The Crypto Cycle and US Monetary Policy

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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**)
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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)

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

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- 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)

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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} + ... + A_q f_{t-q} + \eta_t & \qquad \eta_t &\sim \mathcal{N}(0, \Sigma) \\
\epsilon_{it} &= \rho_i \epsilon_{it-1} + e_{it} & \qquad e_{it} &\sim \mathcal{N}(0, \sigma_{it}^2)
\end{aligned}
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   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.

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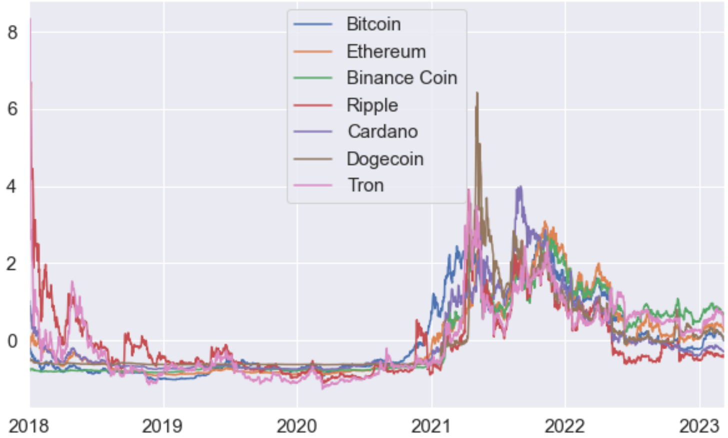

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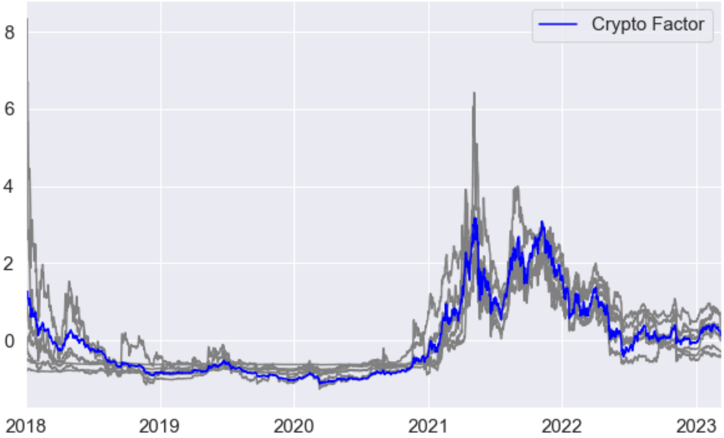

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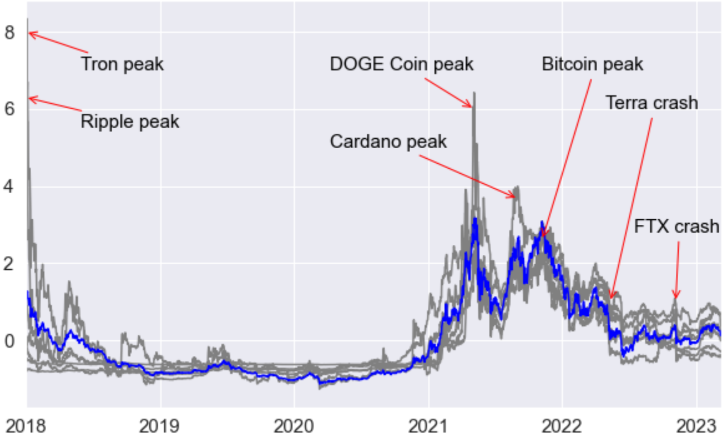
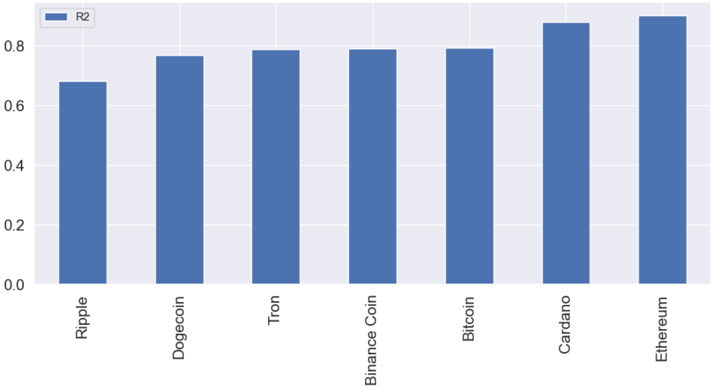


(Internally) Validating the Crypto Factor – Reverse regressions

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



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

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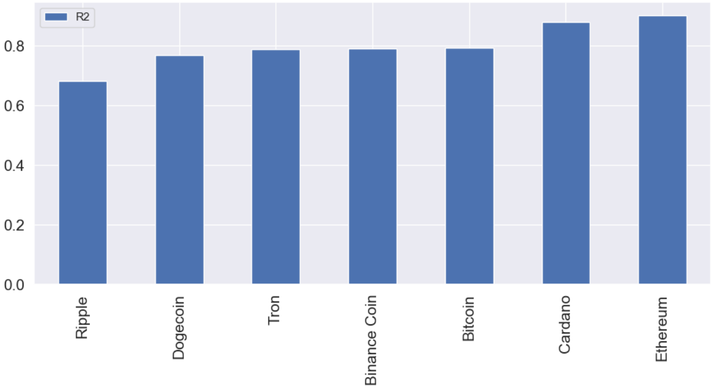

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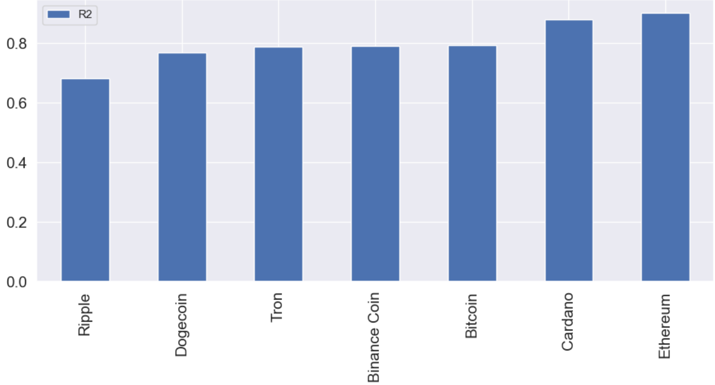

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(Externally) Validating the Crypto Factor – Sub-factors using more assets

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
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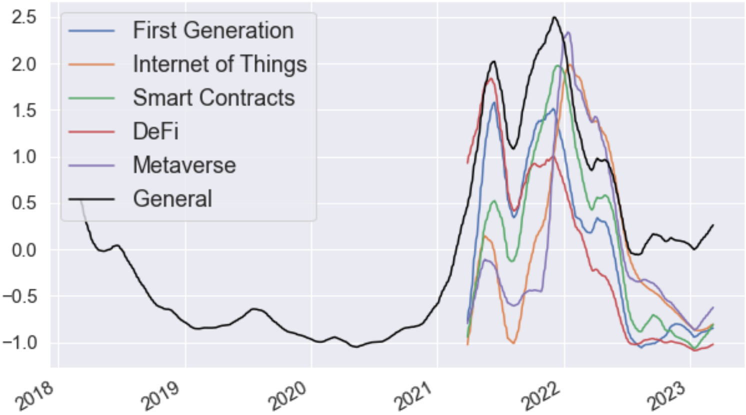
Standardized factor values



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

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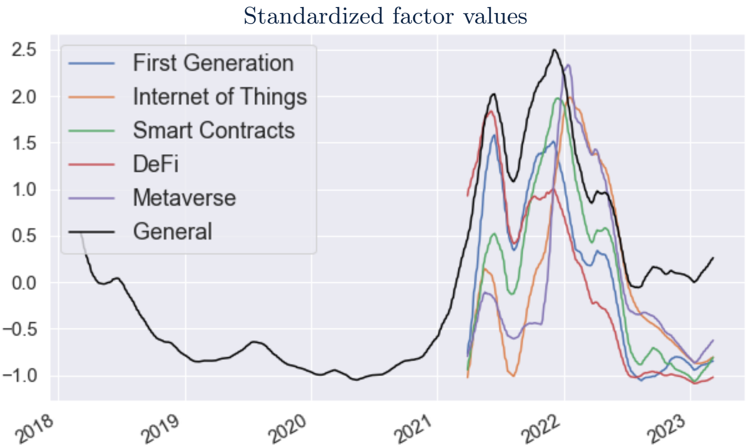

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How does the Crypto Cycle relate to the Global Financial Cycle?

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

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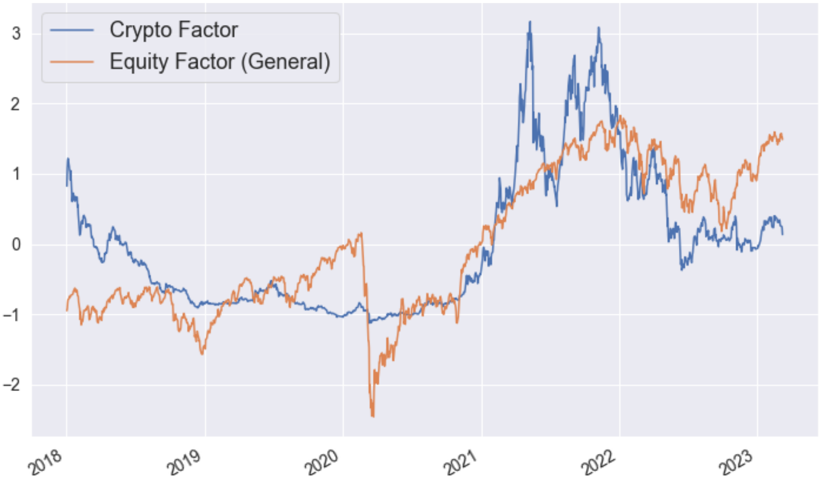

Substantial rise in $Corr$(CF,GFC) 2020-2022H1; then slight decline (Terra, FTX, AI).

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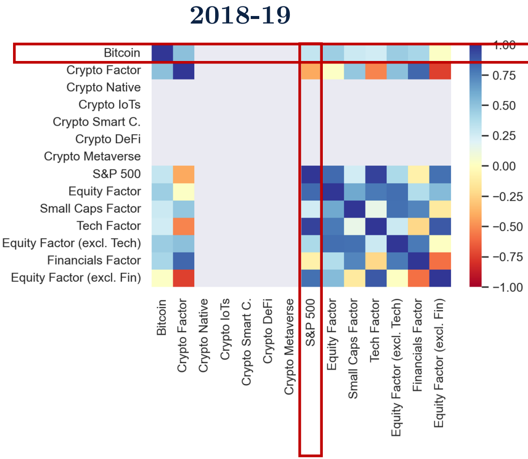

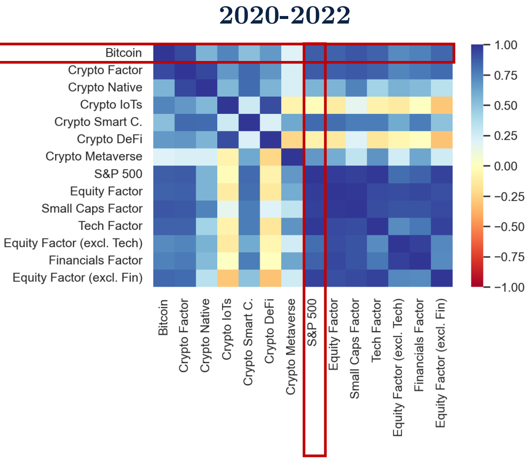

Bitcoin-S&P500 correlation increased... (Adrian, Iyer & Qureshi 2022)

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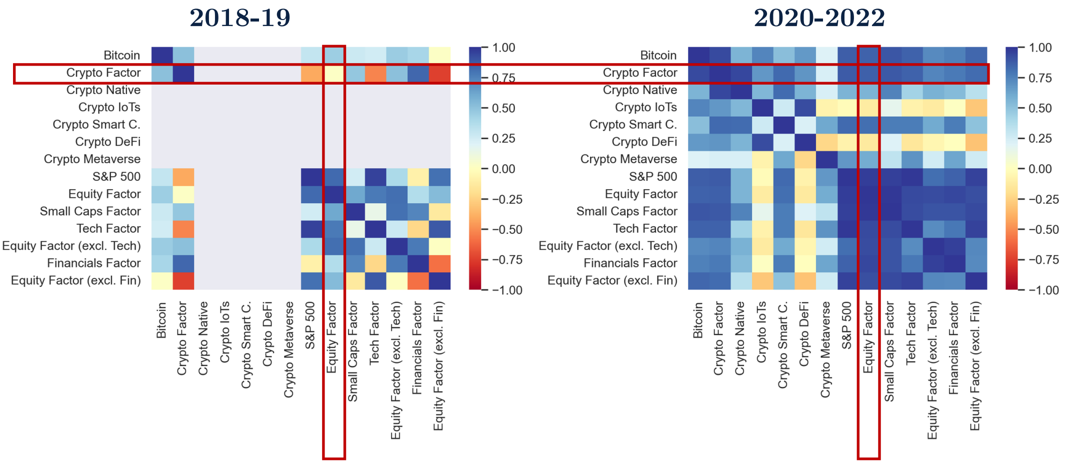

...and so did broader crypto-equity factor correlation.

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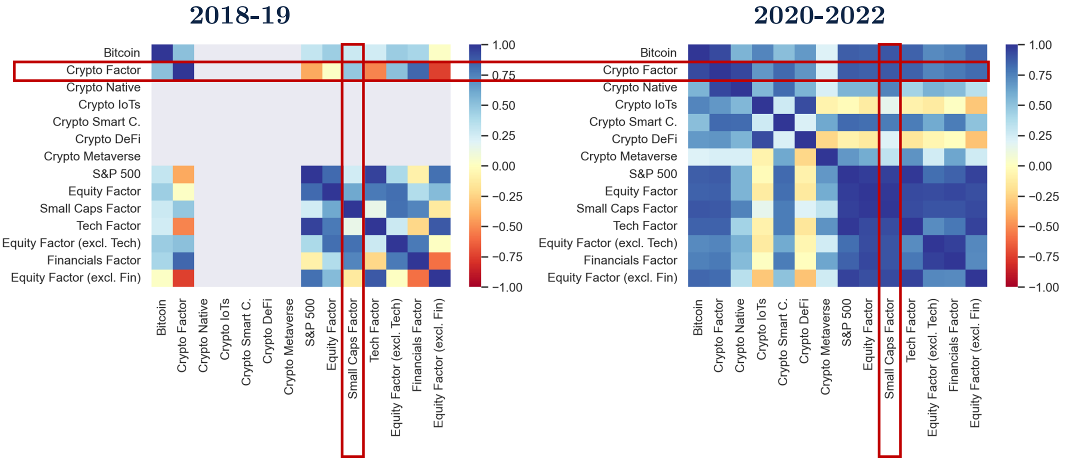

Crypto looks more like small-cap stocks...

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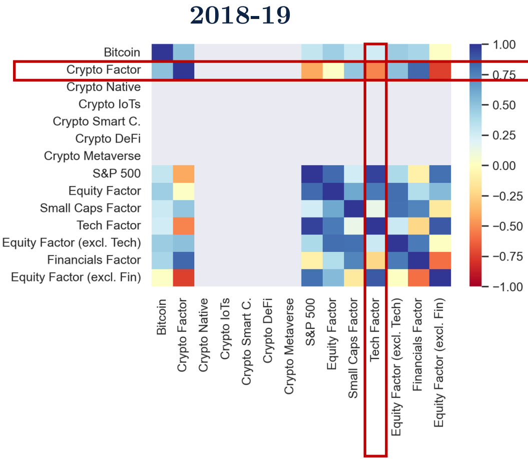

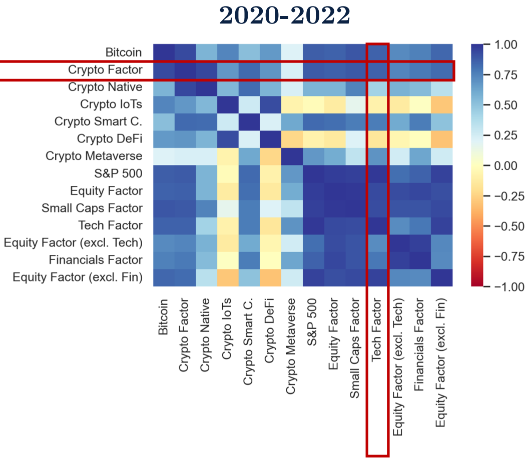

...and more like tech...

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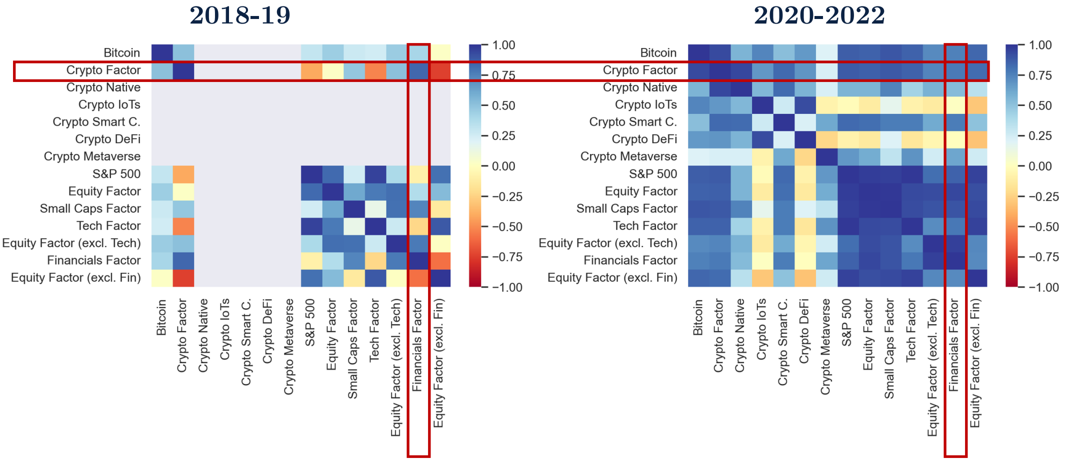

...and less like financial firms.

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)
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What drove the increased correlation between crypto and equities?

Various possible (and mutually compatible) explanations:

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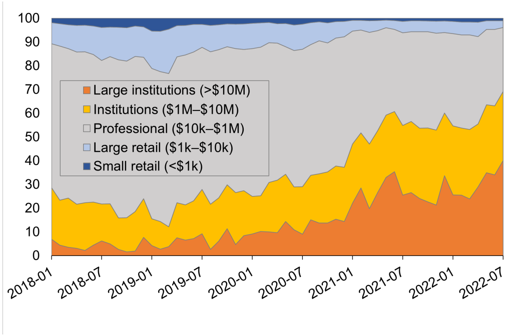
Share of on-chain trading volumes



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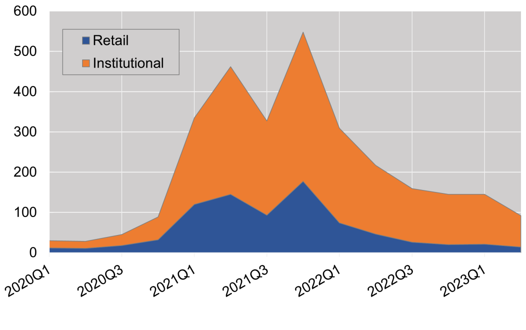

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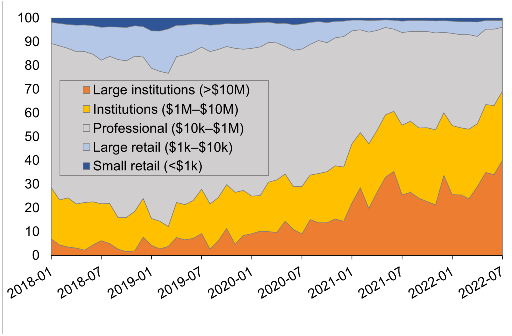

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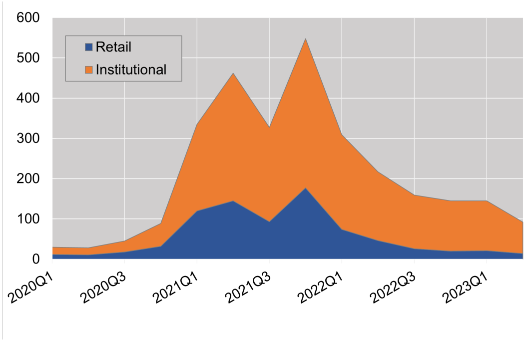

$\Rightarrow$ Given size, focus on institutional entry = changing profile of marginal investor.

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 ⇒ '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.

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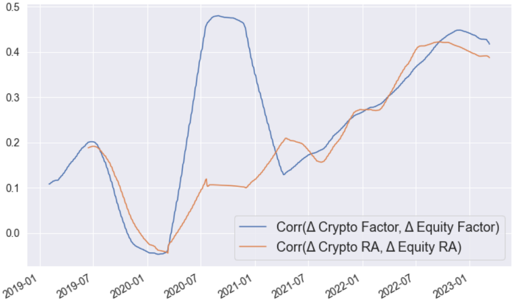

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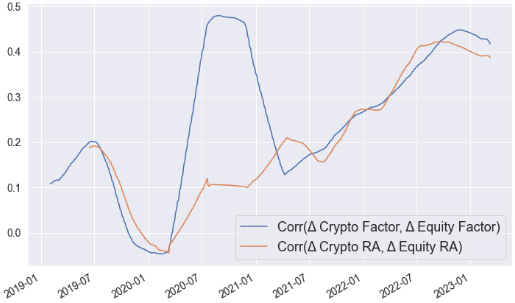

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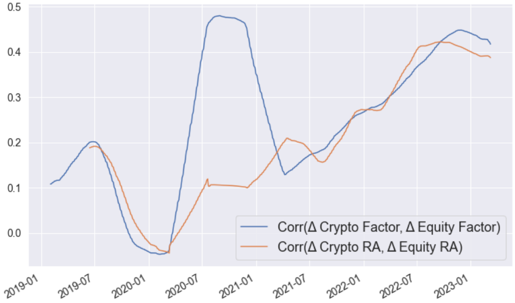

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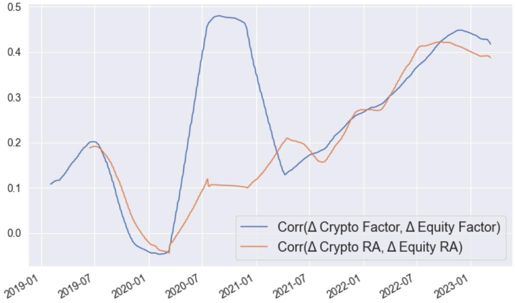

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Indeed, the correlation between the two aggregate effective risk aversions explains a large share of the correlation between the crypto and equity factors

	$Corr(\Delta\text{Crypto Factor}, \Delta\text{Equity Factor})$					
Rolling Window (Days)	(30)	(45)	(90)	(120)	(240)	(360)
$Corr(\Delta\text{Crypto RA}, \Delta\text{Equity RA})$	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

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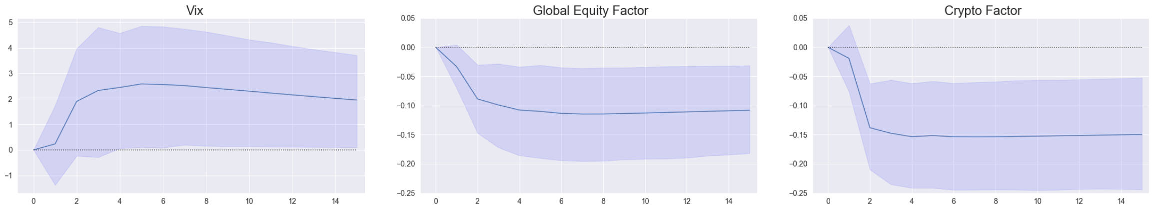
Cumulative 15-day IRFs for 1pp rise in Shadow FFR. 90% confidence intervals from 1000 Monte Carlo simulations.



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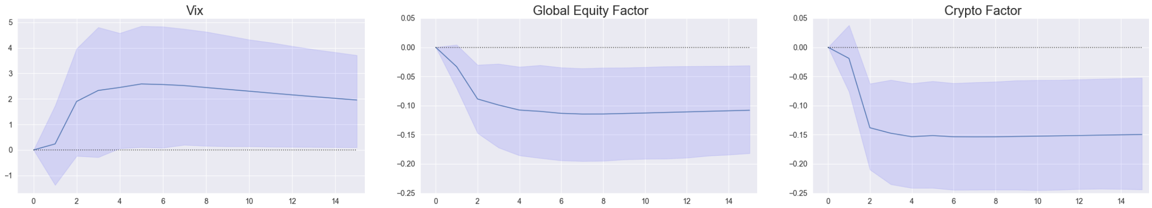

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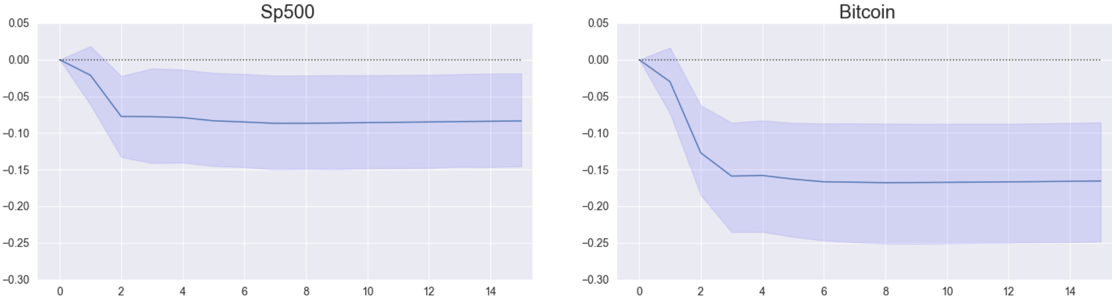

⇒ Results robust to replacing the factors with S&P500 and the Bitcoin price (+ US MP shock measures)

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

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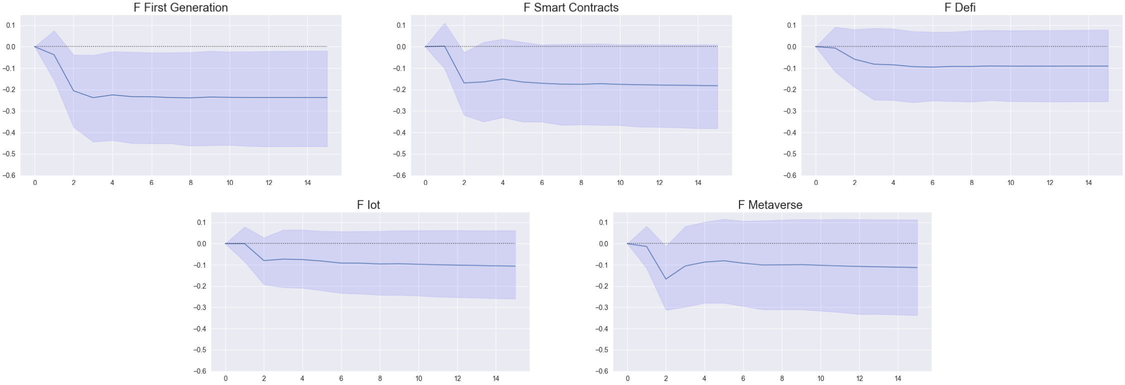
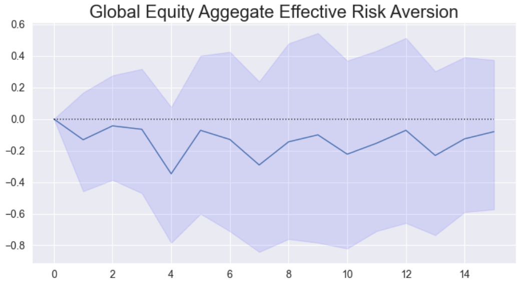
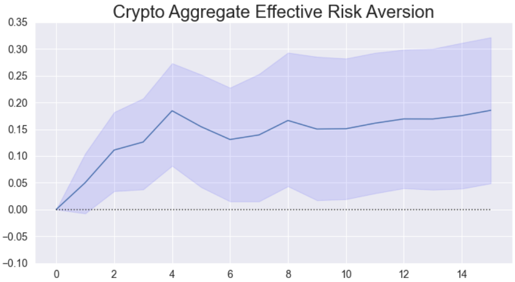


⇒ All sub-factors fall; impact strongest for first generation and smart contract factors, weakest for metaverse (volatile, short sample)

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)
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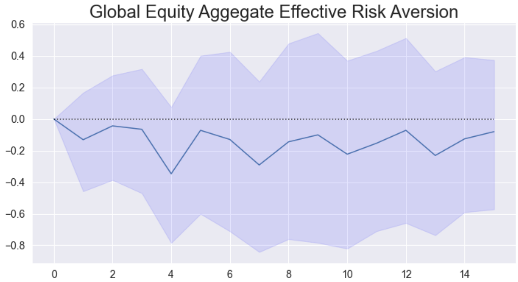

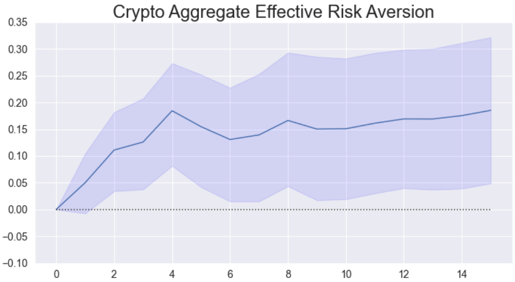

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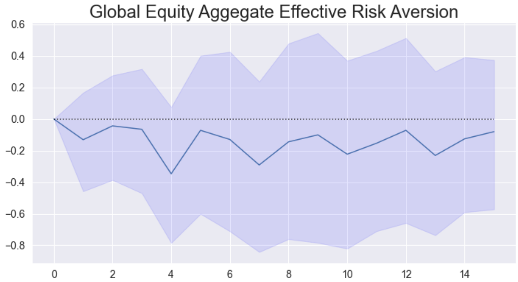

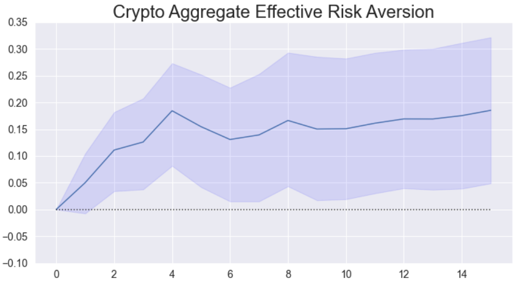

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Stronger post-2020, consistent with increased presence of (more leveraged) institutions:

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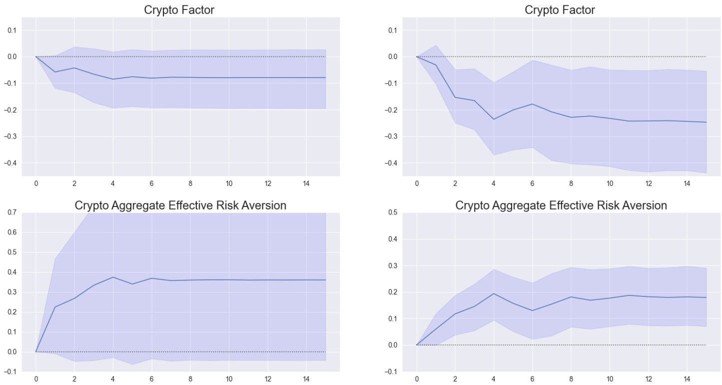

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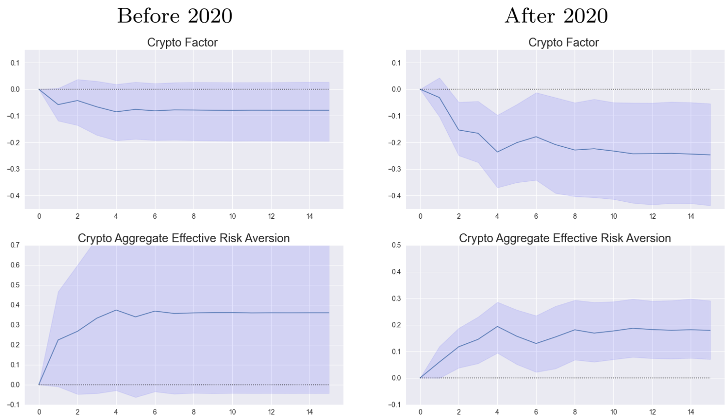

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$$Y_t = \underbrace{(1 - F(s_{t-1}))}_{\text{prob. of state 1}} \overbrace{\left[\sum_{j=1}^{p} A_{1j} Y_{t-j}\right]}^{\text{VAR in state 1}} + \underbrace{F(s_{t-1})}_{\text{prob. of state 2}} \overbrace{\left[\sum_{j=1}^{p} A_{2j} Y_{t-j}\right]}^{\text{VAR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

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).

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⇒ Corroboration: impacts only significant in 'high institutional participation' regime

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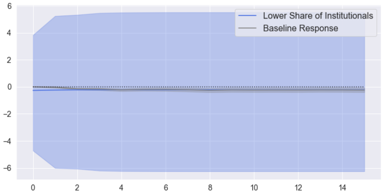
Crypto Factor



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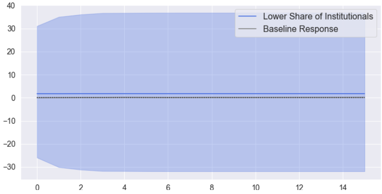

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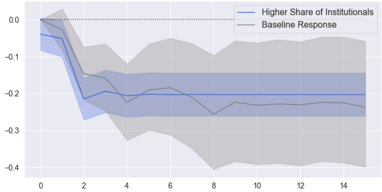

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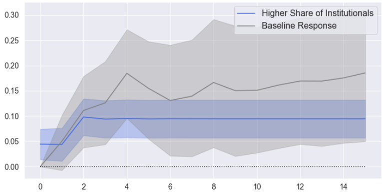

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Other potential channels:

1. USD appreciation in response to tightening makes stablecoin leverage more expensive for non-US investors (as 95% SC market cap USD-denominated)
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Stylized facts:

0. A single crypto factor explains a large share of overall price variation.
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⇒ Construct a simple framework to reflect main features

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  - ⇒ 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

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]
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- *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.

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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.

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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**.

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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.

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$\Rightarrow$ 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.

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

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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.

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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.

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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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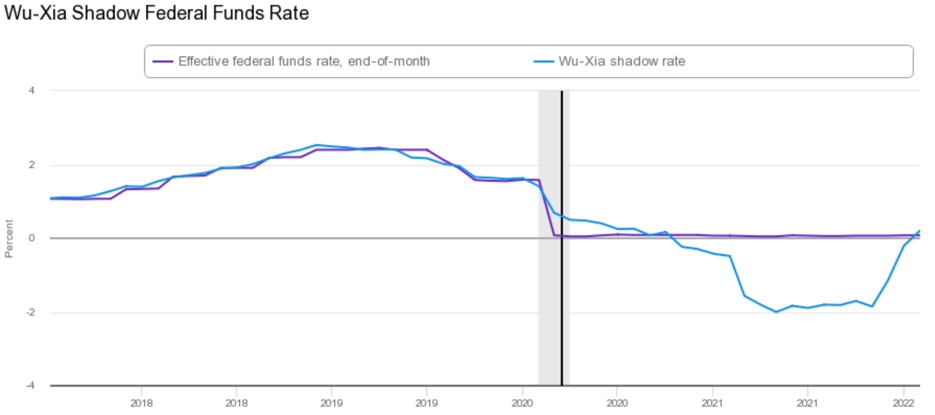
Table 5: Equity Eikon RICs by country.

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

◂ Back



Note: The black vertical lines at December 2008 and March 2020 indicate months where the Federal Open Market Committee lowered the target range for the federal fu
rate to 0 to 1/4 percent.
Sources: Board of Governors of the Federal Reserve System and Wu and Xia (2016)