The Crypto Cycle and Institutional Investors*

Alexander Copestake, Davide Furceri, Tammaro Terracciano†

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ABSTRACT

We study the role of institutional investors in crypto markets and in the transmission of US monetary policy. We find that the participation of institutional investors in crypto markets drives the correlation between crypto and global equity markets, as large investors holding both types of assets create a direct link between the two. We also document that US monetary policy significantly affects the crypto cycle, but only when the participation of institutional investors is high enough. Finally, we show that a heterogeneous-agent model with time-varying aggregate risk aversion can rationalize our empirical findings.

Keywords: Institutional Investors, Cryptoassets; Stock Markets; US Monetary Policy.
JEL classification: G23, E44; E52; F33.

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*Copestake (ACopestake@imf.org) and Furceri (DFurceri@imf.org) are at the International Monetary Fund. Terracciano (TTerracciano@iese.edu) is at the IESE Business School. A previous version of this paper circulated under the title "The Crypto Cycle and US Monetary Policy". We are grateful to Itai Agur, John Campbell, Gabriela Conde Vitureira, Shaen Corbet, Angela Gallo, Harald Hau, Charles Larkin, Jay Peiris, Michael Rockinger, Kenneth Rogoff, Jeremy Stein, Brandon Tan, Saskia ter Ellen, Fabio Trojani and seminar participants at Pompeu Fabra University, the 2024 Winter Econometric Society Conference, Hong Kong Institute for Monetary and Financial Research, the IMF and the University of Geneva for their constructive comments. Remaining mistakes are our own. The views expressed in this paper are those of the authors and should not be attributed to the IMF, its Executive Board, or IMF management.

†Corresponding author.

1 Introduction

Crypto markets have boomed in the past years, going from US$20 billion in 2016 to almost US$3 trillion in November 2021, before declining to US$1.7 trillion at the end of 2023.[1] Exponential returns have not only attracted retail investors but have also led to a substantial increase in participation from institutional investors.[2] The share of institutional investors trading crypto assets rose sharply from roughly 20% in 2019, to more than 80% at the end of 2022, to eventually converge to 60% at the end of 2023.[3] At the same time, crypto and global equity cycles have become more synchronized, with the S&P500 and the Bitcoin price becoming more correlated.[4]

Nevertheless, we know relatively little about the role of institutional investors in crypto markets. This is a fundamental issue as increased institutional participation in crypto markets heightens spillover risks with global equity markets. We address this issue by answering the following questions: What is the role of institutional investors in the synchronization between the crypto and global equity cycle? How does the presence of institutional investors affect the transmission of US monetary policy to crypto markets?

This paper shows that the participation of institutional investors in crypto markets drives the correlation between crypto and global equity markets, as large investors holding both types of assets create a direct link between the two. Moreover, we document that US monetary policy significantly affects the crypto cycle, as it does with the global equity cycle, but only when the participation of institutional investors is high. Finally, we rationalize our empirical findings in a heterogeneous-agent model with time-varying aggregate risk aversion.

[1]Source: CoinMarketCap.com.
[2]For instance, see Benetton and Compiani (2022) or Auer, Farag, Lewrick, Orazem, and Zoss (2022).
[3]Source: CryptoCompare. See also Section 3.
[4]See Adrian, Iyer, and Qureshi (2022).

To study the role of institutional investors in crypto markets, we begin our analysis by providing some stylized facts. Using a dynamic factor model, we identify a single common component in crypto-asset prices –the "crypto factor"– that explains 78% of the variance in crypto prices, which is substantially larger than the 20% observed for global equities by Miranda-Agrippino and Rey (2020). This difference highlights the greater concentration of market capitalization in the largest crypto assets relative to that in the largest equities. We then compare the crypto factor to a set of global equity factors (in the spirit of Rey, 2013; Miranda-Agrippino and Rey, 2020) and find a positive correlation over almost the entire sample, driven by a particularly strong correlation between 2020 and the beginning of 2023. Importantly, the increasing co-movement over that period is not limited to Bitcoin vis-a-vis the S&P500 but pertains more broadly to the crypto and global equity factors. We also find that the crypto factor correlates most strongly with the global tech factor and the small-cap factor, while it is surprisingly less correlated with the global financial factor.

We formally investigate the relationship between institutional participation and the correlation between global equity and crypto factors, by regressing daily changes in the crypto factor onto changes in the equity factor interacted with lagged values of the trading share of institutional investors. In other words, we test whether the share of institutional trading explains the one-day-ahead correlation between crypto and equity markets. To further alleviate endogeneity concerns, we saturate the model with year-month fixed effects to ensure that our results are not driven by any co-occurring trends. We find that the participation of institutional investors explains more than 40% of the correlation between crypto and global equity markets. Since institutional investors trade both stocks and crypto assets, greater institutional participation in crypto increases the overlap between the investor bases of these two asset classes, thereby also expanding the sets of shocks to which they are exposed.

We also conduct a set of robustness tests to mitigate other identification concerns. Specifically, we document that our findings are robust to using different measures of institutional participation (e.g., absolute volumes or retail share). Additionally, we show that our results are consistent with off-chain trading activity by using reporting data from Coinbase, one of the most important centralized exchanges. Finally, we conduct placebo tests on other asset classes to ensure that our results are not driven by unobservables simultaneously moving multiple markets.

The importance of institutional investors in the synchronization between the crypto and global equity cycles raises the questions of whether US monetary policy also affects the crypto cycle and how institutional investors influence its transmission. We test the first hypothesis by using a daily VAR with the shadow federal funds rate (SFFR) by Wu and Xia (2016), which accounts for balance sheet policies that played an important role over our sample period. Our identification relies on the mild assumption that monetary policy is exogenous to crypto prices. Indeed, 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.[5] 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

[5] More formally, our identification 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 global equity and crypto factors. Note that our results are also robust to relaxing the aforementioned variable ordering. Specifically, 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 the global equity factor.[6] Notably, as with the global equity cycle, we find that only the US Fed's monetary policy matters, and not that of other major central banks (i.e., BOE and ECB), likely reflecting that crypto markets are highly dollarized.[7]

Having established that US monetary policy affects the crypto cycle, we examine the role of institutional investors in its transmission. Specifically, we compute the responses to monetary policy in states of the world in which the participation of institutional investors is high and low. To do so, we estimate a smooth transition VAR (as in Auerbach and Gorodnichenko, 2012), where the transition variable is the share of institutional investors. We find that US monetary policy has a significant impact on crypto markets only when the institutional share in crypto markets is high, consistent with the idea that the participation of institutional investors reinforces the transmission of monetary policy to crypto markets.[8] This also corroborates their importance for synchronization between global equity and crypto markets, since US monetary policy is an important driver of fluctuations in global equity markets (Miranda-Agrippino and Rey, 2020).

Finally, we formalize our empirical results using an heterogeneous-agent framework in which the participation of institutional investors in crypto markets affects the expected returns from crypto relative to equities. We assume two types of investors: retail investors who only invest in crypto assets, and institutional investors who can invest in both stocks and crypto assets. Retail investors are risk-averse, while institutional investors are risk-neutral but face a value-at-risk constraint. The equilibrium returns on equity assets are proportional

[6]This refers to standard deviations of variation in crypto or equities over 01/2018-01/2024, the period for which we can construct the crypto factor.

[7]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.

[8]We also discuss three possible complementary explanations of our findings, such as liquidity in crypto markets, fluctuations in the value of the US dollar, and differing valuation models between crypto and equities. Nevertheless, we do not find supporting evidence for any of these.

to their variance and their covariance with crypto returns, and are inversely related to the institutional investors' risk-taking capacity (i.e., value-at-risk constraint). Similarly, 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 time-varying risk aversion, which is a weighted average of risk aversion of the crypto investors and the risk-taking capacity of the institutional investors. This means that the higher the relative wealth of institutional investors, the higher the synchronization between the expected crypto and equity returns. Furthermore, since the presence of institutional investors in crypto markets increases the risk capacity of the marginal crypto investor, we interpret the higher reaction of crypto prices to monetary contraction as consistent with the fact that more levered investors are more sensitive to the economic cycle (see also Coimbra, Kim, and Rey, 2022; Adrian and Shin, 2014).

Overall, our findings highlight the pivotal role of institutional investors in the synchronization between crypto and global equity markets, as well as in the transmission of US monetary policy. Our results thus suggest that policymakers should monitor the participation of institutional investors in crypto markets accordingly –particularly as more traditional financial institutions increase their exposure to crypto markets (for instance, through newly approved Exchange-Traded Funds in the US). While it is true that crypto markets could help investors diversify their portfolios, higher institutional participation would also increase spillover risks between traditional and crypto markets.

The rest of this paper proceeds as follows. Section 2 relates our contributions to the current literature. Section 3 provides some stylized evidence about the crypto and equity cycles, and tests the importance of institutional investors in their synchronization. Section 4 investigates the impact of US monetary policy on the crypto cycle and explores how it depends on institutional participation in crypto markets. Section 5 formalizes our empirical findings with a heterogeneous-agent model. Finally, Section 6 concludes.

2 Literature Review

Our paper contributes to the burgeoning literature on crypto assets and institutional investors. Specifically, we engage with three strands of literature.

First, we draw on the empirical literature studying the composition of crypto investors. 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. Similarly, Hackethal, Hanspal, Lammer, and Rink (2021) and Didisheim, Fraschini, and Somoza (2022) document the behaviour of crypto retail investors and their portfolio allocation between equity and crypto assets. Using transaction-level data from millions of US households, Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter (2023) show that crypto investors, except for high-income early adopters, resemble the general population, spanning all income levels with significant contributions from high-income individuals. In addition, they suggest that most US households treat cryptocurrencies similarly to traditional assets. 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 are starting to hold crypto assets. In particular, Auer et al. (2022) document that banks' exposure to crypto assets is low relative to their balance sheet, but it is significantly large when compared to trading volumes in crypto markets. Furthermore, non-bank financial institutions including hedge funds and asset managers are becoming an increasingly important source of revenue for crypto exchanges. Cornelli, Doerr, Frost, and

Gambacorta (2023) also show differences in trading behaviour between small and large investors during crisis episodes, highlighting their potentially important role in determining prices. We contribute to this literature by studying –both empirically and theoretically– how institutional participation in crypto markets influenced the synchronization with traditional financial markets.

Second, our work builds on the relatively limited strand of literature that assesses the impact of macroeconomic news events, including monetary policy announcements, on Bitcoin returns (Corbet, Larkin, Lucey, Meegan, and Yarovaya, 2020; Pyo and Lee, 2020; Ma, Tian, Hsiao, and Deng, 2022; Karau, 2023). Benigno and Rosa (2023) uses intraday data to investigate whether macroeconomic news affects Bitcoin price and concludes that they are uncorrelated. Nonetheless, they do not consider how institutional investors might impact monetary policy transmission and focus on a very short horizon. Our paper widens the scope beyond Bitcoin to consider the underlying drivers of co-movement in the entire asset class and the changing relationship with the global financial cycle. In doing so, we also build on Iyer (2022), who provides evidence of the positive correlation between equity markets and Bitcoin and Ether prices, and Liu and Tsyvinski (2020) who do similarly for an aggregate of all crypto assets. Elsayed and Sousa (2022) also consider the impact of monetary policy on Bitcoin, Litecoin, and Ripple. The novelty of our contribution lies both in documenting the extent to which monetary policies affect the crypto cycle and in demonstrating the critical role of institutional trading activity. We also explore the possible implications of further integration between the two markets using a standard asset pricing model with heterogeneous agents.

Third, our paper engages with the literature on the global financial cycle pioneered by the seminal contribution of Rey (2013). 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: a change in interest rates forces financial intermediaries to change their leverage and thus the effective risk appetite of the marginal investor. Put differently, a US monetary contraction negatively affects global equity prices. Notably, we find that the same dynamics apply to crypto markets, contrasting starkly with views that they are uncorrelated with the traditional economy and an effective hedge against market risk. Indeed, we argue that crypto assets have become increasingly integrated with the global financial cycle. Within this literature, we also show that a standard asset pricing model with heterogeneous agents can rationalize our results. Specifically, we draw from the models in which the differences in risk aversion across agents determines the aggregate risk of the economy (Coimbra et al., 2022), and the cyclicality of leverage depends on the constraints of financial intermediaries (Adrian and Shin, 2014).[9]

3 Institutional Investors and Crypto-Equity Synchronization

In this section, we first present a set of stylized facts about the crypto markets and how they can be exhaustively described by a single price component, i.e., the crypto factor, which represents the crypto cycle. Next, we study the relation between the crypto and global equity cycles and the role of institutional investors in their synchronization.

3.1 Stylized Facts about the Crypto Cycle

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,

[9]See also Kekre and Lenel (2018) and Gourinchas, Rey, and Govillot (2010).

and much larger than the correlations documented across equity markets (see, for instance, Rey, 2013). For example, Bitcoin has a 58% 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	0.63	0.63	1.00															
Ripple	0.60	0.65	0.50	1.00														
Cardano	0.69	0.74	0.55	0.64	1.00													
Solana	0.48	0.57	0.50	0.42	0.50	1.00												
Dogecoin	0.34	0.31	0.24	0.26	0.31	0.17	1.00											
Polkadot	0.64	0.70	0.57	0.47	0.64	0.54	0.24	1.00										
Tron	0.57	0.60	0.46	0.54	0.57	0.38	0.25	0.56	1.00									
Shiba Inu	0.50	0.48	0.46	0.37	0.43	0.36	0.53	0.45	0.35	1.00								
Maker Dao	0.38	0.45	0.32	0.31	0.38	0.42	0.15	0.51	0.26	0.31	1.00							
Avalanche	0.55	0.59	0.54	0.45	0.64	0.56	0.22	0.61	0.44	0.38	0.48	1.00						
Uniswap	0.53	0.63	0.47	0.43	0.55	0.48	0.16	0.61	0.46	0.44	0.52	0.52	1.00					
Litecoin	0.79	0.81	0.62	0.64	0.71	0.49	0.34	0.65	0.57	0.46	0.38	0.53	0.56	1.00				
FTX	0.44	0.45	0.39	0.31	0.35	0.44	0.19	0.39	0.27	0.25	0.32	0.39	0.35	0.38	1.00			
Chainlink	0.59	0.65	0.51	0.51	0.58	0.53	0.27	0.69	0.49	0.42	0.33	0.58	0.58	0.60	0.41	1.00		
Monero	0.72	0.71	0.57	0.55	0.64	0.41	0.29	0.52	0.53	0.37	0.34	0.44	0.42	0.70	0.34	0.53	1.00	
THETA	0.56	0.57	0.48	0.45	0.53	0.45	0.23	0.62	0.48	0.43	0.27	0.51	0.51	0.55	0.32	0.49	0.52	1.00

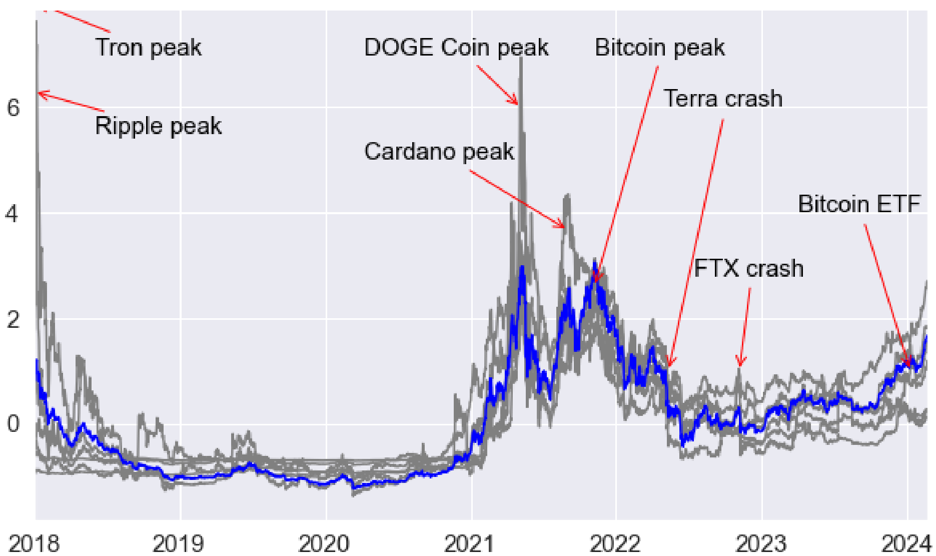
Notes: This table shows pairwise correlations between selected crypto-asset returns. Data is from January 2018 to January 2024.

To represent the fluctuations in crypto markets into one variable, we use dynamic factor modeling, a dimensionality reduction technique.[10] We label the resulting common factor as the "crypto factor" which synthesizes the crypto cycle and therefore the fluctuations in crypto markets.

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 the crypto cycle –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.

[10]Refer to Appendix A for a detailed explanation on the factor construction.

Figure 1: The Crypto Cylce



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, 78% of variation in the underlying series is explained by our crypto factor.[11] This figure is above 60% for all seven assets, underscoring 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. These results strongly suggest that a single crypto factor is sufficient to explain the crypto cycle, i.e., the aggregate fluctuations of crypto markets.

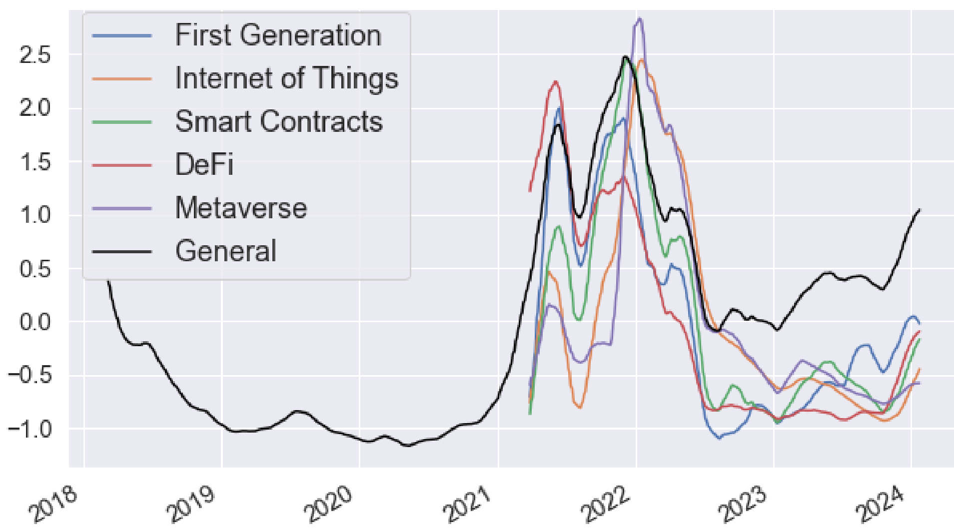
Given the limited range of assets used to calculate our main factor, we also ensure that our crypto factor reflects more recent trends in newer assets.[12] To do so, we examine a

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

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

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.[13] All classes are highly correlated with the general crypto cycle, validating our focus on the common factor. The only 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.

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

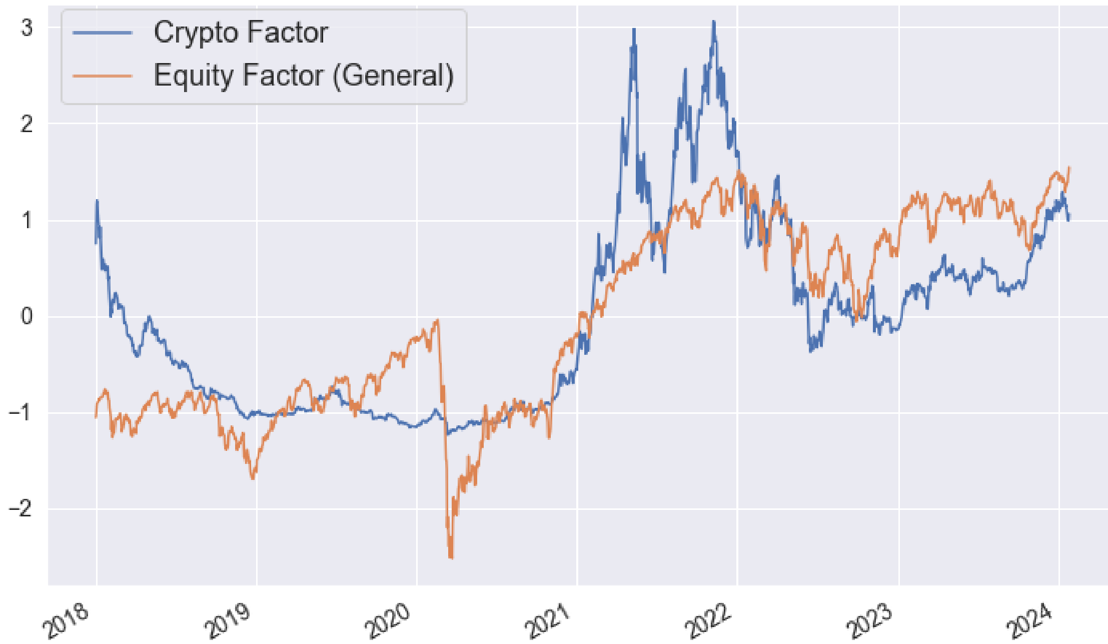
3.2 The Crypto and the Global Equity Cycles

We now turn to the relationship between the crypto factor and global equities. Iyer (2022) documents an increase in correlation between Bitcoin and S&P500 returns from 2020 to 2022. We therefore conjecture that crypto markets may have become more integrated and synchronized with the equity cycle. To assess this, in this subsection, 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.[14] 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 sectors. Figure 3 shows both the equity and the crypto factors. As with the crypto factor, the equity factor reliably 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.

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

Figure 3: The Crypto and Global Equity Cycles



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 3.1.

In Table 2, we regress changes in the crypto factor on changes in each of the other factors. Column (1) shows that, in general, the correlation between the crypto and the equity factor is highly significant, while columns (2) and (7) specifically highlight that this relationship is driven by the technology and small-cap components.

Table 2: Factor Regressions

	Δ Crypto Factor$_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Global Equity Factor (General)$_t$	0.301***						
	(6.75)						
Δ Global Tech Factor$_t$		0.284***				0.256***	
		(7.31)				(4.77)	
Δ Global Equity Factor excl. Tech$_t$			0.165**				
			(2.13)				
Δ Global Financial Factor$_t$				0.188***		0.0335	
				(5.70)		(0.77)	
Δ Global Equity Factor excl. Financials$_t$					0.509***		
					(4.76)		
Δ Global Small Caps Factor$_t$							0.335***
							(6.69)
Constant	-0.000311	-0.000209	0.000204	-0.0000682	0.000204	-0.000218	-0.0000313
	(-0.14)	(-0.10)	(0.09)	(-0.03)	(0.09)	(-0.10)	(-0.01)
Obs.	1522	1522	1522	1522	1522	1522	1522
R^2	0.045	0.045	0.004	0.027	0.023	0.045	0.048

Notes: This table reports the results from regressing the crypto factor on different combinations of equity factors. Data is from January 2018 to January 2024. 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 strongly with the small-cap and technology factors, and relatively less so with the financial factor. In Table B.1 in Appendix B, 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	0.75					
Crypto F	0.75	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	-0.02	0.05					
Equity F (no Tech)	0.03	0.04					
Financials F	-0.02	0.04					
Equity F (no Fin)	0.04	0.08					
Dollar Index	-0.05	-0.01					
VIX	-0.08	-0.19					
Oil	0.01	0.04					
Gold	0.08	0.03					

After 2020

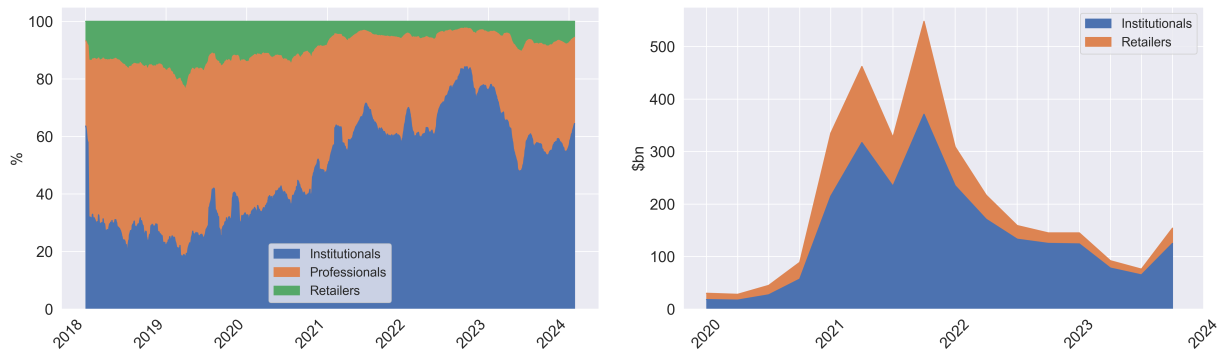
	Bitcoin	Crypto F	First Gen	IoTs	Smart C.	DeFi	Metaverse
Bitcoin	1.00						
Crypto F	0.85	1.00					
First Gen	0.78	0.88	1.00				
IoTs	0.63	0.76	0.74	1.00			
Smart C.	0.79	0.98	0.80	0.73	1.00		
DeFi	0.64	0.85	0.75	0.68	0.85	1.00	
Metaverse	0.39	0.46	0.38	0.43	0.48	0.39	1.00
S&P 500	0.27	0.28	0.25	0.26	0.33	0.22	0.25
Equity F	0.23	0.23	0.21	0.22	0.29	0.21	0.21
Small Caps F	0.24	0.23	0.21	0.21	0.29	0.22	0.21
Tech Factor	0.23	0.23	0.20	0.20	0.27	0.18	0.19
Equity F (no Tech)	0.06	0.07	0.04	0.05	0.07	0.06	0.06
Financials F	0.18	0.18	0.16	0.15	0.21	0.17	0.16
Equity F (no Fin)	0.15	0.16	0.12	0.15	0.19	0.11	0.12
Dollar Index	-0.13	-0.16	-0.13	-0.08	-0.18	-0.13	-0.09
VIX	-0.22	-0.21	-0.23	-0.23	-0.30	-0.22	-0.22
Oil	0.03	0.04	0.03	0.01	0.06	0.04	0.05
Gold	0.05	0.06	0.03	0.02	0.07	0.03	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 B.1 in Appendix B.

Although the increasing synchronization is evident, it is still unclear what drives these correlations. Notably, institutional investors massively increased their exposure to crypto assets starting from 2020. Using a novel supervisory database, Auer et al. (2022) document the growing importance of traditional financial institutions 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 from public blockchains by Chainalysis, we find that institutional investors' share of crypto trading volumes has risen dramatically after 2020 and then declined towards the end of 2023, as shown in Figure 4 Panel (a). Absolute volumes also show a similar pattern. Furthermore, we observe the same evolution on centralized exchanges, using Coinbase reporting data (Figure 4 Panel (b)). Trading volumes, especially by institutional investors, dramatically increased at the end of 2021 and declined in recent years.

Figure 4: Increasing Institutional Participation in Crypto Markets

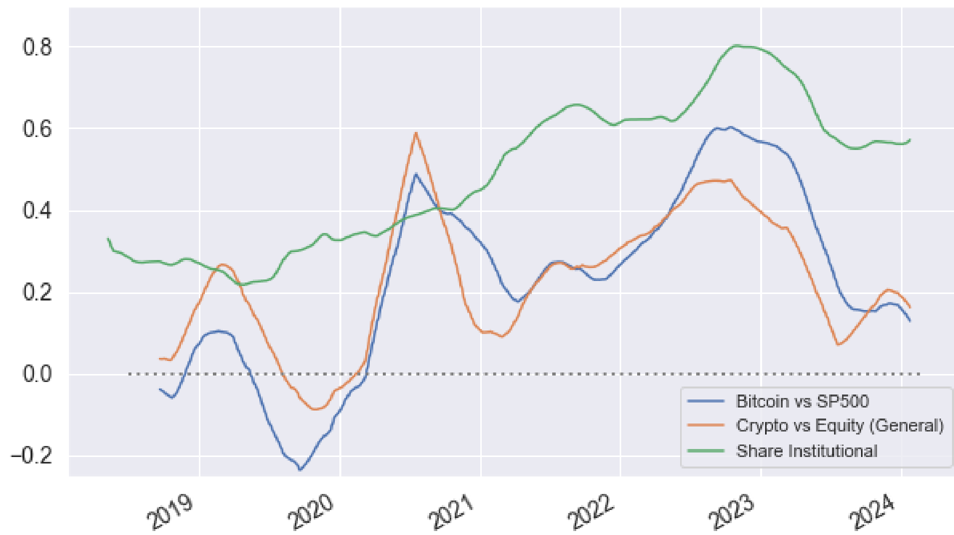
(a) Share of on-chain trading volumes (%) (b) Trading volumes on Coinbase ($bn)



Notes: Panel (a) shows the smoothed share of on-chain trading volumes by investor type over time, using public blockchain by Chainalysis. Investor types are classified according to transaction sizes, i.e., trades under $10k are classified as trades by retail investors, the ones from $10k to $1M by professional investors, and from +$1M by institutional investors. Panel (b) shows the 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 Figure 5, we plot the 90-day rolling correlations of the crypto and equity factor, Bitcoin and S&P500, and of the share of institutional investors. Before 2020, the crypto and equity markets were essentially uncorrelated. Thereafter, on average, the correlations started increasing with the S&P500 and the Bitcoin reaching 60% in 2022. Eventually, in 2023 the correlation steadily decreased to 20%. In parallel, the share of institutional investors was rather low and flat in the first part of the sample and then firmly increased until the end of 2022, going from roughly 25% to 80%. As with the crypto-equity correlations, the share of institutional investors dropped in 2023 by more than 20%. Together, these patterns suggest that institutional investors might play a role in the correlation between crypto and global equity cycles.

Figure 5: Rolling Correlations between Crypto and Equities



Notes: This graph shows the 90-day rolling correlations between the crypto and equity factors, the Bitcoin and the S&P500, and the (smoothed) share of institutional investors trading cryptoassets.

In Table 4, we formally investigate the relationship between the share of institutional investors and the correlation between equity and crypto factors. For identification purposes, we would ideally have exogenous variations in the share of trading by institutional investors. However, they are difficult to pinpoint in this setting. In the absence of such shocks, we advance toward identification by using lagged values of the trading shares and controlling for year-month fixed effects. This way, we substantially alleviate the concern that institutional participation might be explained by the correlation between crypto and equity prices, while absorbing any co-occurring trends.

We start by looking at the simple relations before and after 2020, when the share of institutional investors trading cryptos started increasing (see Figure 4). Table 4 columns (1) and (2) show that there is a significant correlation between the crypto and equity factors, that indeed emerged after 2020. However, one might argue that this is a spurious correlation as the pandemic shock increased the correlation across asset classes. Therefore, we add the price of gold and oil as placebo tests and, consistently with our hypothesis, we do not find any significant correlation with crypto markets.

In column (3), we test the role of institutional investors by looking at the interactions with the lagged share of institutional investors (Figure 4 panel (a)).[15] Our results show that a higher share of institutional investors trading cryptos significantly leads to a higher correlation between equity and crypto markets. Notably, this finding is also significant in economic terms as roughly 40% of the total correlation is explained by this interaction term. As expected, the interaction with gold prices is not significant, suggesting that we are not capturing a spurious relationship due to the pandemic shock.[16]

Our findings are robust to multiple specifications. In column (4), we use the absolute trading volume of institutional investors and find very similar results. As expected, we also find a negative coefficient when using the lagged share of retail investors in column (5). A legitimate concern that might arise is that public blockchain data is not representative of the whole crypto market, given the existence of centralized exchanges. We argue that this is not the case as we reach the same conclusions when we use reporting data from Coinbase in column (6).[17] Furthermore, to ensure that our results are not influenced by the construction of factors, we estimate the specification of Table 4 by using the S&P500 index and the Bitcoin price and find the same results (see Table B.2 in Appendix B).

Finally, it is worth noting that although our results significantly support the idea that institutional investors have a crucial role in the synchronization between the crypto and equity cycles, our analysis does not exclude the existence of other complementary explanations.

[15]Importantly, our findings are robust to using non-smoothed series, which indicates that possible autocorrelation of the trading share is not driving the results.

[16]Note that we only keep the gold placebo test for reporting purposes.

[17]Although Coinbase data is at a quarterly frequency, we still find significant results at the daily level.

Table 4: The Role of Institutional Investors in the Correlation between Crypto and Equity Factors.

	Δ Crypto Factor$_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Global Equity Factor (General)$_t$	0.204***	0.0357	0.187***	0.193***	0.172***	0.239***
	(6.45)	(1.06)	(5.83)	(5.93)	(6.05)	(5.93)
Δ Gold$_t$	0.820	0.407	0.710*	0.709	0.634	0.875
	(1.82)	(0.83)	(1.99)	(1.85)	(1.94)	(1.80)
Δ Oil$_t$	0.115	0.181	0.208	0.143	0.206	0.309
	(0.76)	(0.83)	(0.99)	(0.71)	(0.99)	(1.27)
Δ Global Equity Factor (General)$_t$ # After 2020		0.195***				
		(3.90)				
Δ Gold$_t$ # After 2020		0.367				
		(0.52)				
Δ Oil$_t$ # After 2020		-0.0468				
		(-0.17)				
Δ Global Equity Factor (General)$_t$ # Share of Institutionals$_{t-1}$			0.131***			
			(4.24)			
Δ Global Equity Factor (General)$_t$ # Volume of Institutionals$_{t-1}$				0.160**		
				(2.80)		
Δ Global Equity Factor (General)$_t$ # Share Retailers$_{t-1}$					-0.164***	
					(-4.20)	
Δ Global Equity Factor (General)$_t$ # Share Inst. Coinbase$_{t-1}$						0.0594**
						(2.72)
Share of Institutionals$_{t-1}$			0.170			
			(0.84)			
Volume of Institutionals$_{t-1}$				-0.104		
				(-0.48)		
Share Retailers$_{t-1}$					-0.152	
					(-0.90)	
Share Inst. Coinbase$_{t-1}$						2.254
						(1.50)
Δ Gold$_t$ # Share of Institutionals$_{t-1}$			0.273			
			(0.67)			
Δ Gold$_t$ # Volume of Institutionals$_{t-1}$				0.291		
				(0.45)		
Δ Gold$_t$ # Share Retailers$_{t-1}$					-0.487	
					(-1.02)	
Δ Gold$_t$ # Share Inst. Coinbase$_{t-1}$						0.0147
						(0.05)
Year-Month Fixed Effects	YES	YES	YES	YES	YES	YES
Obs.	1522	1522	1192	1192	1192	794
R^2	0.0856	0.0898	0.109	0.119	0.113	0.104
R^2-adjusted	0.0382	0.0406	0.0466	0.0575	0.0511	0.0403

Notes: This table reports the results from regressing the crypto factor on 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 January 2024. t-statistics are in parentheses. *, **, *** correspond to 10%, 5%, and 1% significance, respectively.

4 The Crypto Cycle and US Monetary Policy

In the first part of the paper, we documented that the participation of institutional investors explains the correlation between the crypto and the global equity cycle. 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. This in turn raises the question of how institutional participation in crypto could affect monetary policy transmission to crypto markets. In this section, we start by assessing the impact of US monetary policy on the crypto cycle, and then investigate the role of institutional investors.

4.1 The Impact of Monetary Policy on the Crypto Cycle

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 5 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, namely, they 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.

We measure monetary policy by using the shadow federal funds rate developed by Wu and Xia (2016) to account for the full policy stance of the Fed. Indeed, the shadow rate not only captures the interest rate policies but also balance sheet policies (e.g., quantitative easing). These latter are especially relevant in our sample period given the primary response of the Fed to the COVID-19 shock.

Table 5: VAR Specifications

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

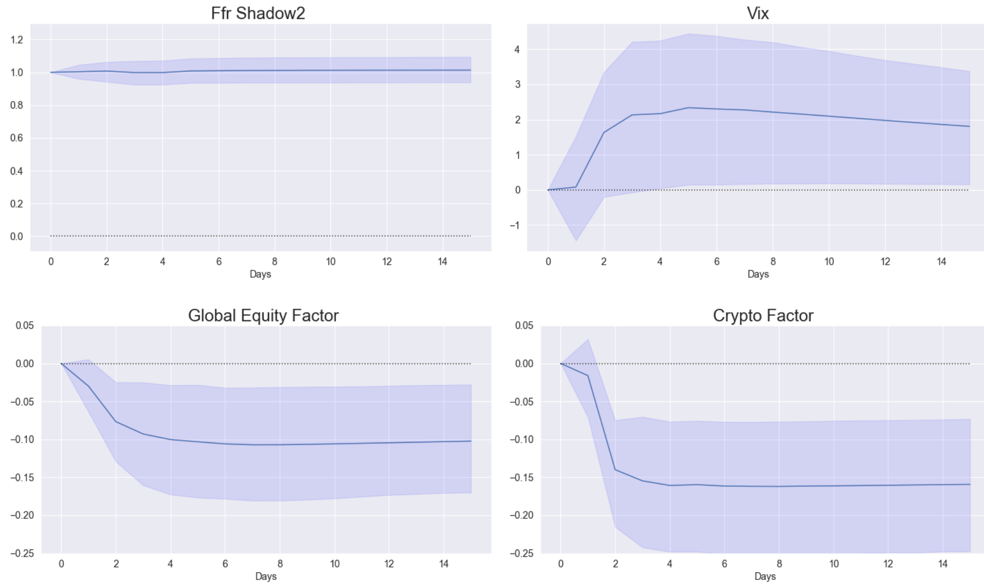
Notes: This table shows the selection and ordering of variables in each of our VAR specifications. Column (1) is our baseline specification. Column (2) tests whether the baseline results are determined by the construction of the crypto and equity factors. Column (3) explores if the crypto factor is affected 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 influences the risk aversion of crypto investors. Data is from January 2018 to January 2024, with the exception of column (4) which is from 2021 due to data availability.

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., 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.

Figure 6 reports the most relevant cumulative impulse response functions for the first specification in Table 5. 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.[18] Overall, this indicates that crypto assets are subject to US monetary policy and the economic cycle similarly to traditional investments, in contrast to some 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.

[18]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 2018-2024 standard deviations–of the factors to a hypothetical one percentage point hike in the shadow FFR.

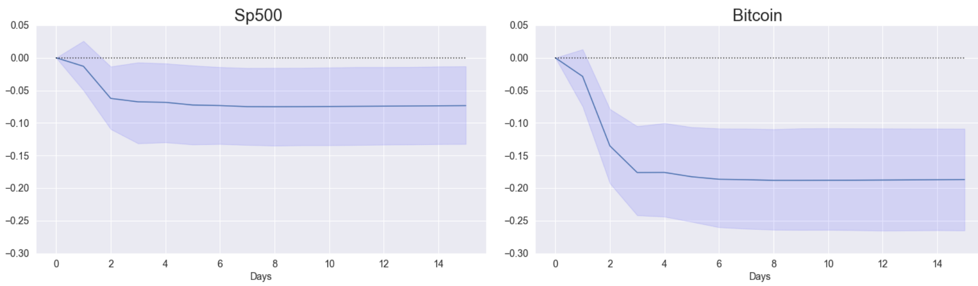
Figure 6: Baseline VAR results



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 5 for details). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. Factors are standardized over the sample period.

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 5). The estimates in Figure 7 are very similar to the responses in Figure 6, 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.

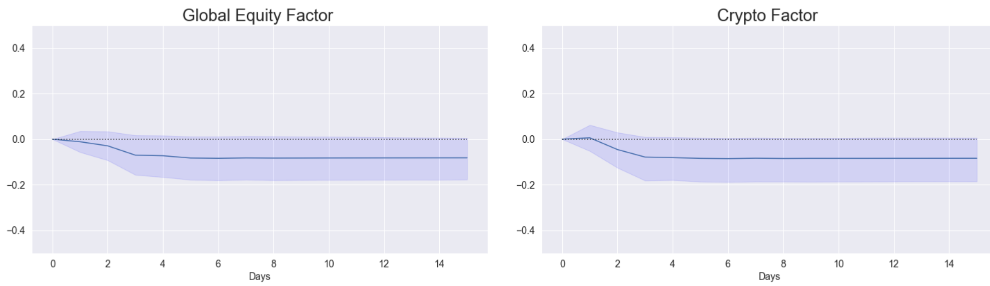
Figure 7: Robustness to Factor Construction



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 5). 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 8). 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.

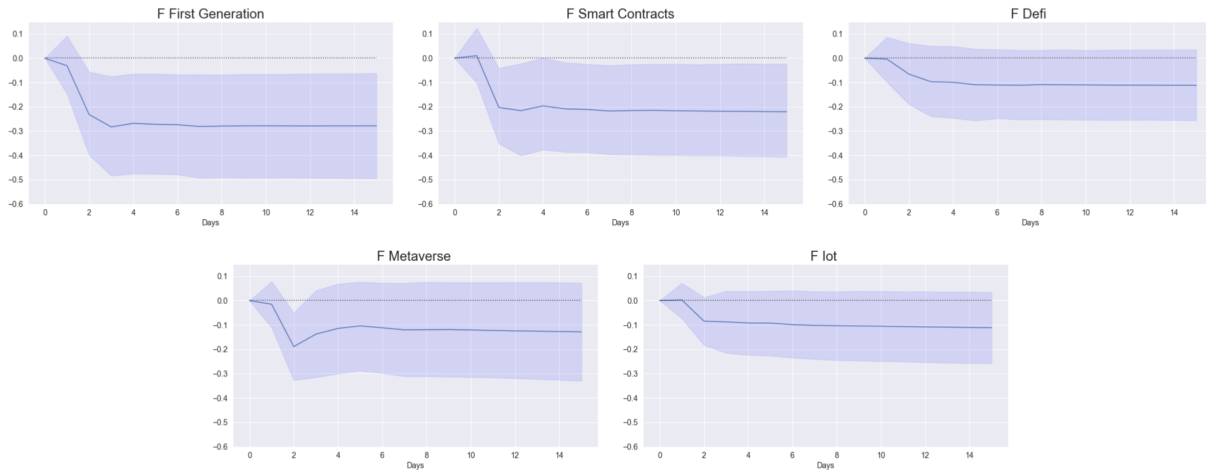
Figure 8: Impacts of Global Tightening



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 5). 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 3.1. Figure 9 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 tokens 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 9: Impacts on Crypto Sub-Factors



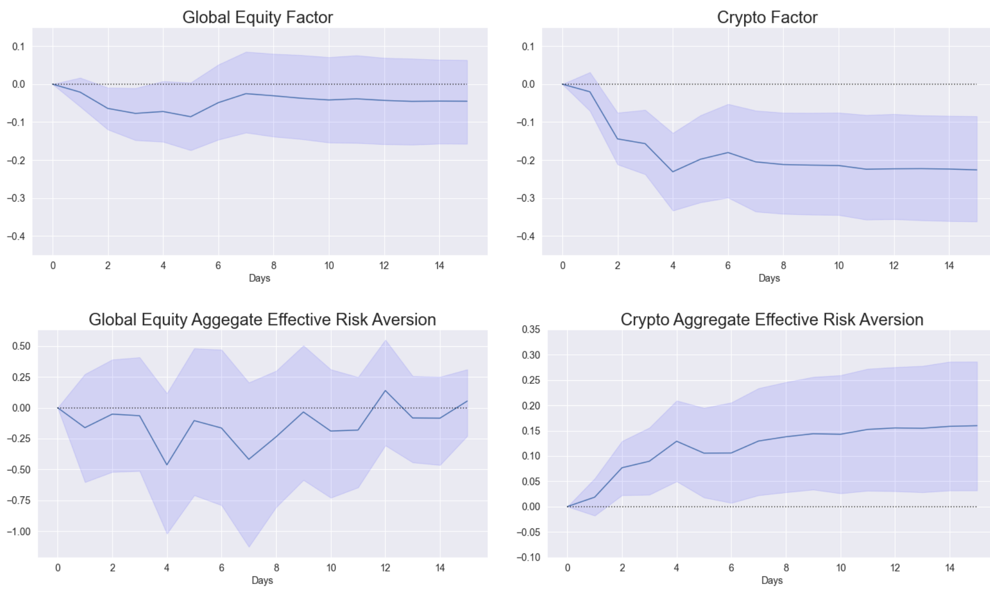
Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR when estimating VAR specification (4) (see Table 5). Clockwise from the top-left, the figures show the results respectively for the First Generation, Smart Contracts, DeFi, Internet 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 Institutional Investors and the Transmission of US Monetary Policy

We now consider potential channels that explain the impact of US monetary policy on the crypto cycle. We first augment our baseline specification to study if US monetary policy affects the risk-taking behavior of crypto investors. Next, we test if the response to US monetary policy depends on the participation of institutional investors in crypto markets.

Following Miranda-Agrippino and Rey (2020), we investigate the so-called risk-taking channel of monetary policy, namely that monetary tightening lowers the risk-taking capacity of investors as higher cost of capital leads them to deleverage their positions and thus prices decrease. We test this hypothesis by using a proxy of the aggregate effective risk aversion of the marginal investors constructed following Miranda-Agrippino and Rey (2020).[19] Specifically, we estimate specification (5) of Table 5, which includes our proxies for the aggregate effective risk aversion of both equity and crypto investors.

Figure 10: 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 5). We report 90% confidence intervals computed from 1000 Monte Carlo simulations. All variables are standardized over the sample period.

The results in Figure 10 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 subsection). Thus, the marginal crypto investor reduces their risky positions as they cannot sustain the same amount of risk given the new rates. This interpretation is also consistent with the fact that leveraged investors are more

[19] Appendix C illustrates the construction of these measures for both the crypto and the global equity marginal investors. In addition, it shows that our proxies strongly correlate with other existing ones in the literature.

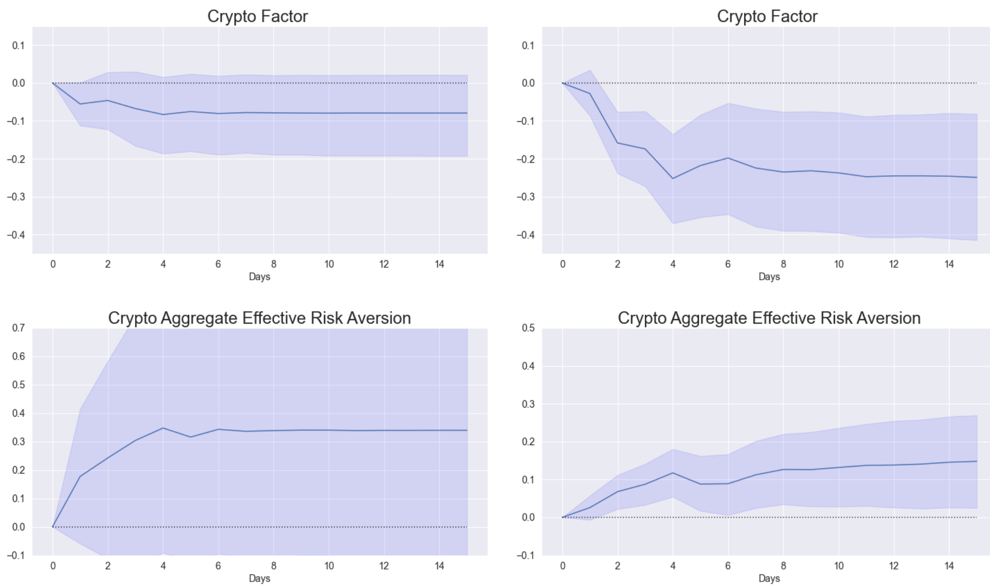
sensitive to the economic cycle (Coimbra et al., 2022; Adrian and Shin, 2014).[20]

Furthermore, we estimate the model before and after 2020, to broadly capture the higher participation of institutional investors starting in 2020 (see Figure 4). We find that the response of crypto risk aversion is only significant in the post-2020 period and that the response of crypto prices to monetary policy is larger in the post-2020 period (see Figure 11). As a robustness check, we also extend the sample back to July 2010 and use the Bitcoin price instead of the crypto factor. As expected, we find that the Bitcoin response to monetary policy is significant only from 2020 (see Figure B.1 in Appendix B). 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 might have reinforced the transmission of monetary policy to crypto markets.

[20] 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.

Figure 11: 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 5 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.

Nonetheless, the share of institutional investors was not constant after 2020. Although it remarkably increased from 20% in 2019 up to 80% in 2022, it declined to less than 60% in 2023 (see Figure 4). Thus, to formally compute how crypto responses to monetary policy change with the investor composition of crypto markets, we resort to a logistic smooth transition VAR with two states à la Auerbach and Gorodnichenko (2012) who estimate how fiscal responses differ depending on whether the economy is in a state of recession or not. In our setting, we estimate the impacts of US monetary policy on the crypto cycle depending on the participation of institutional investors, i.e., we use the share of institutional investors as the state transition variable. This way, we can quantify the role of institutional investors in crypto responses to monetary policy.[21]

Quantitatively, the smooth-transition VAR is defined as follows

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

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 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.

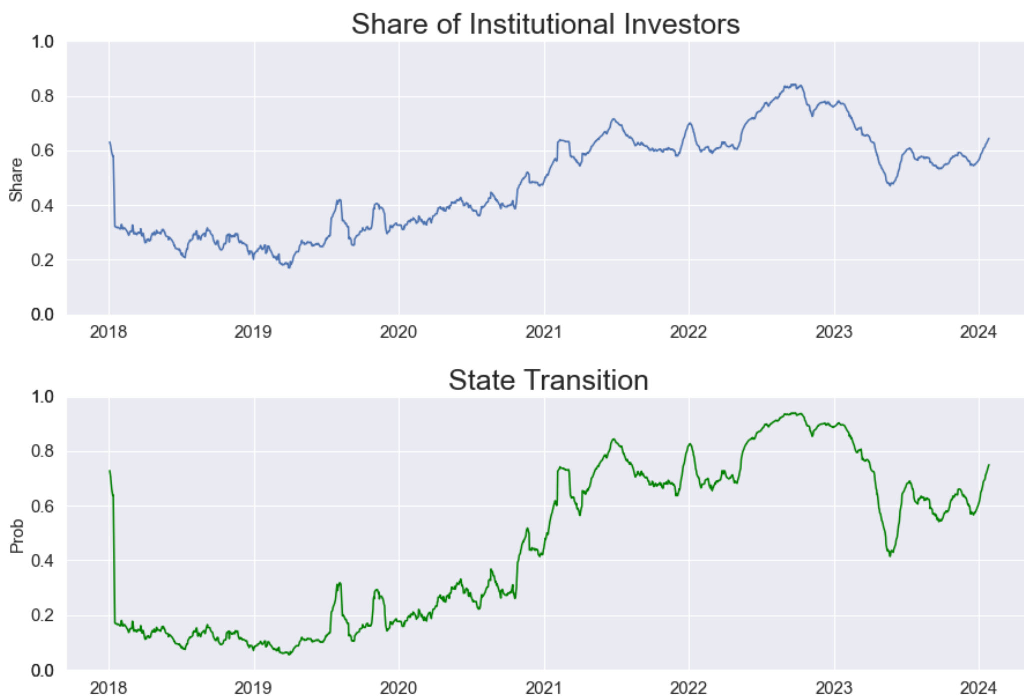
Such a methodology has two main advantages compared to standard approaches to model interactions and assess non-linearities. First, compared to a linear interaction model, it allows the magnitude of the effect of monetary policy shocks to vary non-linearly as a function of the share of institutional 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 12 reports the evolution of the share of institutional investors as well as the state

[21] 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/`.

transition variable which determines the state of the economy.[22] The correlation between the two is 96%, and when the latter is equal to one (zero) the share of institutional investors is high (low).

Figure 12: Transition Variable



Notes: The share of institutional investors is based on Chainalysis data. The state transition is a logistic transformation of the (standardized) share of institutional investors (with $\gamma = 1.5$), thus, when it is equal to one (zero), the share of institutional investors is high (low). The correlation between the two is 96%.

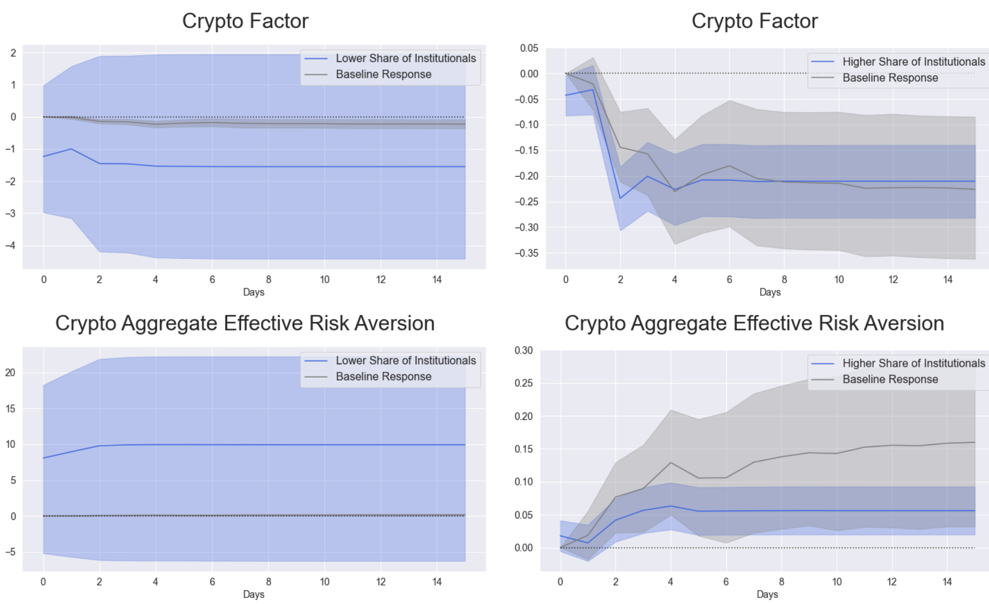
The results are reported in Figure 13 and corroborate the findings of previous specifications. When the share of institutional investors is low, US monetary policy does not significantly affect crypto prices and the response of the aggregate risk aversion is not significant. However, when the share of institutional investors is high, we observe a significant

[22]The transition variable is computed using a logistic function with $\gamma = 3$, but results are robust to alternative values of γ (e.g., $\gamma = 1.5$).

negative effect on crypto prices and a significant change in the risk appetite of the marginal crypto investor. In other words, the presence of institutional investors is essential for monetary policy to influence crypto markets. Overall, these findings, along with those from the preceding sections, highlight the important role of institutional investors in crypto markets.

Figure 13: 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 Alternative Channels

The fact that institutional investors play a crucial role does not rule out the existence of additional mechanisms that could influence the responses of crypto markets to monetary policy. Here, we briefly discuss three: lower liquidity, US dollar 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 use as a proxy the number of traded units. Specifically, 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.

Second, US monetary policy could also indirectly affect the crypto market via the US dollar 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, US dollar stablecoins account for 95% of stablecoins issued, and DeFi lending is largely executed in US dollar stablecoins. When the US dollar 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. US dollar 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 US dollar index (i.e., 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.[23] This mechanism could thus explain our result that monetary policy affects the crypto factor. However, as with

[23]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).

the liquidity channel, it could not explain the proportional increase in the responsiveness of crypto to monetary policy with the share of trading by institutional investors, nor does it account for the greater synchronization of the crypto and equity cycles. We therefore retain our focus on a change in the underlying composition of the crypto investor base.

5 Model

In this section, we provide a stylized model to 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, namely, the risk aversion of the marginal investors. Changes in the composition of the market then affect Γ_t^c, and hence crypto prices. Specifically, changes in the share of institutional investors are mirrored by crypto prices and by their correlation with global equity prices, as in our empirical results in Section 3.2. 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.[24]

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

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

institutional investors i can invest in both crypto and equity markets.[25] Crypto investors are retail investors that trade using their disposable income and personal savings (see, for instance, Toczynski, 2022). Institutional investors are banks, hedge funds, asset managers and other traditional financial institutions that operate in multiple sectors. Crypto investors maximize a mean-variance portfolio and can borrow at the US risk-free rate to leverage up their positions.[26] By contrast, institutional investors are risk-neutral agents that maximize the expected return of their portfolio, given a value-at-risk constraint.[27] 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.[28]

Crypto investors: Crypto investors (retailers) 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:

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

[25]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.

[26]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.

[27]We also note that a setup with two risk-averse agents would generate similar results.

[28]We can equivalently interpret the model as featuring vectors of securities.

where x_t^c is the share of wealth w_t^c 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 $x_t^c = \frac{1}{\sigma}\mathbb{E}_t(R_{t+1}^c)\left[\mathbb{V}ar_t(R_{t+1}^c)\right]^{-1}$. 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.[29] They invest in both crypto assets and equity, and thus choose their holdings of crypto assets to solve the following 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

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

[29]See for instance Adrian and Shin (2014).

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.[30]

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:*

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

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:*

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

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

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

Comparing Equations 1 and 2, we note two mian results. Firstly, changes in institutional wealth w_t^i translate into changes in the risk-taking profile of the marginal investor in the crypto market, making it more or less similar to the risk-taking profile of the marginal investor in 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 $\frac{w_t^i}{w_t^i+w_t^c} \to 1$, $\Gamma_t^c \to 2\theta^2\lambda_t$. 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 changes in the participation of institutional investors in crypto markets are reflected in the correlation between equity and crypto prices, in line with our empirical findings (e.g., Figure 5).

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 trading reduces aggregate effective risk aversion (since $\Gamma_t \geq 2\theta^2\lambda_t$), in line with Figure C.1. 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 participation could increase the sensitivity of crypto markets to the economic cycle, as observed in Figure 11 and 13.

6 Conclusion

Our study highlights the crucial role of institutional investors in the synchronization between crypto and global equity markets and in the transmission of US monetary policy. We provide evidence that the participation of institutional investors in crypto markets significantly drives the correlation between crypto and global equity markets. Furthermore, we show that US monetary policy exerts a significant influence on the crypto cycle, analogous to its impact on global equity markets, only when institutional investor participation is substantial. We argue, both empirically and theoretically, that these patterns can be explained by institutional holdings of crypto assets, which create a strong link between crypto and equity markets.

Policymakers should closely monitor the crypto investor base as higher institutional participation calls for comprehensive regulatory scrutiny. The growing presence of institutional investors in crypto markets could amplify spillover risks, so policymakers should consider strategies to mitigate these, like enhancing transparency and monitoring leverage and liquidity levels. Such a proactive stance could help safeguard the financial system and support sustainable growth in both traditional and crypto markets.

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A Factors Construction

Dynamic factor models allow us to decompose a set of prices into a comment and an idiosyncratic component.[31] 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. These are: Bitcoin, Ethereum, Binance Coin, Ripple, Cardano, DogeCoin, and Tron. 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):

$$\begin{aligned} p_{it} &= \lambda_i(L) f_t + \epsilon_{it} && && (3) \\ f_t &= A_1 f_{t-1} + ... + A_q f_{t-q} + \eta_t && \eta_t \sim \mathcal{N}(0, \Sigma) \\ \epsilon_{it} &= \rho_i \epsilon_{it-1} + e_{it} && e_{it} \sim \mathcal{N}(0, \sigma_{it}^2) \end{aligned}$$

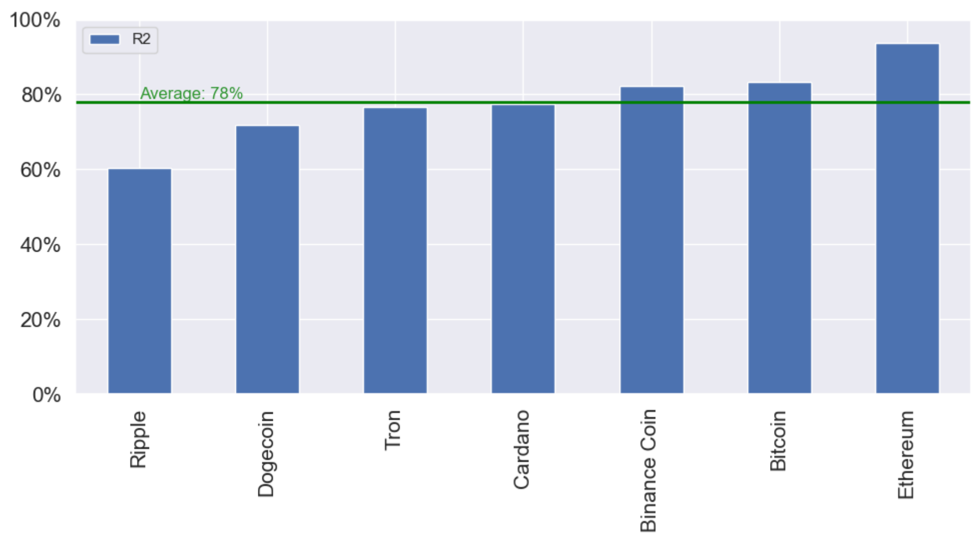
where L is the lag operator and $\lambda_i(L)$ is a q-order vector of factor loadings for asset i. Estimating this system using maximum likelihood, selecting q using information criteria, produces our common factor f_t.[32] It is also possible to specify multiple factors that affect prices differently, and we use this latter specification when we consider multiple distinct sub-classes of crypto assets (see Figure 2).

[31]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).

[32]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`.

Figure A.1 reports the R^2s of the regression of the crypto factor onto each crypto price input: Ripple, Dogecoin, Tron, Cardano, Binance Coin, Bitcoin, and Ethereum. All regressions exhibit substantial R^2 values, indicating a strong explanatory power of the crypto factor across different assets. Ethereum demonstrates the highest R^2, followed closely by Bitcoin and Binance Coin, each exceeding the average R^2 value of 78% marked by the green line. Dogecoin, Tron, and Cardano also display robust R^2 values, though Ripple shows a slightly lower R^2 compared to the other assets.

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 3.1.

Table A.1 details the indices utilized for the construction of the global equity factor and its sub-factors. The indices, sourced from Eikon/Thomson Reuters, are categorized by country and sector.

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.

B Additional Results and Robustness Tests

Table B.1 reports the p-values for the differences in correlation before and after the year 2020. Notably, several factors such as the S&P 500, Equity Factors, Small Caps Factors, Tech Factor, Financials Factor, and VIX show significant changes in correlations post-2020 (p-values below 0.05), highlighted in green. For instance, the S&P 500 has p-values of 0.000 and 0.005 when correlated with Bitcoin and Crypto Factors, respectively, indicating a change in correlation after 2020. Conversely, some factors like Oil and Gold show high p-values (0.817 and 0.953, respectively), meaning that their correlation with Bitcoin and the Crypto Factors did not significantly change after 2020.

Table B.1: 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	0.216	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	0.001	0.007	n.a.	n.a.	n.a.	n.a.	n.a.
Small Caps F	0.001	0.013	n.a.	n.a.	n.a.	n.a.	n.a.
Tech Factor	0.000	0.004	n.a.	n.a.	n.a.	n.a.	n.a.
Equity F (no Tech)	0.497	0.575	n.a.	n.a.	n.a.	n.a.	n.a.
Financials F	0.009	0.042	n.a.	n.a.	n.a.	n.a.	n.a.
Equity F (no Fin)	0.058	0.104	n.a.	n.a.	n.a.	n.a.	n.a.
Dollar Index	0.076	0.012	n.a.	n.a.	n.a.	n.a.	n.a.
VIX	0.000	0.027	n.a.	n.a.	n.a.	n.a.	n.a.
Oil	0.817	0.953	n.a.	n.a.	n.a.	n.a.	n.a.
Gold	0.987	0.605	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 January 2024.

Table B.2 presents the regression results using the SP500 and Bitcoin price to validate our primary findings. The table shows that the coefficients and their significance levels remain consistent with those obtained in Table 4, reaffirming the robustness of our results. This robustness check underscores that the observed relationships are not artifacts of the factor construction methodology.

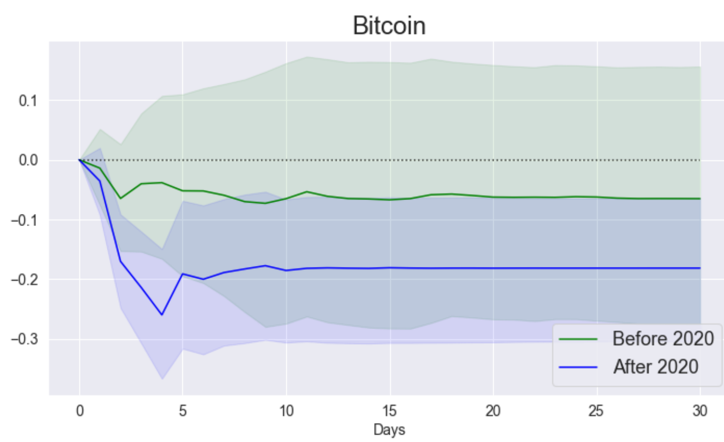
Table B.2: The Role of Institutional Investors in the Correlation between Bitcoin and S&P 500.

	Δ Bitcoin_t					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ $\text{S\&P500}_t$	0.243***	0.0113	0.223***	0.227***	0.203***	0.286***
	(8.82)	(0.30)	(8.66)	(9.12)	(8.63)	(9.66)
Δ Gold_t	0.496	0.762	0.401	0.307	0.417	0.345
	(1.00)	(1.45)	(0.95)	(0.69)	(1.08)	(0.64)
Δ Oil_t	-0.0293	0.0431	0.144	0.101	0.137	0.221
	(-0.18)	(0.21)	(0.64)	(0.45)	(0.61)	(0.87)
Δ $\text{S\&P500}_t$ # After 2020		0.264***				
		(5.38)				
Δ Gold_t # After 2020		-0.451				
		(-0.59)				
Δ Oil_t # After 2020		-0.0521				
		(-0.19)				
Δ $\text{S\&P500}_t$ # Share of $\text{Institutionals}_{t-1}$			0.124***			
			(6.03)			
Δ $\text{S\&P500}_t$ # Volume of $\text{Institutionals}_{t-1}$				0.147***		
				(5.45)		
Δ $\text{S\&P500}_t$ # Share Retailers_{t-1}					-0.168***	
					(-6.74)	
Δ $\text{S\&P500}_t$ # Share Inst. Coinbase_{t-1}						0.0397*
						(1.78)
Share of $\text{Institutionals}_{t-1}$			0.0387			
			(0.25)			
Volume of $\text{Institutionals}_{t-1}$				-0.00436		
				(-0.02)		
Share Retailers_{t-1}					-0.0682	
					(-0.50)	
Share Inst. Coinbase_{t-1}						2.698**
						(1.97)
Δ Gold_t # Share of $\text{Institutionals}_{t-1}$			-0.651			
			(-1.55)			
Δ Gold_t # Volume of $\text{Institutionals}_{t-1}$				-0.566		
				(-1.03)		
Δ Gold_t # Share Retailers_{t-1}					0.578	
					(1.15)	
Δ Gold_t # Share Inst. Coinbase_{t-1}						-0.175
						(-0.48)
Year-Month Fixed Effects	YES	YES	YES	YES	YES	YES
Obs.	1522	1522	1192	1192	1192	794
R^2	0.109	0.116	0.154	0.162	0.160	0.158
R^2-adjusted	0.0626	0.0681	0.0944	0.103	0.101	0.0977

Notes: This table reports the results from regressing the Bitcoin on the S&P500 along with different interactions with time dummies and the share of institutional investors. Variables are standardized. Data is from January 2018 to January 2024. t-statistics are in parentheses. *, **, *** correspond to 10%, 5%, and 1% significance, respectively.

Figure B.1 displays the cumulative impulse response functions of Bitcoin to a one percentage point rise in the shadow Federal Funds Rate (FFR), illustrating the impacts before and after 2020. The green line represents the period before 2020, and the blue line represents the period after 2020. Since we are only using Bitcoin, rather than a range of crypto assets, we can extend the sample to begin in 2010. As expected, the results show a significant negative response of Bitcoin to monetary policy shocks only after 2020, while the pre-2020 period shows a muted reaction. These findings suggest a shift in how Bitcoin reacts to monetary policy post-2020, underscoring the increasing integration and sensitivity of Bitcoin to traditional financial and economic indicators in recent years.

Figure B.1: Impacts of Monetary Policy on Bitcoin Before and After 2020



Notes: This figure shows the cumulative 15-day impulse response functions for a one percentage point rise in the shadow FFR. Data is from July 2010 to February 2024. We report 90% confidence intervals computed from 1000 Monte Carlo simulations. All variables are standardized over the sample period.

C Aggregate Effective Risk Aversions

In this section, we create a proxy of the time-varying effective risk aversion of marginal investors by following Bekaert, Hoerova, and Lo Duca (2013) and Miranda-Agrippino and Rey (2020). Therefore, we decompose movements in prices 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. We capture (i) with realized market risk, measured by the 90-day variance of the MSCI World index as in Miranda-Agrippino and Rey (2020), and we can estimate (ii) as (an inverse function of) the residual ϵ of the following regression in logarithms:

$$f_t^{Equities} = \alpha + \beta_1 \cdot Var(\text{MSCI World})_t + \epsilon_t \tag{4}$$

and similarly for crypto:

$$f_t^{Crypto} = \alpha' + \beta_1' \cdot Var(\text{MSCI World})_t + \beta_2' \cdot Var(\text{BTC})_t + \epsilon_t' \tag{5}$$

where: f_t are the factors estimated using the methodology in Equation 3 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. Regression results are reported in Table C.1. 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.

Table C.1: Risk-Aversion Regressions

		Global Crypto Factor (1)	(2)	(3)	(4)	Global Equity Factor (5)	(6)	(7)	(8)
Var(Bitcoin)	30 days	0.56							
		(0.350)							
	45 days		0.202						
			(0.286)						
	60 days			0.192					
				(0.257)					
	90 days				-0.026				
					(0.242)				
Var(MSCI World)	30 days	-23.747***				-64.085***			
		(1.804)				(3.87)			
	45 days		-18.931***				-49.799***		
			(1.331)				(2.657)		
	60 days			-17.277***				-41.218***	
				(1.154)				(2.083)	
	90 days				-14.703***				-29.895***
					(0.993)				(1.728)
Constant		-0.107***	-0.078***	-0.061**	-0.002	71.514***	55.832***	46.413***	33.981***
		(0.023)	(0.025)	(0.027)	(0.032)	(4.255)	(2.923)	(2.293)	(1.904)
Obs.		1508	1493	1478	1448	1538	1538	1538	1538
R^2		0.067	0.082	0.096	0.121	0.173	0.18	0.174	0.148

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.

The effective equity risk aversion extracted from Equation 4 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 -24% and 38%. At the 30-day horizon, they are -47% and 60% (see Table C.2). 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 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).

Table C.2: 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	0.880	1.000								
Δ 60-day Crpyto Risk Aversion	0.917	0.900	1.000							
Δ 90-day Crpyto Risk Aversion	0.935	0.881	0.927	1.000						
Δ 30-day Global Equity Risk Aversion	0.124	0.117	0.085	0.110	1.000					
Δ 45-day Global Equity Risk Aversion	0.095	0.064	0.083	0.086	0.967	1.000				
Δ 60-day Global Equity Risk Aversion	0.074	0.044	0.053	0.071	0.935	0.989	1.000			
Δ 90-day Global Equity Risk Aversion	0.050	0.030	0.036	0.043	0.855	0.935	0.973	1.000		
Δ Intermediary Capital Ratio	-0.111	-0.066	-0.066	-0.096	-0.473	-0.392	-0.333	-0.239	1.000	
Δ Intermediary Leverage Ratio Squared	0.116	0.051	0.045	0.096	0.599	0.531	0.481	0.383	-0.877	1.000

Notes: This table shows pairwise daily correlations between changes in the measures of risk aversion, computed using Equations 4 and 5, 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.

Figure C.1 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 overall 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. In Section 4, we follow Miranda-Agrippino and Rey (2020) and leverage this measure to test the impact of monetary policy on crypto prices.

Figure C.1: 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.