The Crypto Cycle and US Monetary Policy

Natasha Che[1], Alexander Copestake[1], Davide Furceri[1], Tammaro Terracciano[2]

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[1]International Monetary Fund
[2]IESE Business School Barcelona

Motivation

- Different crypto assets claim a variety of value propositions
  - ⇒ E.g. sound money, more efficient transactions, censorship-resistant computing or property rights
- Yet crypto asset prices tend to move together, and until recently increasingly in parallel with equities
  - ⇒ Common crypto booms and 'winters'
  - ⇒ Bitcoin increasingly correlated with S&P500 (Adrian, Iyer & Qureshi *2022**)
- This raises several questions:

Overview of the paper

1. To what extent is there a common cycle across crypto assets?

2. How does this relate to the Global Financial Cycle? (Rey 2013)

3. Is it also influenced by US monetary policy? (Miranda-Agrippino & Rey 2020)

4. What could this imply for potential spillovers across asset classes? (Iyer 2022)

Overview of the paper

1. To what extent is there a common cycle across crypto assets?
   $\Rightarrow$ Dynamic factor model: single Crypto Factor explains 80% of price variation.

2. How does this relate to the Global Financial Cycle? (Rey 2013)
   $\Rightarrow$ $\uparrow Corr(\text{CF,GFC})$ from 2020, coinciding with entry of 'TradFi' institutions.

3. Is it also influenced by US monetary policy? (Miranda-Agrippino & Rey 2020)
   $\Rightarrow$ VARs: Tightening reduces CF, consistent with the increased cost of leverage reducing the risk appetite of the marginal investor.

4. What could this imply for potential spillovers across asset classes? (Iyer 2022)
   $\Rightarrow$ Model: institutional adoption raises potential crypto $\rightarrow$ equities spillovers.

$\ast$ *Work-in-progress:* mechanism in reverse in 2023? [+AI for S&P500.]

Literature

- The Global Financial Cycle, impact of US monetary policy, and role of heterogeneous risk aversion (Rey 2013, Miranda-Agrippino and Rey 2020, Coimbra et al. 2022, Kekre & Lenel 2018, Gourinchas et al. 2010)

  ⇒ Add in crypto assets

- Value propositions and other drivers of specific crypto asset prices (Schilling & Uhlig 2019, Makarov and Schoar 2020, Scaillet et al. 2020, Cong et al. 2021, Liu et al. 2022)

  ⇒ Examine common movement in whole asset class

- Composition and motivation of crypto investors, including increasing institutional participation (Auer & Tercero-Lucas 2021, Makarov and Schoar 2021, Hackethal et al. 2021, Auer et al. 2022, Didisheim & Somoza 2022)

  ⇒ Use to explain co-movement between crypto and equities + potential spillovers

Stylized fact: High degree of correlation across crypto assets

Pairwise correlations, January 2018 to March 2023

	Bitcoin	*Ethereum*	*Binance Coin*	*Ripple*	*Cardano*	Solana	*Dogecoin*	Polkadot	*Tron*	Shiba Inu	Maker Dao	Avalanche	Uniswap	Litecoin	FTT	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				
FTT	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

$\Rightarrow$ Suggests can model using a common cycle, i.e. a single dynamic factor

Deriving the Crypto Factor

Data: Daily prices for tokens created at the latest by 2018 (excluding stablecoins).

$\Rightarrow$ Seven assets, accounting for 75% of total market capitalization *(6/2022, stable)*.

Methodology:

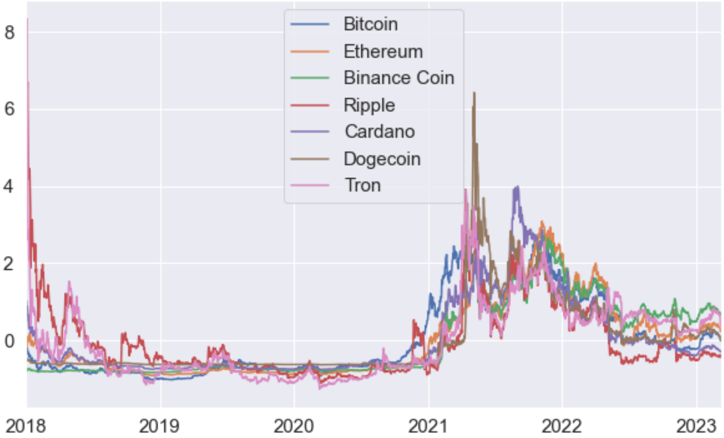
1. Write the panel of crypto prices p_{it} as a linear combination of an AR(q) common factor f_t plus an asset-specific idiosyncratic disturbance ϵ_{it}:

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

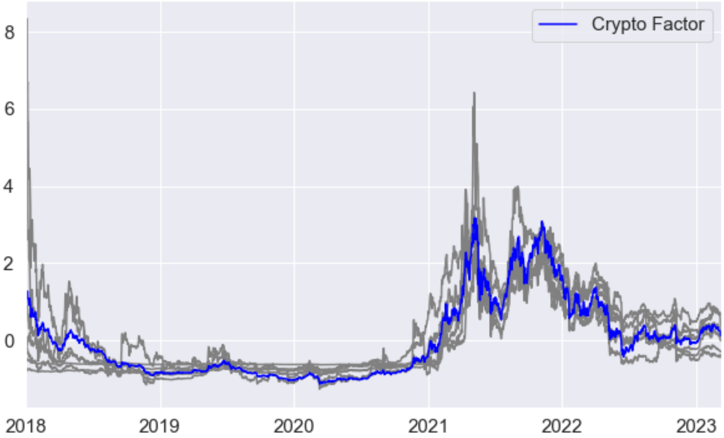
   where L is lag operator and $\lambda_i(L)$ is q-order vector of factor loadings for asset i.

2. Estimate the system using EM-MLE, and select q using information criteria.

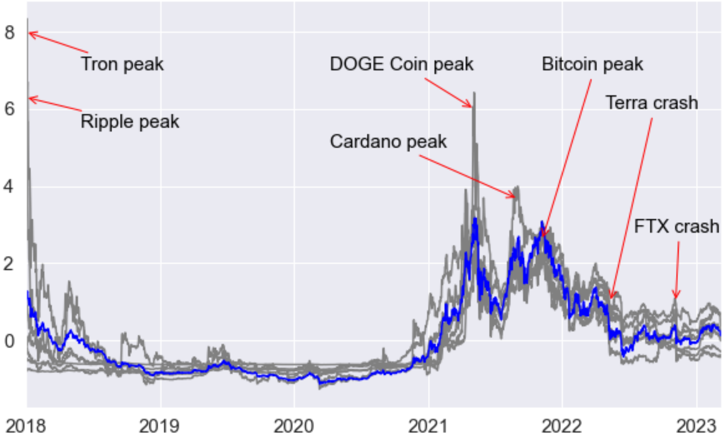
Deriving the Crypto Factor – Inputs



Deriving the Crypto Factor – Output

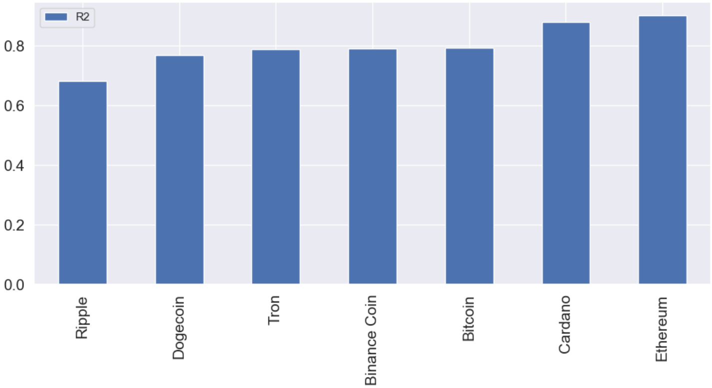


Deriving the Crypto Factor – Output



(Internally) Validating the Crypto Factor – Reverse regressions

So far: $p_{it} \to f_t$. Now see how well f_t explains p_{it}: regress $p_{it} = \alpha + \beta f_t + u_{it}$. Results:



⇒ The Crypto Factor explains on average 80% of variation in the crypto prices.

⇒ Comparison: 20% for MAR's global equity factor (though many more large equities).

(Externally) Validating the Crypto Factor – Sub-factors using more assets

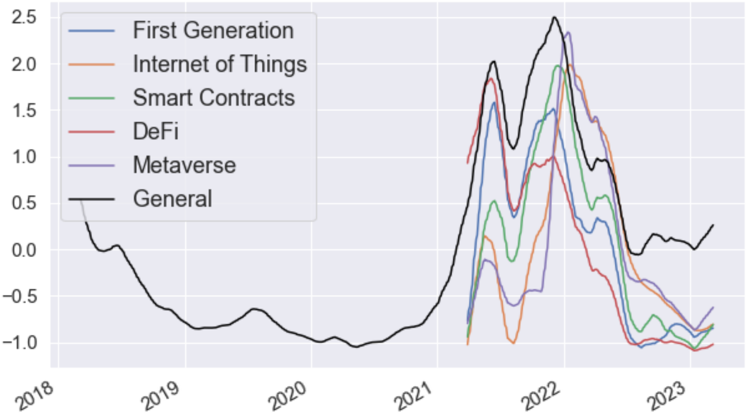
Broaden the sample to include more crypto assets, even though shorter sample (most did not exist pre-2020):

First Gen.	Smart Contract	DeFi	Metaverse	IoT
Bitcoin	Ethereum	Chainlink	Flow	VeChain
Ripple	Binance Coin	Uniswap	ApeCoin	Helium
Dogecoin	Cardano	Maker	The Sandbox	IOTA
	Solana	Aave	Decentraland	IoTeX
	Polkadot		Theta Network	MXC

⇒ Estimate a model with five different (sub-)factors, where each can affect only one class.

(Externally) Validating the Crypto Factor – Sub-factors using more assets

Standardized factor values



⇒ Highly correlated with overall crypto cycle. (Except Meta rebrand jump.)

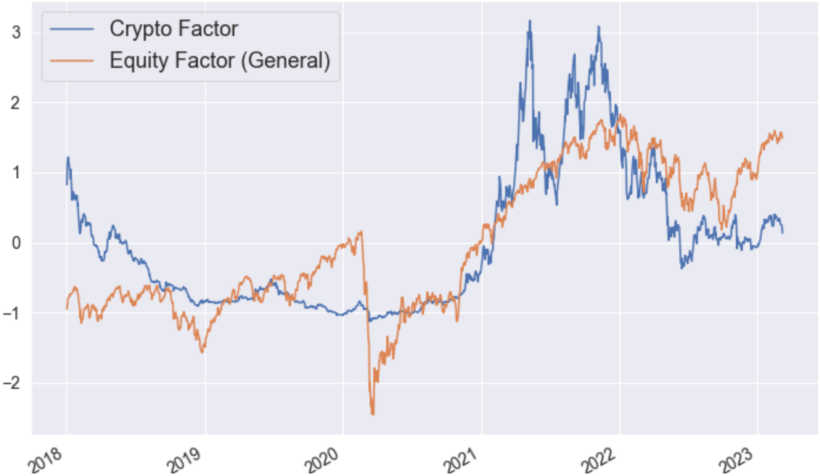
How does the Crypto Cycle relate to the Global Financial Cycle?

- We replicate Rey's Global Financial Cycle variable as closely as possible

  $\Rightarrow$ Use all equity indices available on Eikon/Thomson Reuters for the top 50 countries by GDP Examples

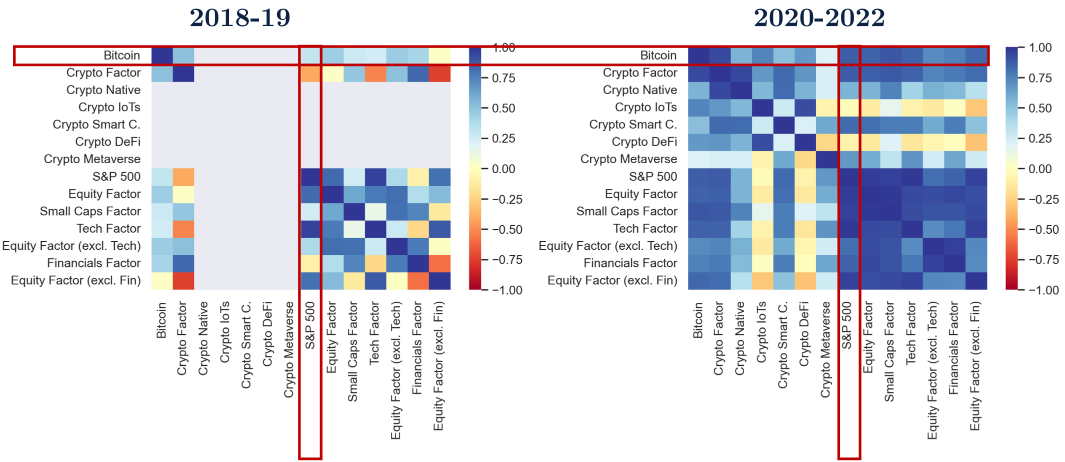
- We use the same methodology as in the previous section to compute both an 'overall' factor and separate tech, finance and small-cap factors

How does the Crypto Cycle relate to the Global Financial Cycle?



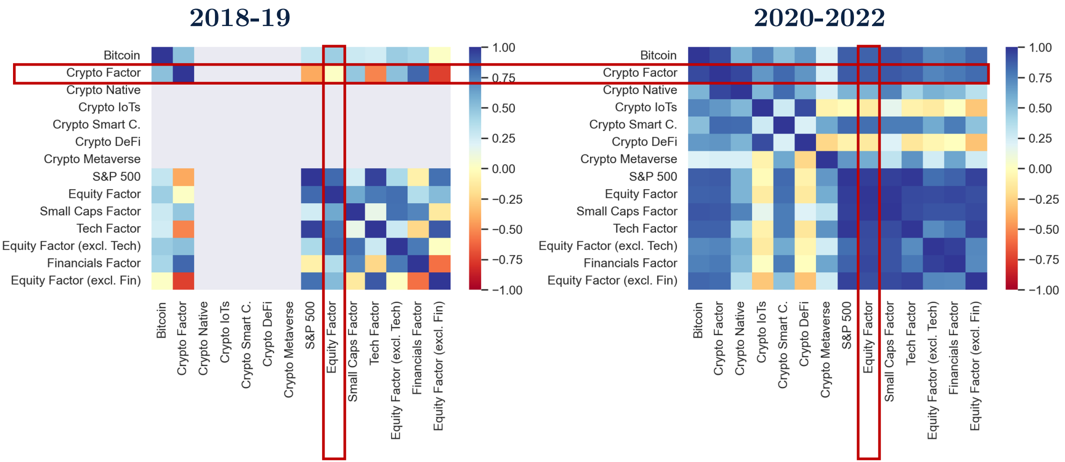
Substantial rise in $Corr$(CF,GFC) 2020-2022H1; then slight decline (Terra, FTX, AI).

How does the Crypto Cycle relate to the Global Financial Cycle?



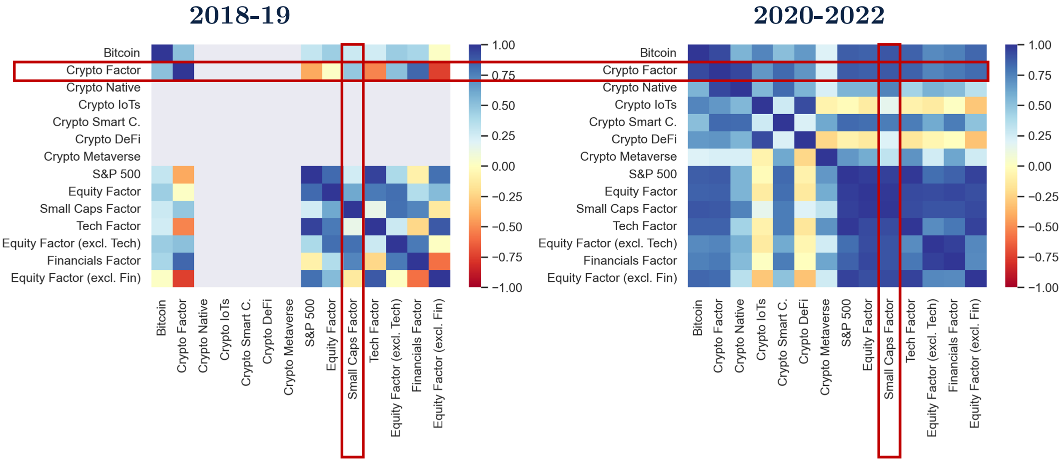
Bitcoin-S&P500 correlation increased... (Adrian, Iyer & Qureshi 2022)

How does the Crypto Cycle relate to the Global Financial Cycle?



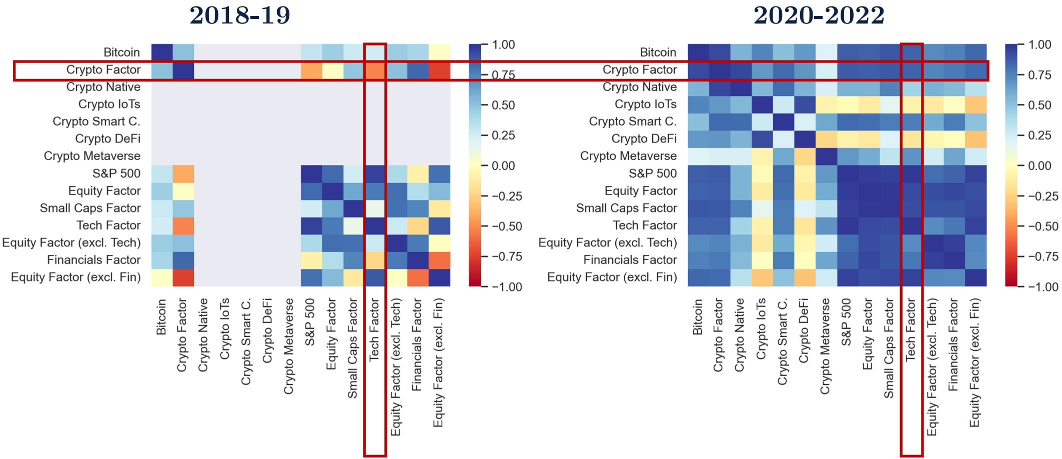
...and so did broader crypto-equity factor correlation.

How does the Crypto Cycle relate to the Global Financial Cycle?



Crypto looks more like small-cap stocks...

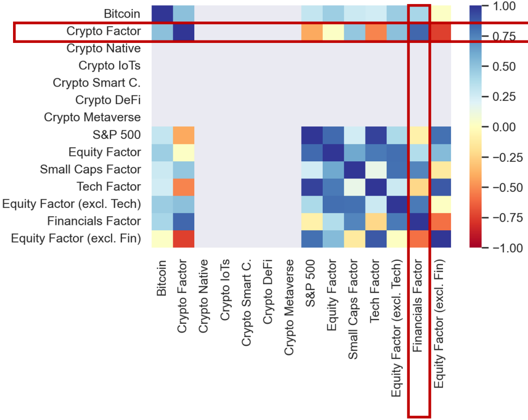
How does the Crypto Cycle relate to the Global Financial Cycle?



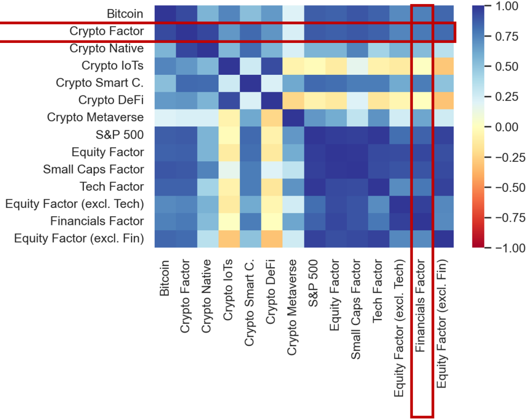
...and more like tech...

How does the Crypto Cycle relate to the Global Financial Cycle?

2018-19



2020-2022



...and less like financial firms.

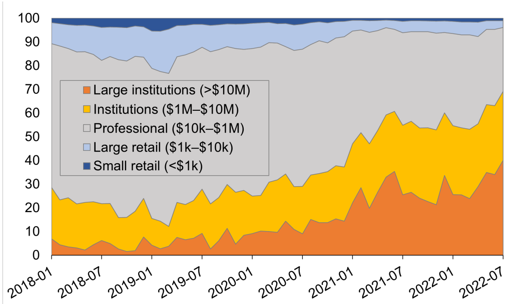
What drove the increased correlation between crypto and equities?

Various possible (and mutually compatible) explanations:

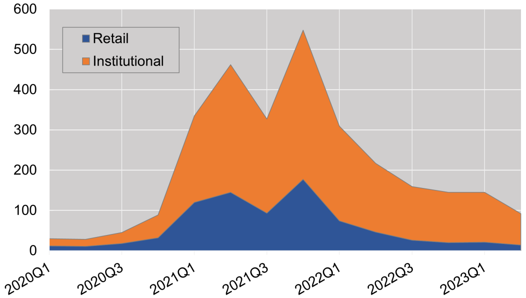
- New on-ramps opened to investors (PayPal & Robinhood offering crypto, Coinbase IPO April 2021, etc.)
- Retail
  - ⇒ COVID lockdowns increased retail trading (Vanda Research 2021, Charles Schwab 2022)
  - ⇒ $15bn of federal stimulus checks invested in crypto (Toczynski 2022)
- Institutional
  - ⇒ Increased participation by hedge funds, asset managers, and some banks (Auer et al. 2022)
  - ⇒ ...

What drove the increased correlation between crypto and equities?

Share of on-chain trading volumes



Trading volumes on Coinbase ($bn)



$\Rightarrow$ Given size, focus on institutional entry = changing profile of marginal investor.

What drove the increased correlation between crypto and equities?

To test for changing profile of the marginal investor, follow Bekaert et al. (2013) and MAR by decomposing movements in the factors into two elements:

1. Changes in market risk
2. Changes in market attitudes towards risk $\Rightarrow$ 'aggregate effective risk aversion' = the wealth-weighted average risk aversion of investors

Proxying the former with realized market risk, estimate the latter as a residual ϵ from regression in logs:

$$f_t^{Equities} = \alpha + \beta_1 \cdot Var(\text{MSCI World}_t) + \epsilon_t \tag{1}$$

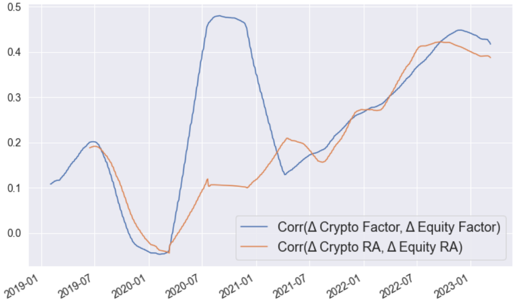
and similarly for crypto:

$$f_t^{Crypto} = \alpha' + \beta_1' \cdot Var(\text{MSCI World}_t) + \beta_2' \cdot Var(\text{BTC}_t) + \epsilon_t' \tag{2}$$

repeating MSCI in second regression to control for overall global market risk.

What drove the increased correlation between crypto and equities?

Graphing the residuals: aggregate effective risk aversion in crypto markets falls since 2020, while correlation with that in equity markets rises



⇒ marginal investor in crypto appears increasingly similar to that in equities, consistent with institutional entry driving synchronization of cycles.

What drove the increased correlation between crypto and equities?

Indeed, the correlation between the two aggregate effective risk aversions explains a large share of the correlation between the crypto and equity factors

	$Corr$(ΔCrypto Factor, ΔEquity Factor)					
Rolling Window (Days)	(30)	(45)	(90)	(120)	(240)	(360)
$Corr$(ΔCrypto RA, ΔEquity RA)	0.854***	0.833***	0.802***	0.733***	0.633***	0.473***
	(0.016)	(0.018)	(0.021)	(0.023)	(0.027)	(0.018)
Constant	Y	Y	Y	Y	Y	Y
Observations	1,183	1,168	1,123	1,093	973	853
R^2	0.648	0.564	0.455	0.408	0.364	0.434

⇒ Characteristics of the marginal investor appear quantitatively important

Does US monetary policy affect the Crypto Cycle?

- *So far:* Crypto Cycle closely related to the Global Financial Cycle...

  ...driven in part by entry of 'TradFi' institutions.

- *Literature:* US MP affects the Global Financial Cycle...

  ...including through impact on risk-taking behavior of financial institutions.

⇒ Likely that US MP also influences Crypto Cycle

⇒ Daily VAR to investigate, following MAR.

Does US monetary policy affect the Crypto Cycle?

Data:

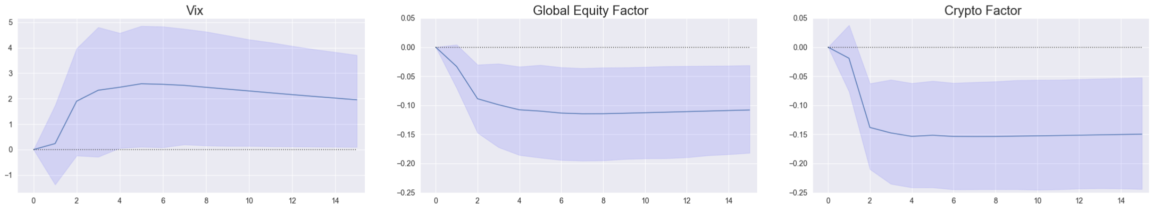
- Shadow Federal Funds Rate from Wu and Xia (2016) – since balance sheet policy important during our sample period ▸ Rates
- T10Y2Y spread – reflecting expectations of future growth
- DXY dollar index, oil and gold prices – as proxies for international trade, credit and commodity cycles
- VIX – reflecting expected future uncertainty
- Standardized daily equity and crypto factors from January 2018 to March 2023

Methodology:

- ID based on variable ordering (Cholesky decomposition)
- Exogeneity of SFFR: Fed doesn't respond to crypto markets, nor on daily frequency. (Also robust to re-ordering so SFFR most endogenous.)

Does US monetary policy affect the Crypto Cycle? – *Results*

Cumulative 15-day IRFs for 1pp rise in Shadow FFR. 90% confidence intervals from 1000 Monte Carlo simulations.

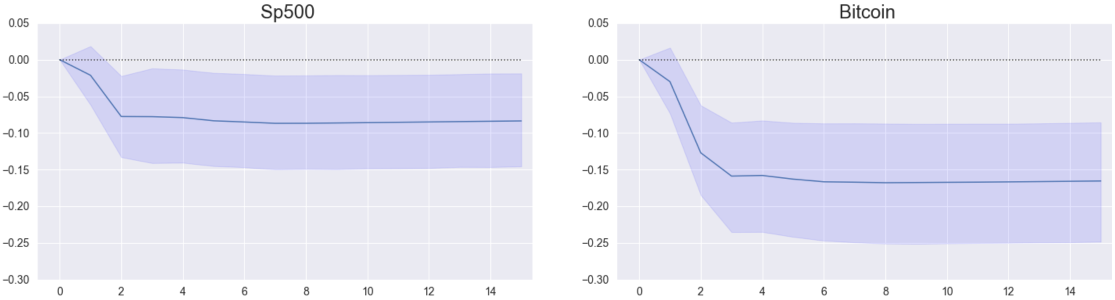


⇒ Global equities fall in response to Fed tightening and higher expected uncertainty, as in MAR

⇒ Crypto prices fall by 50% more than equities and the decline is persistent

Does US monetary policy affect the Crypto Cycle? – *Robustness*

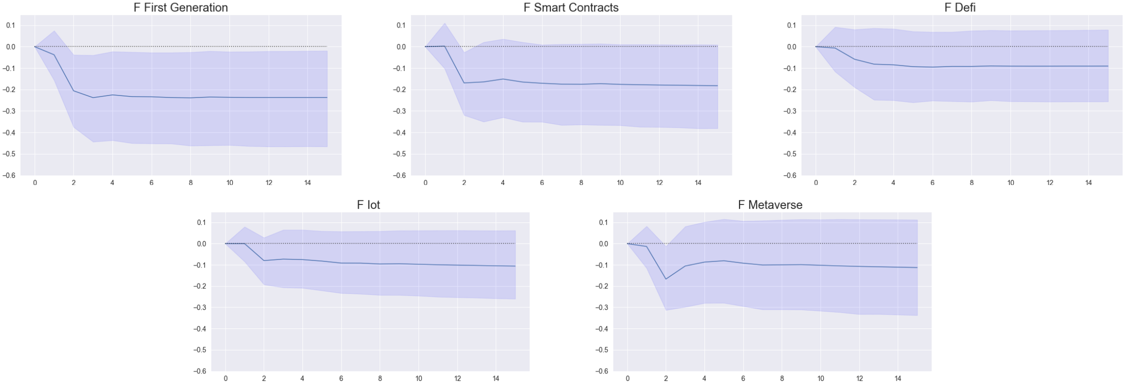
Cumulative 15-day IRFs for 1pp rise in Shadow FFR. 90% confidence intervals from 1000 Monte Carlo simulations.



⇒ Results robust to replacing the factors with S&P500 and the Bitcoin price (+ US MP shock measures)

Does US monetary policy affect the Crypto Cycle? – *Heterogeneity*

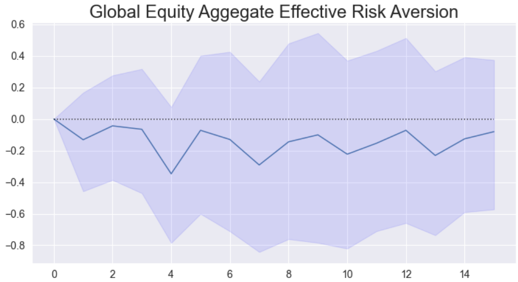
Cumulative 15-day IRFs for 1pp rise in Shadow FFR. 90% confidence intervals from 1000 Monte Carlo simulations.

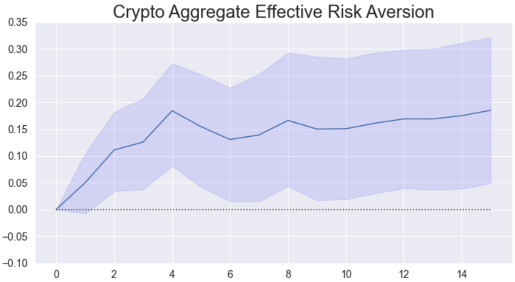


⇒ All sub-factors fall; impact strongest for first generation and smart contract factors, weakest for metaverse (volatile, short sample)

Does US monetary policy affect the Crypto Cycle? – *Channels*

Add aggregate effective risk aversion measures to VAR (before respective factors):





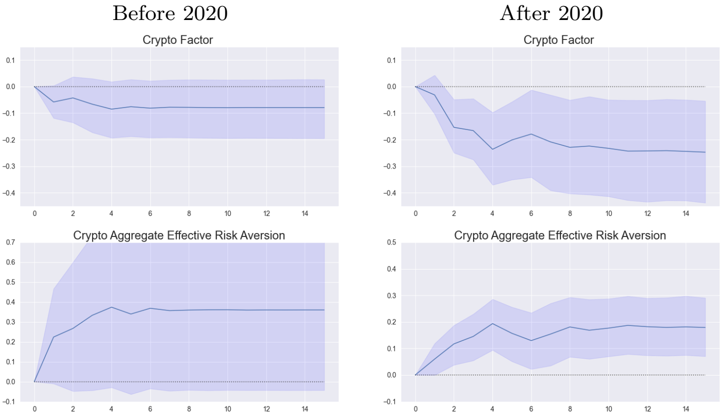
Higher cost of capital:

⇒ deleveraging – especially by least risk-averse institutions, which initially take on more leverage (in line with e.g. Coimbra et al. 2022)

⇒ higher aggregate effective risk aversion + lower crypto prices.

Does US monetary policy affect the Crypto Cycle? – *Channels*

Stronger post-2020, consistent with increased presence of (more leveraged) institutions:



⇒ Consistent with institutional participation not only increasing correlation with equities, but also reinforcing transmission of MP to crypto markets.

Does US monetary policy affect the Crypto Cycle? – *Channels*

Test the role of institutional investors more formally using smooth transition VAR with two states (Auerbach & Gorodnichenko, 2012):

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

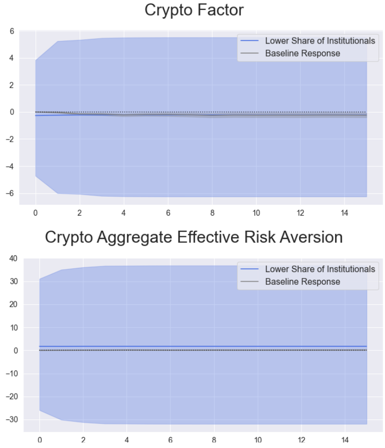
where Y_t is the stacked vector of variables, s_t the transition state variable (the share of institutional investors from Chainalysis), and $F(\cdot)$ a logistic function.

Intuition: weighted average of two VARs—one each for low and high institutional participation—so the impact of MP shocks can vary continuously between the two regimes depending on the weight (a function of the institutional share).

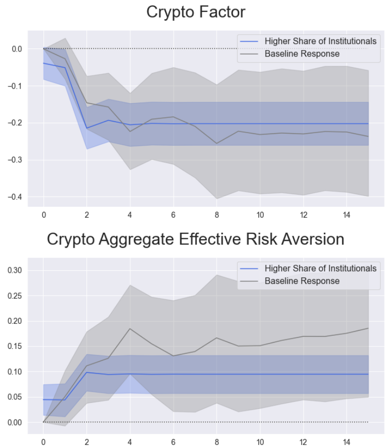
Does US monetary policy affect the Crypto Cycle? – *Channels*

⇒ Corroboration: impacts only significant in ‘high institutional participation’ regime

Lower Share



Higher Share



Does US monetary policy affect the Crypto Cycle? – *Channels*

Other potential channels:

1. USD appreciation in response to tightening makes stablecoin leverage more expensive for non-US investors (as 95% SC market cap USD-denominated)
   ⇒ Test: see if response of crypto factor to DXY; no significant impact.

2./3. More liquid/volatile assets simply react more to MP
   ⇒ Test: see if different responses between the most and least liquid/volatile crypto assets; no significant differences.

Taking stock

Stylized facts:

0. A single crypto factor explains a large share of overall price variation.
1. Correlation between the crypto factor and global equity factor increased from 2020, coinciding with increased entry of institutional investors into crypto markets.
2. A US monetary policy contraction reduces the crypto factor, by substantially more than the equity factor, and by more the larger the share of institutional investors in crypto markets.

⇒ Construct a simple framework to reflect main features

...building on the literature on heterogeneous risk-taking intermediaries

E.g., Zigrand & Danielsson 2021, Adrian & Shin 2014, MAR 2021

Setup

- Two risk-averse agents that each maximise a mean-variance portfolio:
  - ⇒ Individual crypto investors that invest only in crypto assets[1]
  - ⇒ Institutional investors that invest in both crypto and global equities
- Both can access finance at the (US) risk-free rate to lever up their positions
- Institutional investors less risk averse than individual investors[2]
  - ⇒ Greater scale = risk pooling, or explicit/implicit deposit guarantees as in MAR
- *Alternatively*:
  1. Individual investors access both; initially over-represented in crypto
  2. Crypto investors face tighter borrowing constraints

Crypto investors

...invest share x_t^c of their wealth in crypto to maximise

$$\max_{x_t^c} \mathbb{E}_t(x_t^c R_{t+1}^c) - \frac{\sigma}{2} \mathbb{V}ar_t(x_t^c R_{t+1}^c)$$

where R_{t+1}^c is the excess return on crypto and σ is the (constant) risk-aversion of the investor, giving FOC

$$x_t^c = \frac{1}{\sigma} \mathbb{E}_t(R_{t+1}^c) \left[\mathbb{V}ar_t(R_{t+1}^c)\right]^{-1}$$

I.e. c increases their holdings proportionately with the expected return on crypto assets, and decreases them with the variance of the portfolio and their risk aversion.

Institutional investors

...invest share x_t^i (y_t) of their wealth in crypto (equities) to maximise

$$\max_{x_t^i, y_t} \mathbb{E}_t(x_t^i R_{t+1}^c + y_t R_{t+1}^e) - \frac{\theta}{2} \mathbb{V}ar_t(x_t^i R_{t+1}^c + y_t R_{t+1}^e)$$

where R_{t+1}^e is the excess return on global equities and θ is the (constant) risk-aversion of the investor (where $\theta < \sigma$), giving FOC with respect to crypto

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

I.e. i increases their holdings of crypto proportionately with the expected return on crypto assets, and decreases them with the variance of crypto returns, their risk aversion, and the correlation of crypto with equities.

Equilibrium in the crypto market

...requires that supply of crypto assets (normalized by total wealth) s_t equals total holdings

$$s_t = x_t^c \frac{w_t^c}{w_t^c + w_t^i} + x_t^i \frac{w_t^i}{w_t^c + w_t^i}$$

where w_t^c and w_t^i are the wealth of investors. By combining this with the FOCs, we can summarize the expected return on crypto:

$$\mathbb{E}_t(R_{t+1}^c) = \Gamma_t \mathbb{V}ar_t(R_{t+1}^c) s_t + \Gamma_t \mathbb{C}ov_t(R_{t+1}^c, R_{t+1}^e) y_t \frac{w_t^i}{w_t^c + w_t^i}$$

where

$\Gamma_t = (w_t^c + w_t^i)\left[\frac{w_t^c}{\sigma} + \frac{w_t^i}{\theta}\right]^{-1}$ is the **aggregate degree of effective risk aversion**.

Equilibrium in the equity market

...requires that supply of equities (normalized by wealth) y_t^{tot} equals total holdings y_t.

Combining this with the FOC then gives expected return on equities:

$$\mathbb{E}_t(R^e_{t+1}) = \theta \mathbb{V}ar_t(R^e_{t+1}) y_t^{tot} + \theta \mathbb{C}ov_t(R^c_{t+1}, R^e_{t+1}) x_t^i$$

Results

Equities: $$\mathbb{E}_t(R^e_{t+1}) = \theta \mathbb{V}ar_t(R^e_{t+1}) y^{tot}_t + \theta \mathbb{C}ov_t(R^c_{t+1}, R^e_{t+1}) x^i_t$$

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

Aggregate Risk Aversion: $$\Gamma_t = (w^c_t + w^i_t)\left[\frac{w^c_t}{\sigma} + \frac{w^i_t}{\theta}\right]^{-1}$$

---

1. As institutional wealth w^i_t makes up an increasing share of the crypto market, the time-varying risk-taking profile of crypto converges on that of equities.

   ⇒ In the limit of full institutional entry, $\Gamma_t \to \theta$ and $w^i_t/(w^c_t + w^i_t) \to 1$...

   ⇒ ...so crypto and equity returns only differ based on relative supplies and relative variances of the two assets.

Results

Equities: $$\mathbb{E}_t(R^e_{t+1}) = \theta \mathbb{V}ar_t(R^e_{t+1}) y^{tot}_t + \theta \mathbb{C}ov_t(R^c_{t+1}, R^e_{t+1}) x^i_t$$

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Aggregate Risk Aversion: $$\Gamma_t = (w^c_t + w^i_t)\left[\frac{w^c_t}{\sigma} + \frac{w^i_t}{\theta}\right]^{-1}$$

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2. MP tightening reduces crypto returns by more, the larger the share of institutions.

   $\Rightarrow$ Increased institutional entry $w^i_t > 0$ reduces AERA (since $\theta < \Gamma_t < \sigma$), i.e. marginal crypto investor becomes less risk averse.

   $\Rightarrow$ If less risk-averse + more levered agents react more to MP tightening (e.g. Coimbra et al. 2022), then impact accentuated.

Results

Equities: $$\mathbb{E}_t(R^e_{t+1}) = \theta \mathbb{V}ar_t(R^e_{t+1}) y^{tot}_t + \theta \mathbb{C}ov_t(R^c_{t+1}, R^e_{t+1}) x^i_t$$

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Aggregate Risk Aversion: $$\Gamma_t = (w^c_t + w^i_t)\left[\frac{w^c_t}{\sigma} + \frac{w^i_t}{\theta}\right]^{-1}$$

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3. A future crash in crypto, which raises crypto's variance and reduces institutions' allocations x^i_t, could spill over to reduce equity returns – and by more, the larger are institutional holdings of crypto relative to equities y^{tot}_t.

   $\Rightarrow$ Second term in *Equities* currently negligible (x^i_t small), may not be in future

   $\Rightarrow$ Could justify cap $\bar{x}^i_t$ – and easiest to impose when x^i_t is low, as now.

Summary

- A single factor can explain a large share of variation in crypto prices.
- This Crypto Factor has historically been increasingly correlated with the Global Financial Cycle, and reacts even more strongly to US monetary policy than do equities.
- The changing composition of the crypto investor base – in particular the entry of institutional investors since 2020 – can explain these patterns and provide a framework for assessing future developments.

Recent developments

- 'When the tide goes out...'
  - ⇒ Tightening FCs → harder to cover up issues with new liquidity → 3AC, Celsius, Voyager, Alameda, FTX, BlockFi, Genesis/DCG (?), ...
  - ⇒ Reversal? Institutional exit rather than institutional entry → crypto-equity correlation falling.
- Could have been a lot worse...
  - ⇒ ...if later, with crypto a larger share of institutional portolios. Instead, loss (+ embarrassment) confined to small number of private (+ public) entities.
  - ⇒ Now = time to regulate.

Thank you!

The Crypto Cycle and US Monetary Policy

Natasha Che[1], Alexander Copestake[1], Davide Furceri[1], Tammaro Terracciano[2]

August 25, 2023

[1]International Monetary Fund
[2]IESE Business School Barcelona

Equity Index Examples

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Table 5: 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	

Wu-Xia Shadow FFR Path

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