The Crypto Cycle and US Monetary Policy

Natasha Che¹, Alexander Copestake¹, Davide Furceri¹, Tammaro Terracciano²
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¹International Monetary Fund
²University of Geneva & Harvard University
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 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 does this imply for potential spillovers across asset classes? (Iyer 2022)
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* Note: aggregate market not individual prices; pre-FTX (for now).
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• Value propositions and other drivers of specific crypto asset prices (Schilling & Uhlig 2019, Makarov and Schoar 2020, Scailliet et al. 2020, Cong et al. 2021, Liu et al. 2022)
  ⇒ Examine common movement in whole asset class

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The Crypto Factor Comparing Cycles US Monetary Policy Model (WIP) Conclusions

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⇒ 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).

⇒ Seven assets, accounting for 75% of total market capitalization.

**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 \( \epsilon_{it} \):

\[
p_{it} = \lambda_i(L) f_t + \epsilon_{it}
\]

\[
f_t = A_1 f_{t-1} + \ldots + A_q f_{t-q} + \eta_t
\]

\[
\epsilon_{it} = \rho_i \epsilon_{it-1} + \epsilon_{it}
\]

\[
\eta_t \sim \mathcal{N}(0, \Sigma)
\]

\[
e_{it} \sim \mathcal{N}(0, \sigma_{it}^2)
\]

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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Deriving the Crypto Factor – Inputs
Deriving the Crypto Factor – Output
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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:

⇒ 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).
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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):

<table>
<thead>
<tr>
<th>First Gen.</th>
<th>Smart Contract</th>
<th>DeFi</th>
<th>Metaverse</th>
<th>IoT</th>
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<td>Chainlink</td>
<td>Flow</td>
<td>VeChain</td>
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<tr>
<td>Ripple</td>
<td>Binance Coin</td>
<td>Uniswap</td>
<td>ApeCoin</td>
<td>Helium</td>
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<td>Maker</td>
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⇒ Estimate a model with five different (sub-)factors, where each can affect only one class.
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<td>The Sandbox</td>
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⇒ 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

⇒ Highly correlated with overall crypto cycle. (Except Meta rebrand jump.)
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Two observations: #1 Highly correlated
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⇒ Roughly two thirds of variation in crypto factor explained by equity factor
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⇒ Bitcoin-S&P500 correlation has increased... (Adrian, Iyer & Qureshi 2022)
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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)

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→ Given size, focus on institutional entry = changing profile of marginal investor.
What drove the increased correlation between crypto and equities?

$⇒$ Given size, focus on institutional entry = changing profile of marginal investor.
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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’

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

and similarly for crypto:

\[ f_t^{Crypto} = \alpha' + \beta'_1 \cdot Var(MSCI \text{ World}_t) + \beta'_2 \cdot Var(BTC_t) + \epsilon'_t \] (2)

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

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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, particularly over longer horizons.

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<tr>
<th>Rolling Window (Days)</th>
<th>Corr(Crypto Factor, Equity Factor)</th>
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</thead>
<tbody>
<tr>
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<tr>
<td>Corr(Crypto RA, Equity RA)</td>
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<td>(0.023)</td>
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<td>Constant</td>
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<td>Observations</td>
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- *So far:* Crypto Cycle closely related to the Global Financial Cycle...
  
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- *Literature:* US MP affects the Global Financial Cycle...
  
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⇒ Likely that US MP also influences Crypto Cycle

⇒ Daily VAR to investigate, following MAR.
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- 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 2022

Methodology:

- ID based on variable ordering (Cholesky decomposition)
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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.
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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&P and the Bitcoin price.
Does US monetary policy affect the Crypto Cycle? –  **Heterogeneity**

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⇒ The various crypto sub-factors respond similarly
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.

⇒ The various crypto sub-factors respond similarly
⇒ IoT & Metaverse least affected. More recent? ‘*Time to build*’? 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.
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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.
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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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Taking stock

Stylized facts:

0. A single crypto factor explains a large share of overall price variation.

1. The crypto factor and global equity factor are increasingly correlated, 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 since the entry of institutional investors into crypto markets.

⇒ Construct a simple framework to reflect these elements

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

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

- Two risk-averse agents that each maximise a mean-variance portfolio:
  - Crypto investors that invest only in crypto assets
  - Institutional investors that invest in both crypto and global equities

- Both can finance themselves at the (US) risk-free rate to leverage up their positions.

- The risk aversion of institutional investors is lower than that of crypto investors
  - Greater scale = risk pooling, or explicit/implicit deposit guarantees as in MAR.
Setup

- Two risk-averse agents that each maximise a mean-variance portfolio:
  - Crypto investors that invest only in crypto assets
  - Institutional investors that invest in both crypto and global equities

- Both can finance themselves at the (US) risk-free rate to leverage up their positions.

- The risk aversion of institutional investors is lower than that of crypto investors
  - Greater scale = risk pooling, or explicit/implicit deposit guarantees as in MAR.
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Crypto investors

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

$$\max_{x_t^c} E_t(x_t^c R_{t+1}^c) - \frac{\sigma}{2} Var_t(x_t^c R_{t+1}^c)$$

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

$$x_t^c = \frac{1}{\sigma} [Var_t(x_t^c R_{t+1}^c)]^{-1} E_t(x_t^c R_{t+1}^c)$$

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 $x^i_t (y_t)$ of their wealth in crypto (equities) to maximise

$$\max_{x^i_t, y_t} E_t(x^i_t R^{c}_{t+1} + y_t R^{e}_{t+1}) - \frac{\theta}{2} Var_t(x^i_t R^{c}_{t+1} + y_t R^{e}_{t+1})$$

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

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Equilibrium in the crypto market

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

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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}
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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:

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E_t(R_{t+1}^c) = \Gamma_t Var_t(R_{t+1}^c) s_t + \Gamma_t Cov_t(R_{t+1}^c, R_{t+1}^e) y_t
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...requires that supply of equities (normalized by wealth) $y_{t}^{tot}$ equals total holdings $y_{t}$.

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**Equities:**

\[ E_t(R_{t+1}^e) = \theta \text{Var}_t(R_{t+1}^e) y_{tot}^t + \theta \text{Cov}_t(R_{t+1}^c, R_{t+1}^e) x_t^i \]

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\[ \Gamma_t = (w_t^c + w_t^i) \left[ \frac{w_t^c}{\sigma} + \frac{w_t^i}{\theta} \right]^{-1} \]

1. As institutional wealth \( w_t^i \) makes up an increasing share of crypto market, time-varying risk-taking profile of crypto converges on that of equities.

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⇒ If less risk-averse + more levered agents react more to MP tightening (e.g. Coimbra et al. 2022), then impact accentuated. (Extension: het. leverage.)
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Conclusion

- 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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Initial thoughts on FTX

• ‘When the tide goes out...’
  ⇒ Tightening FCs → harder to cover up issues with new liquidity → 3AC, Celsius, Voyager, Alameda, FTX, BlockFi, Genesis/DCG (?), ...

• Could have been a lot worse
  ⇒ If later, with crypto a larger share of institutional portfolios. Instead, loss (+ embarrassment) confined to small number of private (+ public) entities.

• Looking forward: ‘once bitten, twice shy’?
  ⇒ Crypto-equity correlation fell already – FTX collapse × lower US inflation
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Thank you!
The Crypto Cycle and US Monetary Policy

Natasha Che\textsuperscript{1}, Alexander Copestake\textsuperscript{1}, Davide Furceri\textsuperscript{1}, Tammaro Terracciano\textsuperscript{2}
November 29, 2022

\textsuperscript{1}International Monetary Fund  
\textsuperscript{2}University of Geneva & Harvard University
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Wu-Xia Shadow Federal Funds Rate

Note: The black vertical lines at December 2018 and March 2020 indicate months where the Federal Open Market Committee lowered the target range for the federal funds rate to 0 to 1/4 percent.

Sources: Board of Governors of the Federal Reserve System and Wu and Xia (2016)
Non-Cumulative SFFR

Graph: ffr_shadow2ffr_shadow

Y-axis: 0.0 to 1.0
X-axis: 0 to 14
Global Monetary Policy (Fed, ECB, BoE)

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

When using weighted-average shadow FFRs the responses lose significance

⇒ Suggests Fed stance is dominant in crypto markets, as in traditional markets
⇒ Consistent with the dollarization of crypto markets via USD stablecoins.