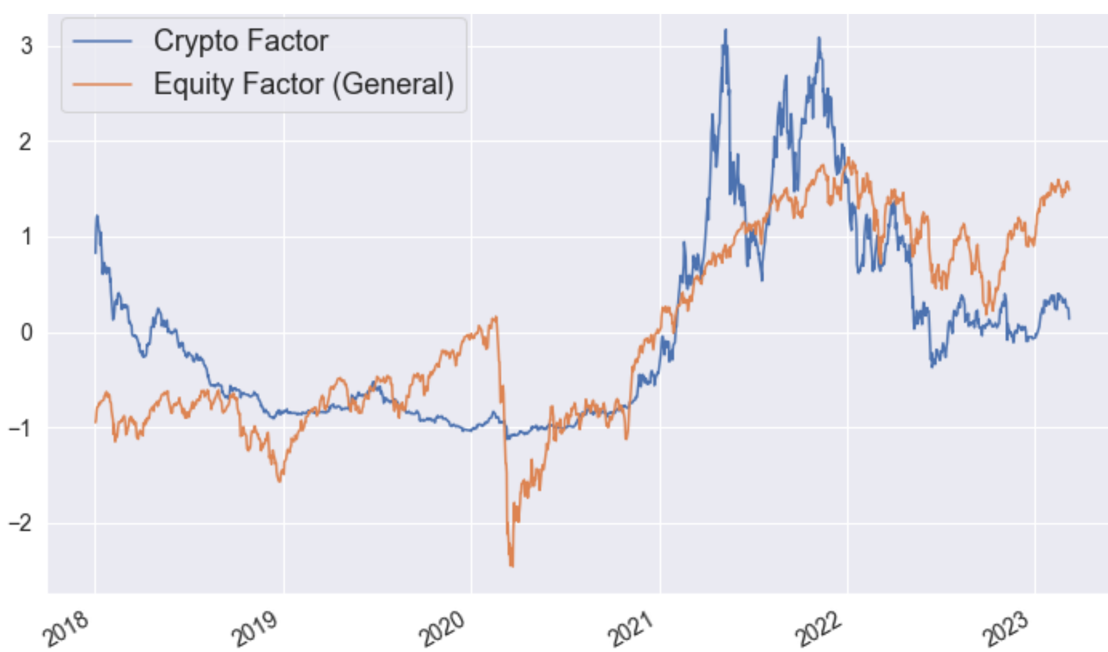
We now turn to the relationship between the crypto factor and global equities. Iyer (2022) has documented an increase in correlation between Bitcoin and S&P500 returns since 2020. We therefore conjecture that crypto markets have become more integrated and synchronized with the equity cycle. To assess this, in this section we compute a global equity factor, then examine its relationship to the crypto factor.

We construct the global equity factor using all the equity indices available on Eikon/Thomson Reuters for the largest fifty countries by GDP.[19] We then follow the same methodology as in the previous section to compute: a general factor using all major stock indices, a factor for small capitalization stocks, and separate factors for each of the technology and financial

[19]Table A.1 in Appendix A details the full list of indices used.

sectors. Figure 4 shows both the equity and the crypto factors. As with the crypto factor, the equity factor credibly replicates the dynamics of global markets, with the sharp decline during the COVID-19 shock, the subsequent recovery and the downturn in early 2022. Generally speaking, the two series are fairly uncorrelated before 2020, then increasingly correlated from the second half of 2020. More formally, in Table 2, we regress changes in the crypto factor on changes in each of the other factors. Model (1) shows that, in general, the correlation between the crypto and the equity factor is highly significant, while models (2) and (7) specifically highlight that this relationship is driven by the technology and small-cap components.

Figure 4: Crypto and equity factors



Notes: This figure shows the standardized time series of the crypto and equity factors, derived using dynamic factor modelling from a large range of crypto prices and equity indices respectively, as described in Section 2.

Table 2: Factor regressions

	Δ Crypto Factor						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Global Equity Factor	0.310***						
	(6.57)						
Δ Global Tech Factor		0.627***				0.663***	
		(8.76)				(6.73)	
Δ Global Equity Factor excl. Tech			0.00916				
			(0.10)				
Δ Global Financial Factor				0.158***		-0.0226	
				(5.55)		(-0.61)	
Δ Global Equity Factor excl. Financials					0.519***		
					(4.90)		
Δ Global Small Caps Factor							0.385***
							(6.61)
Constant	-0.00111	-0.00161	-0.000529	-0.000552	-0.000529	-0.00167	-0.000926
	(-0.43)	(-0.63)	(-0.20)	(-0.21)	(-0.20)	(-0.65)	(-0.36)
Observations	1302	1302	1302	1302	1302	1302	1302
R-squared	0.047	0.069	0.000	0.026	0.027	0.069	0.050

Notes: This table reports the results from regressing the crypto factor on different combinations of equity factors. Data is from January 2018 to March 2023. Variables are standardized. t-statistics are in parentheses. *, **, and *** correspond to significance at the 10%, 5%, and 1% levels respectively.

In Table 3, we report the correlation matrices for a wide range of crypto and equity variables before and after 2020. Consistent with Iyer (2022), the correlation between Bitcoin and the S&P500 was low before 2020 but increased significantly afterward. This is also the case for the correlation between the crypto and global equity factors. In particular, the crypto factor correlated increasingly strongly with the small cap and technology factors, and relatively less so with the financial factor. In Table A.2 in Appendix A, we report the p-values of such differences in correlations, computed by regressing the different crypto factors on equity factors (or other variables, e.g., gold and oil prices), a time dummy and their interactions.

Table 3: Cross-correlations between factors before and after 2020.

Before 2020

	Bitcoin	Crypto F	First Gen	IoTs	Smart C.	DeFi	Metaverse
Bitcoin	1.00						
Crypto F	0.76	1.00					
First Gen							
IoTs							
Smart C.							
DeFi							
Metaverse							
S&P 500	0.01	0.09					
Equity F	0.00	0.07					
Small Caps F	0.01	0.09					
Tech Factor	-0.01	0.06					
Equity F (no Tech)	0.01	0.04					
Financials F	-0.03	0.03					
Equity F (no Fin)	0.05	0.09					
Dollar Index	-0.05	0.00					
VIX	-0.08	-0.19					
Oil	0.01	0.04					
Gold	0.08	0.03					

After 2020

	Bitcoin	Crypto F	First Gen	IoTs	Smart C.	DeFi	Metaverse
Bitcoin	1.00						
Crypto F	0.85	1.00					
First Gen	0.80	0.91	1.00				
IoTs	0.65	0.78	0.76	1.00			
Smart C.	0.80	0.97	0.80	0.73	1.00		
DeFi	0.65	0.85	0.76	0.69	0.85	1.00	
Metaverse	0.40	0.45	0.38	0.43	0.47	0.38	1.00
S&P 500	0.29	0.28	0.26	0.28	0.36	0.24	0.27
Equity F	0.25	0.24	0.23	0.24	0.33	0.23	0.23
Small Caps F	0.26	0.24	0.22	0.23	0.32	0.24	0.23
Tech Factor	0.30	0.29	0.25	0.26	0.35	0.23	0.25
Equity F (no Tech)	0.00	0.00	-0.02	-0.02	-0.02	0.01	-0.02
Financials F	0.19	0.18	0.17	0.16	0.24	0.17	0.17
Equity F (no Fin)	0.17	0.18	0.14	0.17	0.22	0.13	0.14
Dollar Index	-0.14	-0.16	-0.14	-0.09	-0.19	-0.13	-0.09
VIX	-0.26	-0.24	-0.28	-0.29	-0.37	-0.26	-0.26
Oil	0.05	0.05	0.05	0.01	0.08	0.05	0.06
Gold	0.05	0.06	0.05	0.02	0.07	0.04	0.01

Notes: The tables above show the cross-correlations between the crypto and equity factors and sub-factors, before and after 2020. Note that we cannot compute correlations for crypto sub-factors before 2020, as most of the constituent assets from which they are derived did not exist at that time. p-values are reported in Table A.2 in Appendix A.

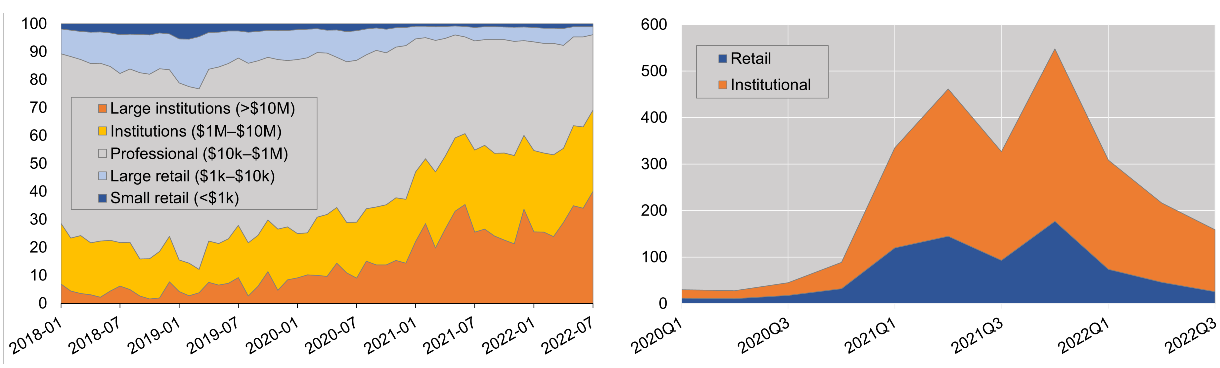
What drove the increased correlation between crypto and equities? Previous literature suggests a range of possible (and mutually compatible) explanations. Retail investors increased their trading during the COVID-related lockdowns, including in crypto assets (Schwab, 2021; Vanda Research, 2021). Indeed, Toczynski (2022) estimates that roughly US$15 billion of the federal stimulus checks was spent on trading crypto assets. New on-ramps also opened to cater for the growing demand. For instance, popular mobile payment applications (e.g., Revolut, Paypal) and trading platforms (e.g., Robinhood) allowed their clients to trade crypto assets. Coinbase, a centralized crypto exchange, was listed on the Nasdaq in April 2021. New investment products, such as the Grayscale Bitcoin Trust, were created to give investors exposure to crypto assets without holding tokens.

Against this backdrop, institutional investors also increased their exposure to crypto assets. Using a novel supervisory database, Auer et al. (2022) document the growing importance of traditional financial intermediaries in crypto markets. They show that banks' exposure to crypto assets has increased, and that, while it remains small relative to their balance sheets, it is significant for the crypto market, which was previously populated predominantly by retail investors. Using data scraped from public blockchains by Chainalysis (2021), we find similarly that institutional investors' share of crypto trading volumes has risen dramatically since 2020 (Figure 5 Panel (a)). While this method relies on proxying for investor type by the size of on-chain transactions (for example, transactions under \$10k are classified as trades by retail traders), we see a similar pattern in self-reported data from centralized exchanges (Figure 5 Panel (b)). By 2022, institutional investors made up a substantial majority of total trading volumes.

Figure 5: Increasing institutional participation in crypto markets

(a) Share of on-chain trading volumes

(b) Trading volumes on Coinbase (\$bn)



Notes: Panel (a) shows the share of on-chain trading volumes by investor type over time, using data scraped by Chainalysis (2021). Investor types are proxied by transactions sizes, e.g. trades under \$10k are classified as trades by retail traders. Panel (b) shows the relative trading volumes on Coinbase of retail and institutional investors, reported in the company's public financial statements (available at `https://investor.coinbase.com/financials/quarterly-results/`).

In Table 4, we further investigate the relationship between the share of institutional investors and the correlation between equity and crypto factors. Consistent with previous findings, the correlation between Bitcoin and the S&P500 is positive and significant only after 2020 (columns (1) and (2)), and the same applies to the crypto and equity factors (columns (3) and (4)). Finally, column (5) shows that the share of institutional investors plays a significant and important role in explaining the correlation between the two factors.

Arguably, the growing participation of institutional investors that are also heavily exposed to traditional stocks creates a direct link between equity and crypto markets.

Table 4: Factor regressions and participation of institutional investors

	Δ Bitcoin		Δ Crypto Factor		
	(1)	(2)	(3)	(4)	(5)
Δ SP500	0.268***	0.00378			
	(8.72)	(0.10)			
Δ SP500 # After 2020		0.304***			
		(5.88)			
After 2020		0.0268		0.0544	
		(0.60)		(1.18)	
Δ Global Equity Factor			0.217***	0.0437	0.180***
			(6.57)	(1.39)	(7.23)
Δ Global Equity Factor # After 2020				0.206***	
				(4.08)	
Δ Global Equity Factor # Share of Institutionals					0.226***
					(5.02)
Share of Institutionals					0.00302
					(0.08)
Constant	-5.45e-10	-0.0163	-1.17e-09	-0.0338	-0.00284
	(-0.00)	(-1.03)	(-0.00)	(-1.81)	(-0.10)
Observations	1302	1302	1302	1302	1148
R^2	0.0721	0.0825	0.0472	0.0535	0.0854
R^2 (adj)	0.0714	0.0804	0.0465	0.0513	0.0830

Notes: This table reports the results from regressing the bitcoin and the crypto factor on the S&P500 and the equity factor along with different interactions with time dummies and the share of institutional investors. Variables are standardized. Data is from January 2018 to March 2023. Standard errors are in parentheses. *, **, *** correspond to 10%, 5%, and 1% significance, respectively.

Given the importance of institutions, we now investigate their role in changing the profile of the marginal crypto investor. To examine this empirically, we follow Bekaert et al. (2013) and Miranda-Agrippino and Rey (2020) in decomposing movements in the factors into two elements: (i) changes in market risk, and (ii) changes in market attitudes towards risk, i.e., 'aggregate effective risk aversion', defined as the wealth-weighted average risk aversion of investors. Proxying (i) with realized market risk, measured by the 90-day variance of the MSCI World index as in Miranda-Agrippino and Rey (2020), we can then estimate (ii) as (an inverse function of) the residual ϵ of the following regression in logarithms:

$$f_t^{Equities} = \alpha + \beta_1 \cdot Var(\text{MSCI World})_t + \epsilon_t \tag{2}$$

and similarly for crypto:

$$f_t^{Crypto} = \alpha' + \beta_1' \cdot Var(\text{MSCI World})_t + \beta_2' \cdot Var(\text{BTC})_t + \epsilon_t' \tag{3}$$

where: f_t are the factors estimated using the methodology in Equation 1 above; we repeat the MSCI World term in the crypto regression to control for overall global market risk; and we add the 90-day variance of the Bitcoin price in the crypto regression as an analogous proxy for realized crypto market risk.[20]

The effective equity risk aversion extracted from Equation 2 is consistent with other proxies of investors' risk-taking in literature. The correlation (in changes) of the 90-day equity risk aversion with the intermediary capital ratio and the square of the intermediary leverage ratio developed by He, Kelly, and Manela (2017) are -0.292 and 0.434, respectively (see Table A.4 in Appendix A). The interpretation of these proxies is the following: when a negative shock hits the equity capital of the intermediaries, their leverage increases; thus, their risk-bearing capacity is impaired, and the effective risk-aversion rises. The correlations are relatively high, given that He et al. (2017) use a very different methodology and we are comparing daily measures. Indeed, their proxies are constructed using capital ratios only

[20]Regression results are reported in Appendix Table A.3. Note that we include both equity and crypto measures of market variance in order to account for *all* risks and to be more conservative about the price variation that we ascribe to the aggregate risk aversion. Such considerations are even more relevant if crypto investors are exposed to both equity and crypto markets.

for the primary dealer counterparties of the New York Federal Reserve, and not from (a dynamic factor computed from) global equity prices (see Equation 6 of their paper).

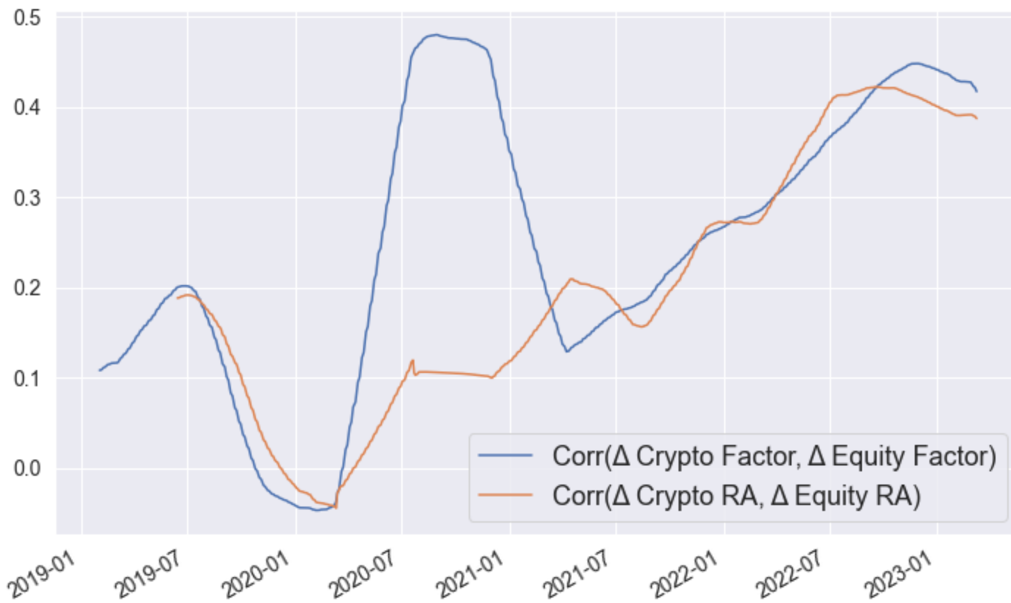
Figure 6 shows the resulting aggregate effective risk aversion for the marginal crypto investor, along with the crypto factor. We identify two main phases, before and after the late 2019 peak. At the beginning of our sample, the effective risk aversion of crypto investors was more volatile and characterized by a somewhat increasing trend. Notably, this coincided with the 'crypto winter', an extensive period of relatively flat or negative returns. After 2020, the effective risk aversion declined fairly steadily and the crypto factor exhibited large returns and high volatility. Interestingly, since the collapse of Terra/Luna in May 2022, the crypto factor is almost a mirror image of effective risk aversion, implying that crypto prices have been driven primarily by changes in the risk appetite of crypto investors. Finally, we note that the decline in the effective risk aversion corresponded with the increase in the participation of institutional investors, who can bear more risk than retail investors and thus change the profile of the marginal crypto investor.

Figure 6: Aggregate effective crypto risk aversion

Notes: This figure shows the crypto factor and the aggregate effective risk aversion in crypto markets, estimated following Bekaert et al. (2013) and Miranda-Agrippino and Rey (2020) as described in the text. Both variables are standardized.

Comparing the estimated risk aversion in crypto to that for equities, we see an increase in correlation since 2020 (Figure 7, orange line). At its peak in 2022, the correlation was more than 40%. This implies that the risk profiles of the marginal crypto and marginal equity investors have become more similar, again coinciding with increased institutional entry into crypto markets (Figure 5). This rise also parallels the aforementioned increasing correlation between the overall crypto and equity factors (Figure 7, blue line).

Figure 7: Rolling correlations between crypto and equities



Notes: This graph shows the 180-day rolling correlations between the crypto and equity factors (blue) and between the risk aversions of the marginal investors in each of the two asset classes (orange), where the risk aversions are calculated following Bekaert et al. (2013) and Miranda-Agrippino and Rey (2020) as described in the text.

To assess the strength of this possible relationship, in Table 5 we regress the rolling correlation between the equity and crypto factors on the correlation between their respective effective risk aversions. The coefficients are positive and highly significant across all specifications and the R^2s are relatively high, even reaching 65% for the 30-day window. This further suggests that the correlation between effective risk aversions can explain a substantial share of the variation in the factors' correlation.

Table 5: Correlations regressions

	Corr(Δ Crypto Factor, Δ Equity Factor)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Corr(Δ Crypto RA, Δ Equity RA)	0.854***	0.833***	0.802***	0.773***	0.705***	0.633***	0.473***
	(0.016)	(0.018)	(0.021)	(0.023)	(0.027)	(0.027)	(0.018)
Constant	0.036***	0.046***	0.074***	0.091***	0.116***	0.130***	0.154***
	(0.006)	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.005)
Rolling window	30	45	90	120	180	240	360
Observations	1,183	1,168	1,123	1,093	1,033	973	853
R-squared	0.648	0.564	0.455	0.408	0.356	0.364	0.434

Notes: This table reports the results of regressing the rolling correlation between the delta crypto and the delta equity factors on the rolling correlation between the delta crypto and delta equity aggregate effective risk aversions. Data is from January 2018 to March 2023. Standard errors are in parentheses. *, **, *** correspond to 10%, 5%, and 1% significance, respectively.

Overall, our findings are consistent with the hypothesis that the entry of institutional investors was a major factor driving the increase in correlation between crypto and equity markets. At the same time as many traditional financial institutions entered crypto markets, the risk aversion of the marginal crypto investor became increasingly similar to that of the marginal equity investor, and this correlation in turn can explain an important share of the correlation between the crypto and equity factors.

4 Crypto and US Monetary Policy

In the first part of the paper, we documented the existence of a single crypto factor that explains a large share of the variation in crypto prices, and highlighted that it is increasingly correlated with the global equity factor. Since the literature has shown that US monetary policy influences the global financial cycle (Rey, 2013; Miranda-Agrippino and Rey, 2020), it is plausible that it might also affect the crypto cycle. In this section, we therefore assess the impact of US monetary policy on the crypto cycle, and the channels through which this occurs.

4.1 The impact of monetary policy on the crypto factor

To assess the impact of monetary policy on crypto markets, we use a daily vector autoregressive model (similarly to Miranda-Agrippino and Rey, 2020). Table 6 shows the order of the variables and the various controls that we include in each of our main specifications. We identify monetary policy shocks using a Cholesky decomposition in which the policy variable and controls are ordered first. In this setup, endogeneity is not likely to be an issue as the Fed does not tune interest rates or its open market operations in response to the evolution of crypto markets. Furthermore, we use variables at a daily frequency, such that reverse causation would only occur if the Fed adjusted its policy in response to the crypto market on a day-to-day basis. Nonetheless, among the battery of robustness tests we run, we also invert the order of the variables to allow the policy rate to be the most endogenous with respect to all other variables. We find that results are robust, i.e., do not depend on an arbitrary ordering of the variables, and—as expected—that the policy rate does not respond to changes in the crypto factor.[21]

We measure the monetary policy stance using the shadow federal funds rate developed by Wu and Xia (2016), as it reflects that balance sheet policy is now part of the conventional tool kit of modern central banking. If we only used the federal funds rate, we would omit relevant information. This is especially the case given our recent sample period, with the primary response to the COVID shock occurring through balance sheet policies.

In our specifications, beyond the variables related to equity and crypto prices, we account for a set of variables that proxy for global economic activity. Specifically, we include: (i) the spread between ten- and two-year yields on US government bonds, reflecting investors' expectations of future economic growth; (ii) the dollar index, to proxy for the status of international trade and credit flows—which the literature has shown to be cyclical (e.g.,

[21]In addition, in Table A.5 in Appendix A, we estimate a simple monthly regression of the crypto factor and bitcoin on the Wu and Xia (2016) shadow rate and on monetary policy shocks from Bu et al. (2021). For the latter, we use latest updated series, which includes data up to end-2021. Although the sample size is very small, we still find a significant negative effect of US monetary policy on the crypto cycle.

Bruno and Shin, 2022); (iii) oil and gold prices, as they are usually associated with the economic cycle; and (iv) the VIX to capture anticipated future uncertainty and effective risk-aversion.

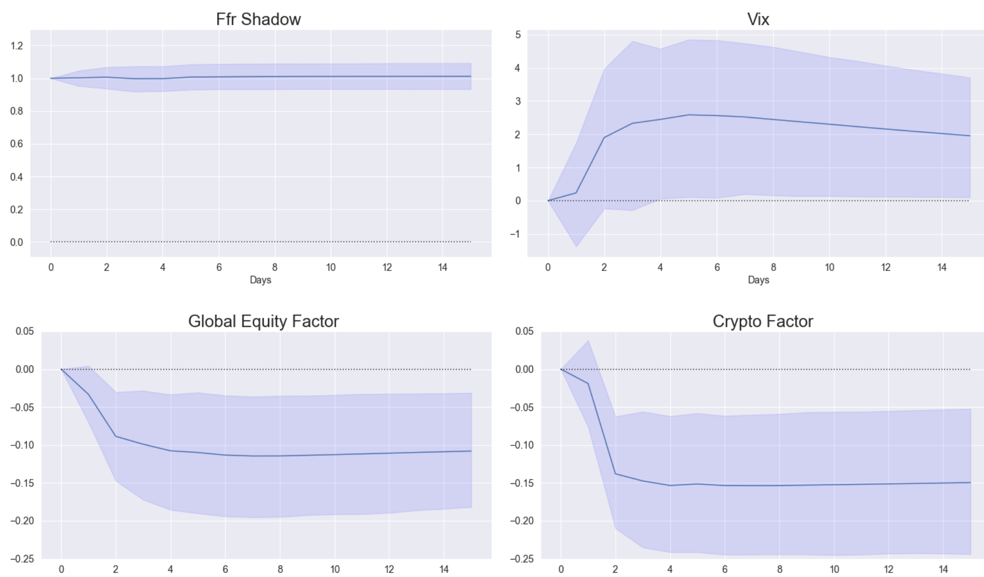
Table 6: VAR specifications

Variable Ordering	(1)	(2)	(3)	(4)	(5)
Interest Rates					
Wu-Xia Shadow FFR	✓	✓		✓	✓
Average S-FFR (BOE,ECB,Fed)			✓		
Conjuncture					
10-2 Y Treasury Yield Spread	✓	✓	✓	✓	✓
Dollar Index	✓	✓	✓	✓	✓
VIX	✓	✓	✓	✓	
Oil	✓	✓	✓	✓	✓
Gold	✓	✓	✓	✓	✓
Equity Variables					
Aggregate Equity Risk Aversion					✓
S&P500		✓			
Global Equity Factor	✓		✓	✓	✓
Crypto Factors					
Aggregate Crypto Risk Aversion					✓
Bitcoin		✓			
Crypto Factor	✓		✓		✓
First Generation Factor				✓	
Smart Contracts Factor				✓	
DeFi Factor				✓	
Metaverse Factor				✓	
IoT Factor				✓	

Notes: This table shows the selection and ordering of variables in each of our VAR specifications. Column (1) is our baseline specification. Column (2) tests whether the baseline results are determined by the construction of the crypto and equity factors. Column (3) explores if the crypto factor is affected by other (major) monetary policies. Column (4) investigates the heterogeneous effects of the responses by crypto sub-classes. Finally, column (5) tests whether US monetary policy affects the crypto factor via the risk-taking channel (as in Miranda-Agrippino and Rey, 2020). Data is from January 2018 to March 202, with the exception of column (4) which is from 2021 due to data availability.

Figure 8 reports the most relevant cumulative impulse response functions for the first specification in Table 6. Overall, the signs of the responses are consistent with the literature. A Fed monetary contraction leads to an increase in the VIX and to a decline in the global equity factor as in Miranda-Agrippino and Rey (2020). Importantly, we also find that Fed monetary policy has a large and persistent impact on the crypto factor, as with traditional stocks. Specifically, the crypto factor declines by 0.15 standard deviations, while the equity factor declines only by 0.1 standard deviation.[22] This indicates that crypto assets are subject to US monetary policy and the economic cycle similarly to traditional investments, in contrast to claims of orthogonality to the traditional financial system or usefulness as a hedge against market risk. We postpone the discussion of the drivers of these findings to Sections 4.2 and 4.3.

Figure 8: Baseline VAR results

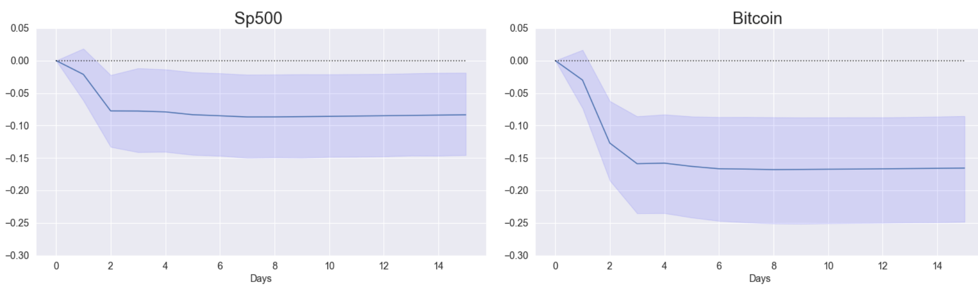


Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (1) (see Table 6 for details). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. Factors are standardized over the sample period.

[22]Note that for comparability the factors are both standardized with respect to the same sample period. The magnitudes of the effects can therefore be interpreted as the responses—measured in 2018-2023 standard deviations—of the factors to a hypothetical one percentage point hike in the shadow FFR.

To confirm that our results are not biased by the construction of the factors, we re-estimate the impulse responses using the S&P500 and the Bitcoin price instead of the factors (specification (2) in Table 6). The estimates in Figure 9 are very similar to the responses in Figure 8, reassuring us that the previous results are not artifacts of our particular methodology for deriving the factors, nor are they due to the selection of assets we considered.

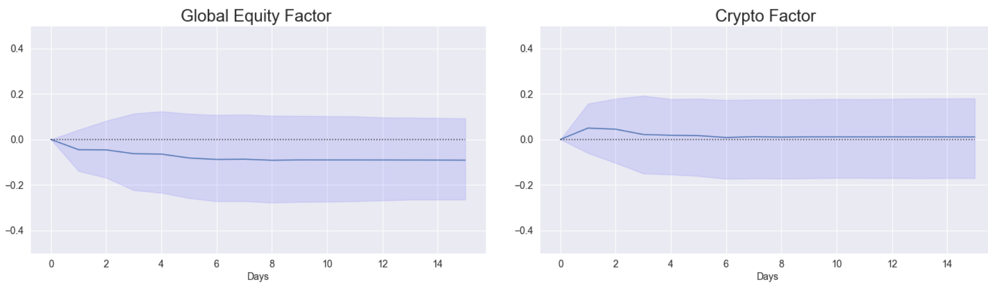
Figure 9: Robustness to factor construction



Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (2) (see Table 6). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. Variables are standardized over the sample period.

We also check whether our results are specific to Fed policy, or hold equally across major central banks. In specification (3), we instead define the policy variable as the average shadow rate of the Fed, the Bank of England and the European Central Bank, weighted by the size of their balance sheets. Consistent with the extensive literature on dollar dominance, we find much weaker responses to this broader policy tightening (see Figure 10). There is no longer a significant impact on the global equity factor, and this is also the case for the crypto factor, possibly reflecting that crypto markets are increasingly dollarized. For instance, the largest stablecoins are USD-denominated, most crypto borrowing and lending occurs in USD stablecoins, and crypto prices are usually expressed in dollars. Indeed, Auer et al. (2022) document that a large share of total global crypto trading occurs in North America.

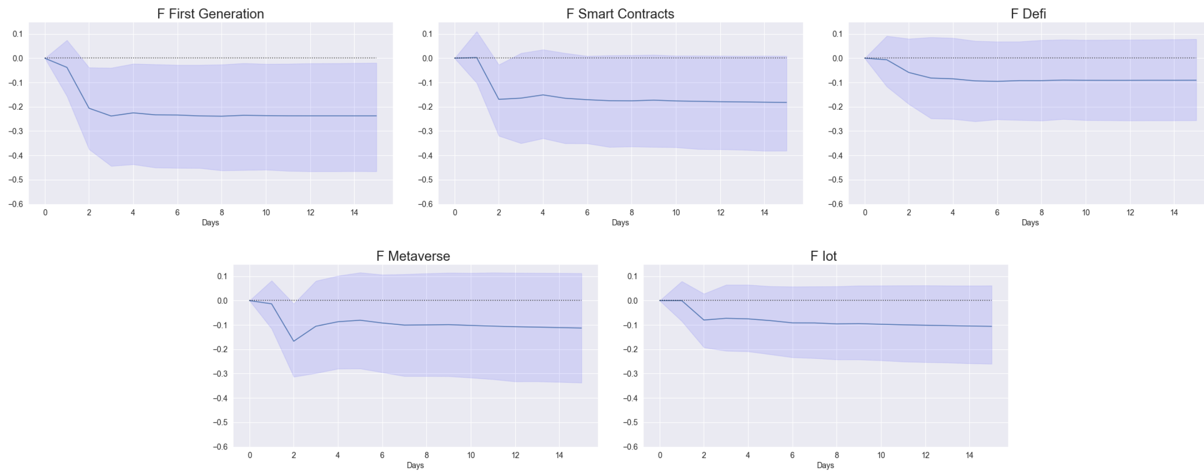
Figure 10: Impacts of global tightening



Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (3) (see Table 6). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. Factors are standardized over the sample period.

Next, we disaggregate across the different crypto sub-classes, as described in Section 2. Figure 11 shows the results from running VAR specification (4). Since many of the tokens did not exist in 2018, we shorten the sample in each case to start from the first date for which the respective prices are available. Overall, our results show that the reaction of First Generation coins is consistent with our baseline. However, while the other sub-factors show a similar shape, their response is insignificant, in part reflecting the shorter estimation sample. The category that is farthest from having a significant reaction is the Metaverse, possibly because such tokens are relatively newer with smaller market caps and a mostly retail investor base.

Figure 11: Impacts on crypto sub-factors

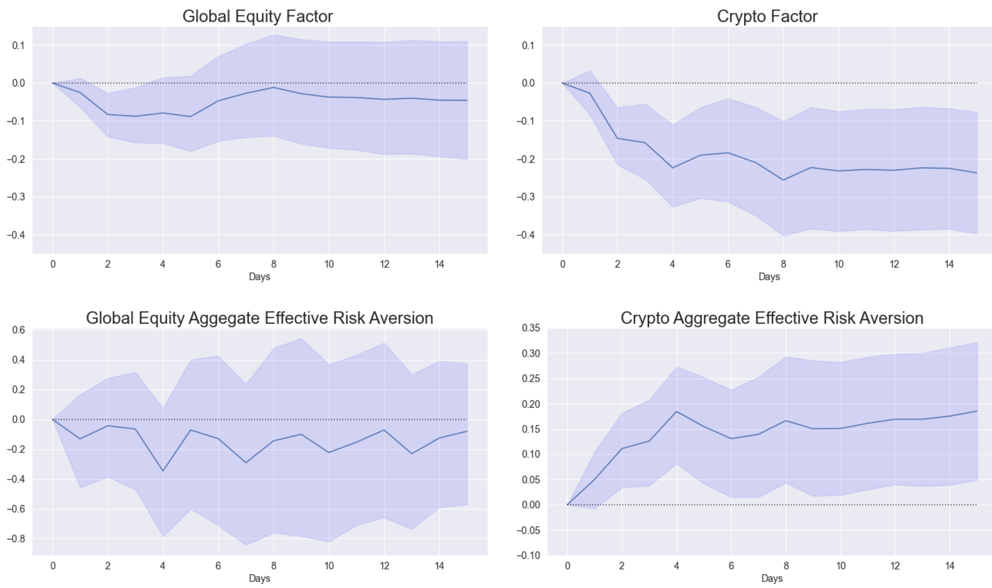


Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (4) (see Table 6). Clockwise from the top-left, the figures show the results respectively for the First Generation, Smart Contracts, DeFi, Internet of Things and Metaverse factors. We report 90% confidence intervals computed from 1000 Monte Carlo simulations. Factors are standardized over the sample period.

4.2 The risk-taking channel and institutional investors

Given this impact of monetary policy on the crypto factor, we now consider potential transmission channels. Following Miranda-Agrippino and Rey (2020), we investigate the risk-taking channel of monetary policy, where a monetary policy shock changes the effective risk aversion of the marginal investor. Using specification (5) of Table 6, we include our proxies for the aggregate effective risk aversion of both equity and crypto investors. The results in Figure 12 show that a monetary policy contraction leads to a persistent increase in the effective risk aversion of the marginal crypto investor as well as to lower crypto prices (as described in the previous section). This suggests that the marginal crypto investor reduces their risky positions as they cannot tolerate the same amount of risk given the new rates. In other words, a higher cost of capital leads crypto investors to deleverage and this in turn is associated with lower crypto prices. This interpretation is also consistent with the fact that leveraged investors are more sensitive to the economic cycle (Coimbra et al., 2022; Adrian and Shin, 2014).[23]

Figure 12: Impacts on aggregate effective risk aversion



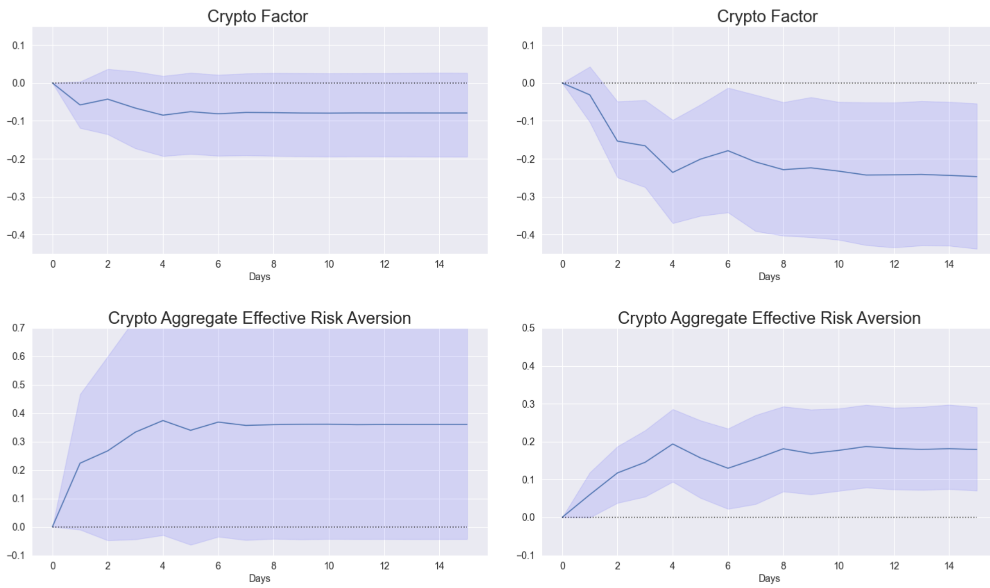
Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (5) (see Table 6). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. All variables are standardized over the sample period.

Furthermore, when estimating the model before and after 2020, we find that the response of crypto risk aversion is only significant in the post-2020 period and the response of crypto prices to monetary policy is larger in the post-2020 period (see Figure 13). This suggests that the participation in crypto markets of institutional investors who take on more leverage not only increased the correlation between equity and crypto prices, but also reinforced the transmission of monetary policy to crypto markets.

[23] In addition, the global equity factor responds negatively to the monetary tightening, as expected, while we do not observe any significant effect on the aggregate effective risk aversion of the marginal equity investor. This may simply reflect that equity investors are more sophisticated and thus better anticipate monetary policy changes.

Figure 13: Impacts of monetary policy before and after 2020

(a) Before 2020 (b) After 2020



Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (5) (see Table 6 for details) before 2020 (left-hand charts) and after 2020 (right-hand charts). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. All variables are standardized over the full sample period, while the VAR models are estimated on each sub-sample.

We test this hypothesis more formally by estimating a logistic smooth transition VAR with two states à la Auerbach and Gorodnichenko (2012), where the transition variable is the share of institutional investors.[24] Specifically, we run

$$Y_t = \underbrace{(1 - F(s_{t-1}))}_{\text{prob. of state 1}} \overbrace{\left[\sum_{j=1}^{p} A_{1j} Y_{t-j}\right]}^{\text{VAR in state 1}} + \underbrace{F(s_{t-1})}_{\text{prob. of state 2}} \overbrace{\left[\sum_{j=1}^{p} A_{2j} Y_{t-j}\right]}^{\text{VAR in state 2}} + u_t$$

where Y_t is the stacked vector of variables, s_t the transition state variable and $F(\cdot)$ a logistic function. Intuitively, we estimate a linear combination of two VARs, one when the share of

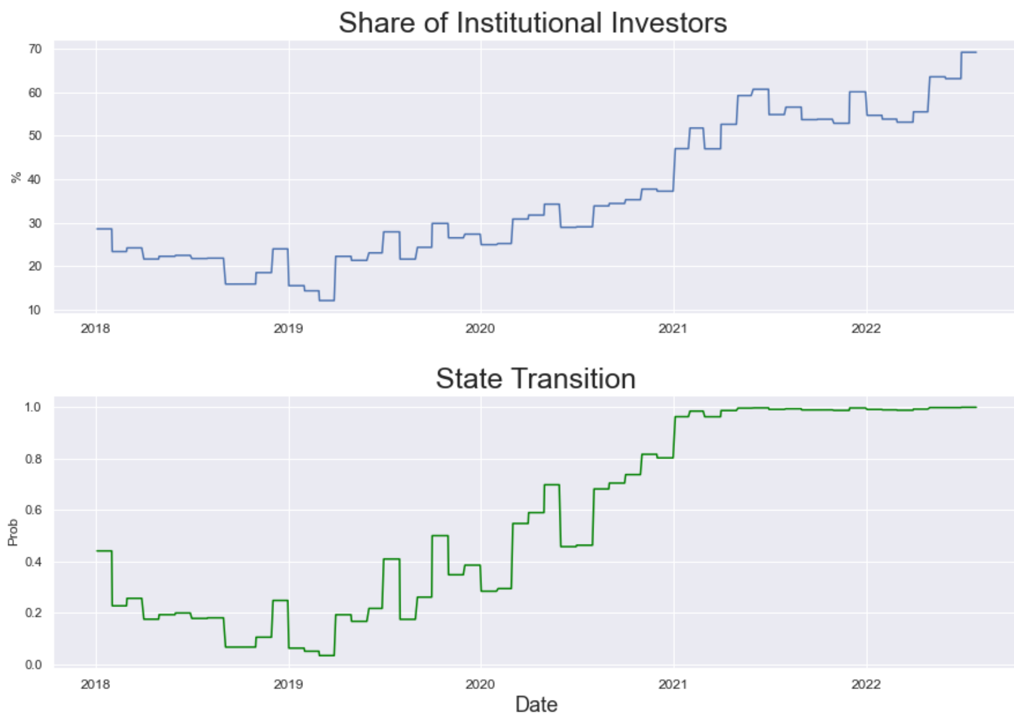
[24]We use the *macrometrics* toolbox of Gabriel Zuelling, which is based on the replication code of Auerbach and Gorodnichenko (2012). Link: `https://gabrielzuellig.ch/macrometrics/`.

institutional investors is low and one when it is high, where the weights are the probability of being in that state. The approach is similar to considering a dummy variable that takes value 1 when the share of institutional investors is above the sample median. The difference is that, instead of considering two discrete values (0 and 1), the smooth transition approach allows the regimes to continuously vary between 0 and 1. Such a methodology has two main advantages compared to standard approaches to model interactions and assess non-linearities. First, compared to a linear interaction model, it allows the magnitude of the effect of monetary policy shocks to vary non-linearly as a function of the share of institutional investors. Hence, it is possible to compute the impulse response functions when the share of institutional investors is high or low. Second, compared to estimating structural vector autoregressions for each regime, it allows the effect of monetary policy shocks to change smoothly between regimes by considering a continuum of states to compute the impulse response functions, thus making the response more stable and precise.

Figure 14 reports the evolution of the share of institutional investors as well as the state transition variable which determines the state of the economy.[25] The correlation between the two is 96%, and when the latter is equal to one (zero) the share of institutional investors is high (low).

[25]The transition variable is computed using a logistic function with $\gamma = 3$. Yet, results are robust to using a different γ (e.g., $\gamma = 1.5$).

Figure 14: Transition Variable

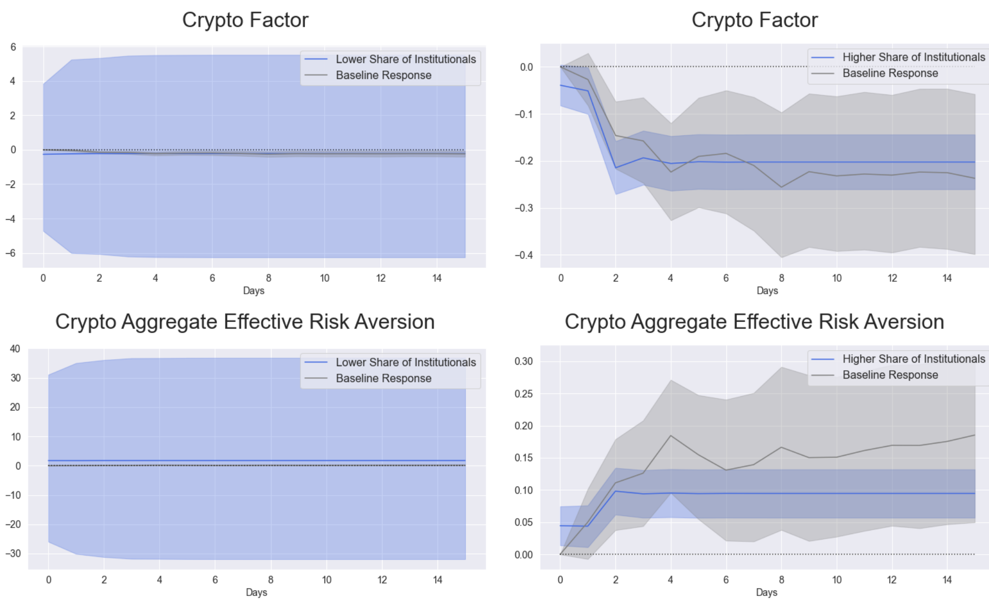


Notes: The share of institutional investors is from Chainalysis (2021). The state transition is a logistic transformation of the (standardized) share of institutional investors (with $\gamma = 3$), thus, when it is equal to one (zero), the share of institutional investors is high (low). The correlation between the two is 96%.

The results are reported in Figure 15 and corroborate the findings of previous specifications. When the share of institutional investors is low, US monetary policy does not significantly affect crypto prices and the response of the aggregate risk aversion is not significant. However, when the share of institutional investors is high, we observe a significant negative effect on crypto prices and a significant change in the risk appetite of the marginal crypto investor.

Figure 15: Impacts of monetary policy depending on the share of institutional investors

(a) Lower Share (b) Higher Share



Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating a logistic smooth transition VAR (as in Auerbach and Gorodnichenko, 2012). The STVAR includes the shadow FFR, the crypto aggregate risk aversion, and the crypto factor. We report 90% confidence intervals computed using Markov chain Monte Carlo techniques. For comparison, we also report the baseline responses of the linear VAR estimated in Section 4.2. All variables are standardized over the sample period.

4.3 Other mechanisms

Our analysis does not rule out the existence of additional mechanisms that could influence the responses of crypto markets to monetary policy. Here we discuss three: lower liquidity, USD appreciation and an alternative valuation model.

First, the lower liquidity of crypto markets may drive different responses to monetary policy. Specifically, illiquid securities may react more strongly to monetary policy shocks, regardless of the composition of the investor base. To test the liquidity hypothesis, we sort crypto assets by the number of units traded daily, extracting factors for the most and least liquid securities, and then repeat our previous analysis. We do not find significant differences between the two factors in their response to monetary policy, suggesting that differences in liquidity do not explain our results. In addition, we note that the crypto market became increasingly liquid from 2020 as more investors entered the asset class. According to the liquidity channel above, this would reduce the responsiveness to monetary policy –whereas we find that in fact the responsiveness to monetary policy has increased (Figure 13).

US monetary policy could also indirectly affect the crypto market via the USD valuation channel, with the dollar being the main funding currency and unit of account in the crypto market. Crypto tokens are mostly priced in dollars, USD stablecoins account for 95% of stablecoins issued, and DeFi lending is largely executed in USD stablecoins. When USD appreciates, tokens become de facto more expensive for non-US investors whose purchasing power is based in other fiats, which mechanically reduces inflows into the crypto market. USD stablecoin borrowing also becomes more expensive as the dollar appreciates, potentially reducing the demand for leverage. However, we do not find strong evidence for this channel in our empirical analysis: our VARs do not show significant responses of the crypto factors to shocks in the DXY index.

Finally, investors may have a different valuation model for crypto assets. If investors price crypto assets as bubbles, a rise in discount rates would compress risk premia, leading more investors to divest, putting downward pressure on the price.[26] However, this channel does not explain the increase in responsiveness of crypto to monetary policy since 2020, as with the liquidity channel, nor does it account for the increased synchronization of the crypto and equity cycles. We therefore retain our focus on a change in the underlying composition of the crypto investor base.

[26]Nevertheless, there is relatively little consensus in the literature on the effects of monetary policy on bubbles. For a discussion see Brunnermeier and Schnabel (2015) and Dong, Miao, and Wang (2020).

5 Model

In this section, we provide a stylized model to help interpret our empirical results, building on the literature on heterogeneous risk-taking intermediaries (see, for instance: Danielsson, Shin, and Zigrand, 2010; Adrian and Shin, 2014; Miranda-Agrippino and Rey, 2021). We derive an expression for crypto excess returns as a function of the aggregate effective risk aversion (Γ_t^c) in the crypto market. Changes in the composition of the market then affect Γ_t^c, and hence crypto prices. Specifically, the entry of more institutional investors implies that crypto prices are increasingly correlated with those in equity markets, as in our empirical results in Section 3. A US monetary contraction disproportionately reduces the wealth of institutional investors, reducing crypto demand and prices, and does so to a greater extent the larger the share of institutional investors in the market, as in Section 4.[27]

Our framework features two representative heterogeneous agents and two asset classes, namely crypto and equity. Crypto investors c can only invest in crypto markets, whereas institutional investors i can invest in both crypto and equity markets.[28] Crypto investors are retail investors that trade using their disposable income and personal savings (see, for instance, Toczynski, 2022). Institutional investors are banks and similar financial intermediaries that operate in multiple sectors (Auer et al., 2022). Crypto investors maximize a mean-variance portfolio and can borrow at the US risk-free rate to leverage up their positions.[29] By contrast, institutional investors are risk-neutral agents that maximize the

[27]For a sophisticated model of heterogeneous agents and monetary policy, see Coimbra and Rey (2017).

[28]We make this simplifying assumption to clarify the exposition of the model, while noting that, empirically, retail investors also have access to the equity market (e.g., through mobile trading apps), but less so than larger institutional investors. Our main results would be unaffected by extending the model to allow both types of investor to participate in both asset classes, with the only constraint that institutional investors are initially under-represented in the crypto market. The key feature of the model is not the difference in the investable universes but the difference in investors' constraints/risk appetite.

[29]This is a simplifying assumption: arguably, such investors are not granted loans at the risk-free rate but at a rate proportional to it. Indeed, introducing heterogeneous borrowing costs—where borrowing is more expensive for small crypto investors—would support our findings, as the entry of institutional investors would imply an even greater increase in crypto leverage.

expected return of their portfolio, given a value-at-risk constraint.[30] The outside option of both agents is to invest in risk-free deposits, which pay zero excess return. Without loss of generality, we interpret the model as having only one crypto asset and only one global stock, which respectively represent the crypto and global equity factors in the empirical analysis.[31]

Crypto investors: Crypto investors maximize a mean-variance portfolio and have a constant risk aversion coefficient σ. They can hold only crypto assets, which pay an excess return R^c_{t+1}. They, therefore, face the following problem:

$$\max_{x^c_t} \; \mathbb{E}_t(x^c_t R^c_{t+1}) - \frac{\sigma}{2}\mathbb{V}ar_t(x^c_t R^c_{t+1})$$

where x^c_t is the share of wealth w^c_t invested in the crypto asset, while $\mathbb{E}_t$ and $\mathbb{V}ar_t$ represent the expected value and the variance, respectively. The first order condition is simply $x^c_t = \frac{1}{\sigma}\mathbb{E}_t(R^c_{t+1})\left[\mathbb{V}ar_t(R^c_{t+1})\right]^{-1}$. Thus, crypto investors increase their holdings proportionally with the expected return on the crypto asset and decrease them proportionally with their risk aversion and the variance of their portfolio.

Institutional investors: Institutional investors are risk-neutral agents that maximize the expected returns on their portfolios given a value-at-risk constraint.[32] They invest in both crypto assets and equity, and thus choose their holdings of crypto assets to solve the following

[30] We also note that a setup with two risk-averse agents would generate similar results.
[31] We can equivalently interpret the model as featuring vectors of securities.
[32] See for instance Adrian and Shin (2014).

maximization problem:

$$\max_{x_t^i} \mathbb{E}_t \left(x_t^i R_{t+1}^c + y_t R_{t+1}^e \right)$$

$$\text{subject to: } \underbrace{\theta w_t^i \sqrt{\mathbb{V}ar_t \left(x_t^i R_{t+1}^c + y_t R_{t+1}^e \right)} \leq w_t^i}_{\text{value-at-risk constraint}}$$

where x_t^i is the share of wealth w_t^i invested in crypto and y_t is the share invested in equities, and R_{t+1}^e is the excess return on equity investments. Similarly to Miranda-Agrippino and Rey (2020), the value-at-risk constraint is expressed in terms of a multiple θ of the investors' portfolio. The first order condition is

$$x_t^i = \frac{1}{2\theta^2 \lambda_t} \left[\mathbb{E}_t(R_{t+1}^c) - 2\theta^2 \lambda_t \mathbb{C}ov_t(R_{t+1}^c, R_{t+1}^e) y_t \right] \left[\mathbb{V}ar_t \left(R_{t+1}^c \right) \right]^{-1}$$

where λ_t is the Lagrange multiplier. Institutional investors' optimal investment in crypto is positively related to the expected payoff of crypto assets and negatively related to (i) the variance of crypto returns, (ii) the covariance of crypto returns with returns on equities, and (iii) the tightness of their financial constraints.[33]

Equilibrium: Equilibrium in the crypto market requires that the total supply of crypto assets (normalized by total wealth) s_t equals total holdings: $s_t = x_t^c \frac{w_t^c}{w_t^c + w_t^i} + x_t^i \frac{w_t^i}{w_t^c + w_t^i}$. Similarly, we impose the equity market clearing condition that the total supply of equities (normalized by institutional investors' wealth) y_t^{tot} equals total holdings: $y_t^{tot} = y_t$. By combining these conditions with the first-order conditions of the investors, we derive the following propositions.

[33] We assume that institutional investors are able to take on more risk than the average crypto investor, i.e. $2\theta^2 \lambda_t < \sigma$.

Proposition 1: **Crypto excess returns are a function of the time-varying aggregate risk aversion in the market.** *The excess return on crypto assets can be rewritten as:*

$$\mathbb{E}_t\left(R^c_{t+1}\right) = \Gamma^c_t \mathbb{V}ar_t\left(R^c_{t+1}\right) s_t + \Gamma^c_t \mathbb{C}ov_t\left(R^c_{t+1}, R^e_{t+1}\right) y^{tot}_t \frac{w^i_t}{w^c_t + w^i_t} \tag{4}$$

where $\Gamma^c_t = \left(w^c_t + w^i_t\right)\left[\frac{w^c_t}{\sigma} + \frac{w^i_t}{2\theta^2\lambda_t}\right]^{-1}$ *is the aggregate effective risk aversion. In equilibrium, crypto excess returns must be higher to compensate for their variance, in proportion to the average degree of risk aversion in the market. Similarly, a higher correlation with equities implies lower diversification benefits for institutional investors, increasing the required return on crypto assets in equilibrium, and this matters more the larger the share of wealth held by institutional investors.*

Proposition 2: **Equity excess returns are a function of the financial constraints of institutional investors and of their portfolio allocation to crypto assets.** *The expected excess equity return can be rewritten as the sum of an equity and a crypto component:*

$$\mathbb{E}_t\left(R^e_{t+1}\right) = 2\theta^2\lambda_t \mathbb{V}ar_t\left(R^e_{t+1}\right) y^{tot}_t + 2\theta^2\lambda_t \mathbb{C}ov_t\left(R^c_{t+1}, R^e_{t+1}\right) x^i_t \tag{5}$$

Once again, in equilibrium investors must be compensated for higher variance or lower diversification benefits in proportion to their financial constraint.

Comparing Equations 4 and 5, we note three results. Firstly, as institutional wealth w^i_t makes up an increasing share of the crypto market, the risk-taking profile of the crypto market converges on that of the equity market. For instance, in the extreme case where institutions entirely dominate the crypto market, the aggregate effective risk aversion converges to the financial constraint of the institutional investors—i.e., as $\frac{w^i_t}{w^i_t + w^c_t} \to 1$, $\Gamma^c_t \to 2\theta^2\lambda_t$. Crypto and equity returns in this case only differ based on the relative supplies and relative variances of the two assets. More generally, the aggregate effective risk aversion depends on the relative wealth of the investors, so greater participation of institutional investors in crypto markets renders the effective risk aversion more similar to that of equity investors and increases the correlation between equity and crypto prices, in line with our empirical findings (e.g., Figure 7).

Secondly, since our stylized framework focuses on excess returns, a rise in the risk-free rate of interest mechanically reduces real returns for both crypto and equities. To proceed further, we note existing evidence that more levered agents are more sensitive to the economic cycle (Coimbra et al., 2022; Adrian and Shin, 2014). Increased institutional entry reduces aggregate effective risk aversion (since $\Gamma_t \geq 2\theta^2\lambda_t$), in line with Figure 6. Since the marginal crypto investor is less risk averse, they take on more leverage, since borrowing at the risk-free rate to invest in risky returns is increasingly attractive. Thus, following Coimbra et al. (2022) and Adrian and Shin (2014), institutional entry could increase the sensitivity of crypto markets to the economic cycle—as observed in Figure 13 and 15.

Thirdly, this framework implies the potential for future spillovers from crypto markets onto equities. Currently the second term in Equation 5 is negligible, as traditional financial institutions' holdings of crypto assets x_t^i are very small relative to their holdings of equities y_t (Auer et al., 2022). However, if such holdings became significant, a subsequent crash in crypto markets that led to a reduction in x_t^i implies a decline in equity returns $\mathbb{E}_t\left(R_{t+1}^e\right)$ —and by more, the larger are pre-crash crypto holdings. Such potential spillovers could motivate a cap $\bar{x}_t^i$ or other risk-based constraints on crypto holdings by traditional financial institutions (as discussed in, for instance, Basel Committee on Banking Supervision, 2021, 2022; Bains, Ismail, Melo, and Sugimoto, 2022).

6 Conclusion

Crypto assets vary substantially in their design and value propositions, yet their prices largely move together. A single crypto factor can explain 80% of the variation in crypto prices, and has become more correlated with the global financial cycle since 2020, particularly with technology and small-cap stocks. We provide evidence that such correlations are driven by the increased presence of institutional investors in crypto markets, which has made the risk profile of the marginal equity and crypto investors increasingly similar. Furthermore, crypto markets are very sensitive to US monetary policy, with a monetary contraction significantly reducing the crypto factor, similarly to global equities.

We outline a minimal theoretical framework that can explain our empirical results. We show that crypto returns can be expressed as a function of the time-varying aggregate risk aversion in the crypto market, which in turn is affected by the changing composition of the crypto investor base. As institutional investors make up an increasing share of the crypto market, the risk-taking profile of the marginal investor in crypto converges on that in equities. A rise in the risk-free rate reduces returns, and increasingly so if institutional investors hold a larger share of crypto and more levered agents are more sensitive to the economic cycle (Adrian and Shin, 2014; Coimbra et al., 2022).

Our results also inform the policy debate about crypto assets.[34] We find that these assets do not provide a hedge against the economic cycle—in contrast, our estimates suggest they respond even more than stocks. Furthermore, the increasing correlation between crypto and equity markets, coupled with the fact that institutional investors trade both crypto assets and stocks, implies potential spillover effects that could eventually raise systemic risk concerns. In particular, our framework implies that—in a possible future world where crypto makes up a substantial share of institutional investors' portfolios—a crash in the crypto market could have significant negative repercussions in equity markets. For these reasons, policymakers

[34] See, for instance, International Monetary Fund (2021, 2023).

could take advantage of the fact that institutional investors' exposure to crypto is still limited to develop and implement an improved regulatory framework.

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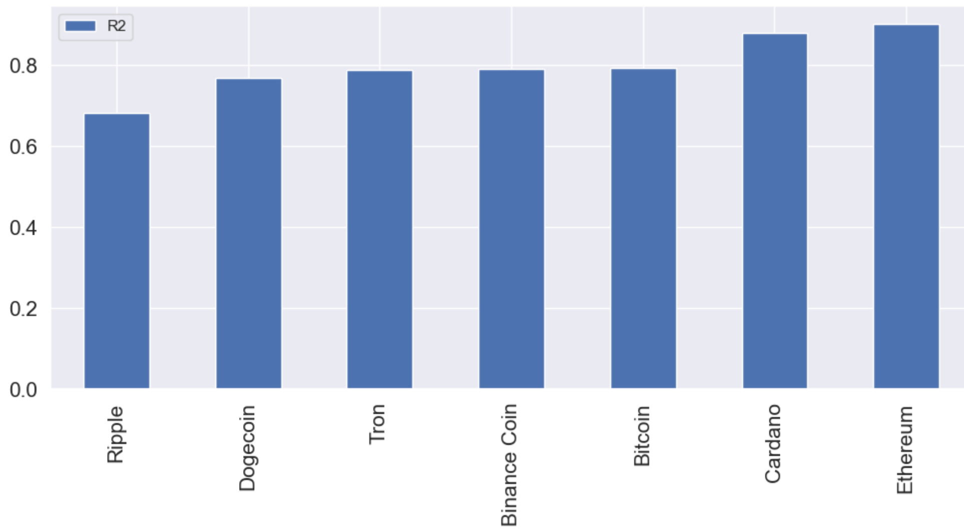
A Additional Descriptives and Results

Figure A.1: Reverse regressions



Notes: This figure shows the R^2s from regressions of the crypto factor on each of the input price series, as described in Section 2.

Table A.1: Equity Eikon RICs by country

Country	Equity Indexes	Tech Indexes	Financial Indexes	Small Caps Indexes
United States	.SPX	.SPLRCT	.SPSY	.SPCY
China	.SSEC	.SZFI	.SZFI	
Japan	.JPXNK400			.TOPXS
Germany	.GADXHI	.CXPHX	.CXPVX	
India	.BSESN	.BSETECK	.BSEBANK	
UK	.FTSE	.FTTASX		.FTSC
France	.FCHI	.FRTEC	.FRFIN	.CACS
Brazil	.BVSP		TRXFLDBRPFIN	.SMLL
Italy	.FTMIB			.FTITSC
Canada	.GSPTSE	.SPTTTK	.SPTTFS	.SPTSES
Russia	.IRTS		.RTSFN	

South Korea	.KS11	.KRXIT	.KRXBANK	
Australia	.AXJO	.AXIJ	.AXFJ	.AXSO
Spain	.IBEX		.IFNC.MA	.IBEXS
Mexico	.MXX		.MXSE07	.MXXSM
Indonesia	.JKSE			
Turkey	.XU100		.XUMAL	
Netherlands	.AEX		.SXFP	.ASCX
Saudi Arabia	.TASI			
Switzerland	.SSHI	.C9500T	.C8700T	.SSCC
Argentina	.IBG		.TRXFLDARPFIN	
Sweden	.OMXS30			.OMXSSCPI
Poland	.WIG	.COMP	.BNKI	
Belgium	.BFX	.BETEC	.BEFIN	.BELS
Thailand	.SET100	.THTECH	.THFINCIAL	
Iran				
Austria	.ATX		.TRXFLDATPFIN	
Norway	.OBX			.OSESX
UAE	.DFMGI		.DFMIF	
Nigeria	.NGSEINDEX			
Israel	.TRXFLDILT			
South Africa	.JALSH	.JTECH	.JFINA	.JSMLC
Hong Kong	.HSI	.HSCIIT	.HSCIF	.HSSI
Ireland	.ISEQ			
Denmark	.OMXCBPI			
Singapore	.STI			.FTFSTS
Malaysia	.KLSE	.KLTE	.KLFI	.KLFTSC
Colombia	.COLCAP			
Philippines	.PSI		.PSFI	
Pakistan	.KSE		.TRXFLDPKPFIN	
Chile	.SPCLXIGPA		.TRXFLDCLPFIN	
Finland	.OMXHPI			

Bangladesh	.dMIBD00000P			
Egypt	.EGX30		.TRXFLDEGPFIN	
Vietnam	.VNI			
Portugal	.PSI20	.PTTEC	.PTFIN	
Czech Republic	.PIX			
Romania	.BETI			
Peru	.SPBLPGPT			
New Zealand	.NZ50			.NZSC

Notes: This table lists the indices used for constructing the global equity factor and each of the equity sub-factors. The selected countries are the fifty largest by GDP. All indices are from Eikon/Thomson Reuters.

Table A.2: p-values of the differences in correlation before and after 2020.

	Bitcoin	Crypto F	First Gen	IoTs	Smart C.	DeFi	Metaverse
Bitcoin	n.a.						
Crypto F	0.390	n.a.					
First Gen	n.a.	n.a.	n.a.				
IoTs	n.a.	n.a.	n.a.	n.a.			
Smart C.	n.a.	n.a.	n.a.	n.a.	n.a.		
DeFi	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	
Metaverse	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
S&P 500	0.000	0.005	n.a.	n.a.	n.a.	n.a.	n.a.
Equity F	0.000	0.006	n.a.	n.a.	n.a.	n.a.	n.a.
Small Caps F	0.000	0.012	n.a.	n.a.	n.a.	n.a.	n.a.
Tech Factor	0.000	0.001	n.a.	n.a.	n.a.	n.a.	n.a.
Equity F (no Tech)	0.876	0.765	n.a.	n.a.	n.a.	n.a.	n.a.
Financials F	0.004	0.029	n.a.	n.a.	n.a.	n.a.	n.a.
Equity F (no Fin)	0.037	0.090	n.a.	n.a.	n.a.	n.a.	n.a.
Dollar Index	0.060	0.010	n.a.	n.a.	n.a.	n.a.	n.a.
VIX	0.000	0.008	n.a.	n.a.	n.a.	n.a.	n.a.
Oil	0.673	0.890	n.a.	n.a.	n.a.	n.a.	n.a.
Gold	0.962	0.544	n.a.	n.a.	n.a.	n.a.	n.a.

Notes: The matrix reports the p-values of the interaction coefficient of the following set of regressions: y = constant $+\beta_1$x + β_2After2020 + β_3xAfter2020 + ϵ. After2020 is equal to one from January 2020. Standard errors are robust. Data is from January 2018 to March 2023.

Table A.3: Risk-aversion regressions

		Global Crypto Factor				Global Equity Factor			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Var(Bitcoin)	30 days	2.061***							
		(0.315)							
	45 days		1.711***						
			(0.265)						
	60 days			1.763***					
				(0.245)					
	90 days				1.851***				
					(0.249)				
Var(MSCI World)	30 days	-27.939***				-63.585***			
		(1.686)				(4.020)			
	45 days		-22.804***				-49.620***		
			(1.290)				(2.813)		
	60 days			-21.133***				-41.336***	
				(1.141)				(2.245)	
	90 days				-18.727***				-30.706***
					(1.006)				(1.876)
Constant		-0.163***	-0.172***	-0.200***	-0.266***	70.975***	55.650***	46.562***	34.904***
		(0.022)	(0.025)	(0.028)	(0.037)	(4.421)	(3.095)	(2.471)	(2.067)
Observations		1,273	1,258	1,243	1,213	1,275	1,261	1,246	1,217
R-squared		0.084	0.1	0.121	0.159	0.176	0.185	0.182	0.163

Notes: The table reports the results of regressing the equity and the crypto factor on the variances of the MSCI World Index and Bitcoin. Standard errors are in parentheses. *, **, and *** correspond to significance at the 10%, 5%, and 1% levels respectively.

Table A.4: Correlations across risk-taking proxies

	Δ 30-day Crypto Risk Aversion	Δ 45-day Crypto Risk Aversion	Δ 60-day Crypto Risk Aversion	Δ 90-day Crypto Risk Aversion	Δ 30-day Global Equity Risk Aversion	Δ 45-day Global Equity Risk Aversion	Δ 60-day Global Equity Risk Aversion	Δ 90-day Global Equity Risk Aversion	Δ Intermediary Capital Ratio	Δ Intermediary Leverage Ratio Squared
Δ 30-day Crpyto Risk Aversion	1.000									
Δ 45-day Crpyto Risk Aversion	0.791	1.000								
Δ 60-day Crpyto Risk Aversion	0.798	0.820	1.000							
Δ 90-day Crpyto Risk Aversion	0.761	0.787	0.821	1.000						
Δ 30-day Global Equity Risk Aversion	0.181	0.176	0.190	0.205	1.000					
Δ 45-day Global Equity Risk Aversion	0.124	0.156	0.154	0.170	0.973	1.000				
Δ 60-day Global Equity Risk Aversion	0.090	0.110	0.124	0.133	0.951	0.992	1.000			
Δ 90-day Global Equity Risk Aversion	0.050	0.062	0.066	0.079	0.900	0.959	0.984	1.000		
Δ Intermediary Capital Ratio	-0.122	-0.144	-0.170	-0.182	-0.485	-0.414	-0.366	-0.292	1.000	
Δ Intermediary Leverage Ratio Squared	0.110	0.116	0.172	0.197	0.613	0.551	0.510	0.434	-0.872	1.000

Notes: This table shows pairwise daily correlations between changes in the measures of risk aversion, computed using Equations 2 and 3, and changes in the intermediary risk-appetite measures by He et al. (2017) available at `https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/`. Series are standardized, and data is from January 2018 to March 2023.

Table A.5: Crypto Returns and US Monetary Policy

	Δ Bitcoin		Δ Crypto Factor	
	(1)	(2)	(3)	(4)
Δ Shadow FFR	-0.0531		-0.101*	
	(-1.41)		(-2.00)	
BRW Shocks		-0.0613*		-0.0791**
		(-1.75)		(-2.28)
Constant	0.0366	0.0366	0.0141	0.0141
	(0.78)	(0.78)	(0.26)	(0.26)
N	48	48	48	48
R^2	0.0263	0.0351	0.0705	0.0431
R^2 (adj)	0.00516	0.0141	0.0503	0.0223

Notes: Variables are standardized. Frequency is monthly and data is from January 2018 to December 2021. Shadow FFR are from Wu and Xia (2016) and BRW shocks are from Bu et al. (2021). Standard errors are robust and t-statistics are parentheses. *, **, *** correspond to 10%, 5%, and 1% significance, respectively.

PUBLICATIONS

The Crypto Cycle and US Monetary Policy

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