

Econometric Studies of Crypto Asset Markets

Carol Alexander

Professor of Finance, University of Sussex
Visiting Professor, HSBC Business School, Peking University

16 March 2021

1. Overview of Crypto Assets

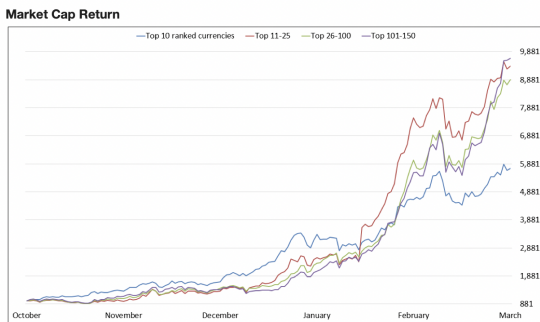
Market Watch

| Name | Current Price | 7d % | 30d Vol | 90d Vol | 21d EMA | 50d EMA |
|--------------|---------------|--------|---------|---------|-------------|-------------|
| Bitcoin | \$59,692.58 | 18.36% | 81.81% | 92.66% | \$52,769.33 | \$46,876.84 |
| Ethereum | \$1,858.25 | 8.11% | 98.01% | 120.13% | \$1,724.49 | \$1,584.30 |
| Binance Coin | \$263.420 | 11.47% | 277.46% | 181.23% | \$242.18 | \$196.47 |
| Polkadot | \$37.71 | 8.62% | 100.35% | 167.23% | \$34.69 | \$29.11 |
| Cardano | \$1.05 | -8.04% | 127.13% | 159.59% | \$1.09 | \$0.8999 |
| XRP | \$0.44 | -4.89% | 106.63% | 207.97% | \$0.4618 | \$0.4543 |
| Uniswap | \$30.99 | -8.42% | 172.45% | 171.49% | \$28.41 | \$23.15 |
| Litecoin | \$216.28 | 14.97% | 116.54% | 126.83% | \$197.36 | \$181.22 |
| Chainlink | \$28.73 | 0.21% | 130.43% | 143.75% | \$28.99 | \$26.82 |

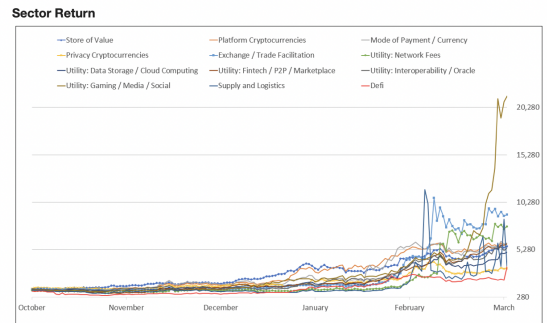
*As of 3/15/2021 5:27 am UTC

Source: GSG Digital Asset Management

Returns by Market Cap – Last 6 Months



Returns by Sector – Last 6 Months




Correlation of BTC Returns with Gold and US Equities




Main Players in the Crypto Ecosystem


Issuers




Stable Coins



Ranking Sites



Exchanges



Increasingly also traditional asset managers, regulators, central banks and shadow banks....

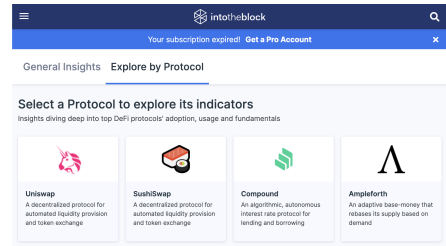
Central Bank Digital Currencies

Digital money on private blockchains controlled by central banks



Decentralized Finance (DeFi)

Using crypto and other assets as collateral for P2P high-yield loans



IntoTheBlock

Ranking Sites

| # | Coin | Price | Direct Vol. (1) | Total Vol. | Top Tier Vol. (1) | Market Cap. (1) | Least 7 Days | 24h |
|----|------------------|--------------|-----------------|-------------|-------------------|-----------------|--------------|--------|
| 1 | Bitcoin BTC | \$ 54,085.65 | \$ 2.91 B | \$ 15.55 B | \$ 15.53 B | \$ 1,008.65 B | B+ | 7.55% |
| 2 | Ethereum ETH | \$ 1,821.92 | \$ 1.20 B | \$ 8.27 B | \$ 8.22 B | \$ 209.48 B | A- | 6.45% |
| 3 | Chiliz CHZ | \$ 0.2807 | \$ 1.37 M | \$ 2.70 B | \$ 2.70 B | \$ 2.50 B | C | 72.63% |
| 4 | Binance Coin BNB | \$ 273.87 | \$ 33.81 M | \$ 2.29 B | \$ 2.29 B | \$ 46.70 B | C | 18.01% |
| 5 | Cardano ADA | \$ 1.179 | \$ 98.75 M | \$ 1.72 B | \$ 1.71 B | \$ 37.68 B | B- | 5.74% |
| 6 | Litecoin LTC | \$ 198.81 | \$ 147.08 M | \$ 1.27 B | \$ 1.26 B | \$ 13.35 B | B- | 9.15% |
| 7 | XRP XRP | \$ 0.4793 | \$ 42.60 M | \$ 1.01 B | \$ 1.01 B | \$ 47.93 B | C+ | 1.96% |
| 8 | Polkadot DOT | \$ 36.11 | \$ 37.26 M | \$ 984.61 M | \$ 984.61 M | \$ 38.06 B | C+ | 7.12% |
| 9 | Dogecoin DOGE | \$ 0.05721 | \$ 38.56 M | \$ 921.56 M | \$ 919.01 M | \$ 7.35 B | C | 4.30% |
| 10 | Chainlink LINK | \$ 30.98 | \$ 133.93 M | \$ 829.33 M | \$ 829.33 M | \$ 30.98 B | C | 6.50% |

CryptoCompare

De-Fi Token Rankings

Chainlink is a blockchain-base middleware that allows smart contracts to communicate with external resources by acting as a bridge between them and off-chain resources like data feeds, web APIs and traditional bank account payments

| # | Coin | Price | Direct Vol. (1) | Total Vol. | Top Tier Vol. (1) | Market Cap. (1) | Least 7 Days | % 24h |
|----|----------------------|------------|-----------------|-------------|-------------------|-----------------|--------------|--------|
| 1 | Chainlink LINK | \$ 30.98 | \$ 112.84 M | \$ 710.47 M | \$ 710.47 M | \$ 30.98 B | | 6.52% |
| 2 | Uniswap Protocol UNI | \$ 1.691 | \$ 39.84 M | \$ 717.94 M | \$ 706.61 M | \$ 1.69 B | | 2.55% |
| 3 | SushiSwap SUSHI | \$ 1.32 | \$ 81.63 M | \$ 449.22 M | \$ 449.22 M | \$ 1.32 B | | -0.06% |
| 4 | Compound COMP | \$ 11.32 | \$ 562.85 M | \$ 562.85 M | \$ 562.85 M | \$ 10.70 B | | 22.55% |
| 5 | MakerDAO MKR | \$ 537.40 | \$ 239.53 M | \$ 239.53 M | \$ 239.53 M | \$ 747.95 M | | -8.88% |
| 6 | Yearn Finance YFI | \$ 2,470 | \$ 3.02 M | \$ 348.45 M | \$ 348.45 M | \$ 486.89 M | | 3.61% |
| 7 | Aave AAVE | \$ 426.29 | \$ 36.42 M | \$ 222.57 M | \$ 222.57 M | \$ 4.62 B | | 4.96% |
| 8 | Bancor Network 1 BNT | \$ 9.113 | \$ 38.62 M | \$ 189.76 M | \$ 189.76 M | \$ 1.64 B | | 4.79% |
| 9 | SushiSwap SUSHI | \$ 1.32 | \$ 5.30 M | \$ 159.36 M | \$ 157.35 M | \$ 3.68 B | | 5.50% |
| 10 | JUST | \$ 0.05900 | \$ 0 | \$ 143.17 M | \$ 143.17 M | \$ 584.09 M | | 3.36% |
| 11 | Curve DAO Token CRV | \$ 2.345 | \$ 2.19 M | \$ 140.75 M | \$ 140.75 M | \$ 3.40 B | | 3.49% |
| 12 | Bancor Rights BCR | \$ 0.07381 | \$ 0 | \$ 130.75 M | \$ 130.75 M | \$ 25.07 M | | 6.22% |

Non-Fungible Tokens (NFT)

IP on blockchains: digital images, music, game cards, cryptokitties....

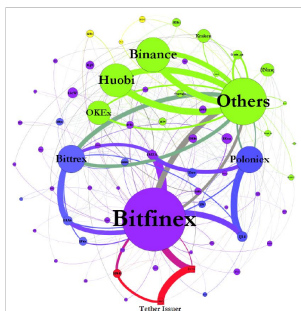
| # | Name | Marketcap | Price | 24h Volume | Blockchain | Change 24h | Change 7d |
|----|-------------------------|------------|------------|------------------|----------------|------------|-----------|
| 1 | Bayle Coin BAYLE | \$ 1.52B | \$ 1.62479 | \$ 1,382,208,101 | Ethereum | +13.17% | +122.24% |
| 2 | Decentraland MANA | \$ 916.49M | \$ 0.58209 | \$ 813,793,363 | Ethereum | +30.9% | +109.82% |
| 3 | Flow (Pepper Labs) FLOW | \$ 882.38M | \$ 37.881 | \$ 112,601,102 | Own Blockchain | +13.7% | +31.38% |
| 4 | WAX WAX | \$ 298.48M | \$ 0.19490 | \$ 213,376,269 | Ethereum | +13.39% | +156.05% |
| 5 | Uzle UZLE | \$ 127.38M | \$ 0.65337 | \$ 5,466,918 | Ethereum | +10.91% | +66.7% |
| 6 | The Sandbox SAND | \$ 286.57M | \$ 0.56626 | \$ 309,428,816 | Ethereum | +38.87% | +125.89% |
| 7 | RealFXX Labs RFXL | \$ 205.21M | \$ 0.15640 | \$ 3,286,221 | Own Blockchain | +6.9% | +6.8% |
| 8 | BakeryToken BAKE | \$ 193.88M | \$ 1.44774 | \$ 38,265,262 | Binance Chain | +21.94% | +7.43% |
| 9 | WHALE WHALE | \$ 182.72M | \$ 34.8817 | \$ 2,148,379 | Ethereum | +8.57% | +49.8% |
| 10 | Axe Infinity AXI | \$ 152.78M | \$ 3.64994 | \$ 89,628,363 | Ethereum | +7.36% | +69.73% |
| 11 | SuperFarm SFARM | \$ 114.72M | \$ 1.14148 | \$ 4,442,287 | Ethereum | -1.81% | -1.86% |
| 12 | NFTX NFTX | \$ 114.38M | \$ 258.85 | \$ 7,146,447 | Ethereum | -6.86% | -15.89% |

Stable Coins

| # | Name | Marketcap | Price | 24h Volume | Blockchain | Change 24h | Change 7d |
|----|--------------------|------------|------------|-------------------|---------------|------------|-----------|
| 1 | Tether USDT | \$ 36.82B | \$ 1.00066 | \$ 94,729,465,435 | Omni | +0.01% | -0.01% |
| 2 | USD Coin USDC | \$ 8.94B | \$ 1.00017 | \$ 1,658,089,001 | Ethereum | +0.01% | +0.01% |
| 3 | Binance USD BUSD | \$ 3.05B | \$ 1.00020 | \$ 3,845,534,389 | Ethereum | +0.01% | +0.02% |
| 4 | Dai DAI | \$ 2.6B | \$ 1.01015 | \$ 501,415,877 | Ethereum | +0.05% | -0.08% |
| 5 | TerraUSD UST | \$ 815.37M | \$ 1.00061 | \$ 50,450,576 | Ethereum | +0.03% | +0.08% |
| 6 | Paxos Standard PAX | \$ 801.68M | \$ 1.00008 | \$ 82,891,916 | Ethereum | +0.38% | +0.31% |
| 7 | HUSD HUSD | \$ 603.06M | \$ 1.00079 | \$ 1,120,443,190 | Ethereum | +0.11% | +0.09% |
| 8 | TrueUSD TRUSD | \$ 291.75M | \$ 0.99926 | \$ 65,464,705 | Ethereum | +0.01% | -0.07% |
| 9 | Veil VEIL | \$ 153.00M | \$ 0.99550 | \$ 5,339,626 | Binance Chain | +0.56% | -0.18% |
| 10 | JUST | \$ 135.1M | \$ 0.05977 | \$ 213,886,790 | Tron | +9.04% | +26.61% |
| 11 | Gemini Dollar GUSD | \$ 119.17M | \$ 0.99998 | \$ 13,391,672 | Ethereum | -0.27% | -0.42% |
| 12 | Neutrino USD USDN | \$ 172M | \$ 0.99935 | \$ 1,092,848 | Waves | +0.63% | -0.31% |

Tether market cap exceeds \$36 Billion 10 × greater than in June 2019

Tether and BitFinx



Griffin and Shams (2020)

Tether and Bitfinx agree to pay \$18.5m penalty after New York probe



Adam Sisman in London FEBRUARY 23 2021

FT, June 2019

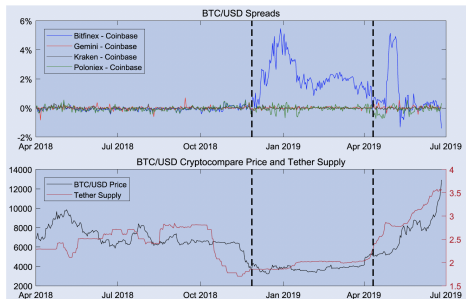
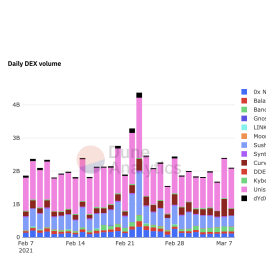


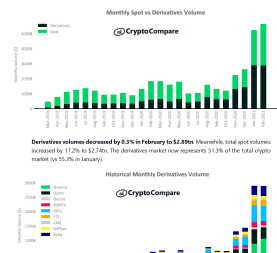
Figure 4. BTC tether-adjusted price spreads, BTC price level and USDT supply. Upper graph: Bitfinx-Coinbase, Gemini-Coinbase, Kraken-Coinbase and Poloniex-Coinbase BTC price spreads, all expressed relative to Coinbase's BTC price. Bitfinx and Poloniex prices are expressed in USD via the Kraken USD/USD cross-rate. Lower graph: BTC price index from CC. The data frequency is daily, and the sample period is 1 April 2018-26 June 2019. Vertical dotted lines denote dates of interest.

2. On-Chain and Off-Chain Exchanges

Decentralised Exchanges (DEX) On Chain



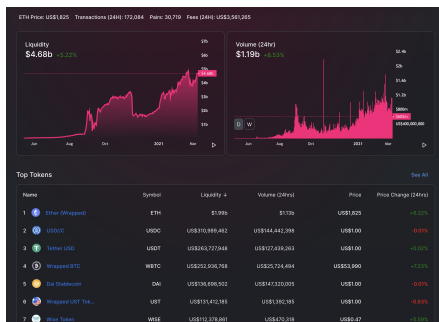
Centralised Exchanges (CEX) Off-Chain



Centralised Exchanges

| CryptoCompare Exchange Benchmark Feb 2021 | | | | | | | | | | | | | | | CryptoCompare Exchange Benchmark Feb 2021 | | | | | | | | | | | | | | |
|---|----------------|--------------|--------|------------|----------|----------|-----|---------------|---------------|----------------|----------------|------|----------------|--------------|---|------------|----------|----------|-----|---------------|---------------|----------------|----------------|-----|--|--|--|--|--|
| Rank | Chain Exchange | Active Sides | Log10P | FXA Assets | Security | Reserves | ATV | Systemic Risk | Asset Quality | Market Reports | Market Quality | Rank | Chain Exchange | Active Sides | Log10P | FXA Assets | Security | Reserves | ATV | Systemic Risk | Asset Quality | Market Reports | Market Quality | | | | | | |
| 1 | Bit | 100 | 1.0 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 1 | Bit | 100 | 1.0 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | | | | | |

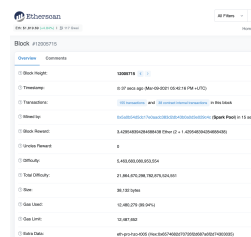
Decentralized Exchanges



How to swap ERC-20 tokens

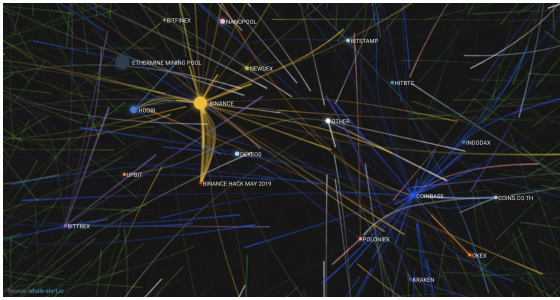
Block Explorer

Records all transactions on a blockchain including smart contract transactions for protocols like Ethereum, Polkadot, etc. [Etherscan](#)



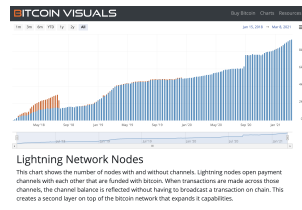
Visualisation of bitcoin blocks

Recording On-Chain BTC Flows



Whale Alert

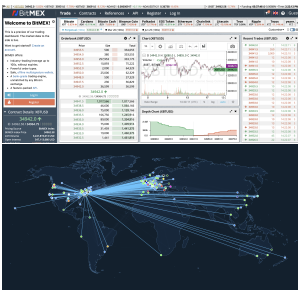
Bitcoin Lightning Network



- Currently more than 9000 nodes and millions of channels
- USD value locked in channels exceeds \$52 million (5 times more than a year ago)

Channel Explorer

BitMEX Research Node



OSATO IWANOYAMA JAN 03, 2021

After Know Your Customer debacle, BitMEX reports 100% of users are verified

Controversial crypto derivatives trading platform BitMEX says its entire user base has completed the obligatory know your Customer process.

BitMEX

3. Data Matters

Alexander C. and M. Dakos (2020) A Critical Investigation of Cryptocurrency Data and Analysis *Quantitative Finance*, 20(2), 173-188

- Compares traded prices of BTC and ETH on 3 CEXs with non-traded VWAP prices provided by ranking sites **Coingecko (CG)**, **Coinmarketcap (CM)** and **Cryptocompare (CC)**
- Compares crypto market indices **CCI30**, **CRIX** and **MVDA25**
- Results presented include:
 - Sample statistics
 - Capital Asset Pricing Model (CAPM) estimations
$$r_{it} = \alpha_i + \beta_i R_t + \varepsilon_{it},$$

where r_{it} is the daily return on the i^{th} source of the coin price and R_t is the daily return on the market index
- Volatility estimations using various statistical models

Crypto Price Indices

The daily price index p_t^i for each coin i is obtained using p_t^{ij} , the price of coin i from source j at time t , and v_t^{ij} , the corresponding 24-hour volume traded from $t-1$ to t , both expressed in USD, in the VWAP formula:

$$p_t^i = \left(\sum_{j=1}^N v_t^{ij} \right)^{-1} \sum_{j=1}^N p_t^{ij} v_t^{ij}, \quad (1)$$

where N is the total number of price sources, e.g. in the BTC/USD price index, at the time N was approximately 300 for **CG**, 400 for **CM**, but only 40 for **CC**.

Crypto Market Indices

The **CCI30**, **CRIX** and **MVDA25** are cap-weighted indices derived from 25–50 large cap coins, typically constructed as:

$$I_t = d_t^{-1} \sum_{i=0}^k p_t^i q_s^i, \quad (2)$$

where: k is the number of coins included; p_t^i is the price index of coin i at time t , based on (1); q_s^i is the circulating supply of coin i at time $s \leq t$, which is typically the point when the index was last rebalanced; and the normalizing divisor d_t resets when the index composition changes

The **CRIX** and **MVDA25** indices are constructed as per (2), while the **CCI30** index here employs a variant of (2) that weights coin prices by the square root of their market cap. In (2), k is 30 for the CCI30 and 25 for the MVDA25 (it varies for the CRIX). The p_t^i is constructed as per (1) but uses different data sources: CCI30 uses CoinAPI data; CRIX uses **CG** price indices; MVDA25 uses **CC** price indices.

Summary Statistics (BTC)

Table A1. Sample statistics on BTC non-traded price indices and traded prices.

| | BTC Non-Traded | | | BTC Traded | | | | |
|-------------------------------|----------------|--------|--------|------------|----------|--------|--------|----------|
| | CG | CM | CC | Bitfinex | Coinbase | Gemini | Kraken | Poloniex |
| 1 Apr 2016–31 Mar 2017 | | | | | | | | |
| Mean (p.a.) | 113.1% | 110.8% | 112.6% | 111.3% | 113.5% | 113.1% | 113.4% | 113.9% |
| Volatility | 38.9% | 36.6% | 38.0% | 35.9% | 38.5% | 38.3% | 40.0% | 39.9% |
| Skewness | -0.74 | -0.73 | -0.84 | -0.58 | -0.50 | -0.84 | -0.79 | -0.88 |
| Ex. Kurtosis | 6.24 | 6.01 | 6.62 | 5.79 | 6.03 | 6.11 | 6.51 | 7.09 |
| 1 Apr 2017–31 Mar 2018 | | | | | | | | |
| Mean (p.a.) | 241.7% | 241.2% | 240.4% | 243.0% | 238.5% | 239.7% | 238.0% | 242.0% |
| Volatility | 105.2% | 104.1% | 104.3% | 107.8% | 103.9% | 104.7% | 102.5% | 106.7% |
| Skewness | 0.41 | 0.33 | 0.28 | 0.35 | 0.46 | 0.42 | 0.27 | 0.34 |
| Ex. Kurtosis | 4.57 | 2.57 | 2.20 | 2.06 | 2.68 | 2.68 | 1.97 | 2.01 |
| 1 Apr 2018–31 Mar 2019 | | | | | | | | |
| Mean (p.a.) | -33.9% | -33.9% | -31.9% | -29.2% | -31.7% | -31.4% | -31.3% | -31.6% |
| Volatility | 61.8% | 61.6% | 63.8% | 65.6% | 64.4% | 64.6% | 64.6% | 64.2% |
| Skewness | -0.15 | -0.13 | -0.16 | -0.07 | -0.19 | -0.17 | -0.18 | -0.18 |
| Ex. Kurtosis | 2.96 | 3.02 | 2.90 | 3.12 | 3.20 | 3.13 | 3.14 | 3.20 |

Note: Sample statistics of the daily returns on BTC prices from CG, CM and CC, and from Bitfinex, Coinbase, Gemini, Kraken and Poloniex.

Summary Statistics (ETH)

Table A2. Sample statistics on ETH non-traded price indices and traded prices.

| | ETH Non-Traded | | | ETH Traded | | | | |
|-------------------------------|----------------|--------|--------|------------|----------|--------|--------|----------|
| | CG | CM | CC | Bitfinex | Coinbase | Gemini | Kraken | Poloniex |
| 1 Jul 2016–31 Mar 2017 | | | | | | | | |
| Mean (p.a.) | 238.8% | 247.8% | 249.8% | 241.7% | 252.1% | 250.1% | 247.9% | 249.5% |
| Volatility | 113.4% | 114.1% | 115.3% | 110.0% | 118.1% | 117.9% | 114.6% | 115.9% |
| Skewness | 0.97 | 1.32 | 1.17 | 1.49 | 1.32 | 0.84 | 1.15 | 1.08 |
| Ex. Kurtosis | 8.49 | 8.12 | 6.87 | 6.66 | 6.70 | 5.38 | 6.63 | 6.69 |
| 1 Apr 2017–31 Mar 2018 | | | | | | | | |
| Mean (p.a.) | 290.8% | 293.8% | 292.7% | 294.4% | 291.6% | 298.2% | 289.6% | 293.2% |
| Volatility | 130.7% | 133.6% | 132.9% | 133.3% | 132.7% | 136.2% | 130.2% | 132.4% |
| Skewness | 0.54 | 0.76 | 0.66 | 0.41 | 0.81 | 0.79 | 0.60 | 0.43 |
| Ex. Kurtosis | 2.06 | 2.74 | 1.81 | 1.24 | 2.37 | 2.11 | 1.41 | 1.16 |
| 1 Apr 2018–31 Mar 2019 | | | | | | | | |
| Mean (p.a.) | -56.9% | -57.5% | -52.2% | -51.3% | -52.7% | -52.5% | -51.9% | -53.9% |
| Volatility | 95.5% | 95.0% | 99.2% | 99.0% | 99.5% | 99.6% | 99.7% | 97.9% |
| Skewness | 0.05 | -0.04 | -0.02 | 0.02 | -0.07 | -0.03 | -0.04 | -0.01 |
| Ex. Kurtosis | 2.02 | 2.08 | 1.98 | 1.95 | 2.05 | 2.11 | 2.00 | 1.99 |

Note: Sample statistics of the daily returns on ETH/USD prices from CG, CM and CC, and from Bitfinex, Coinbase, Gemini, Kraken and Poloniex.

CAPM Estimations

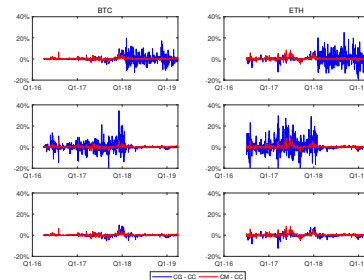
Table 1. Market betas of BTC and ETH w.r.t. CCI30, CRIX and MVDA25 indices.

| | CG | CM | CC | Bitfinex | Coinbase | Gemini | Kraken | Poloniex |
|------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| BTC | | | | | | | | |
| CCI30 | 0.374 (14.6) | 0.730 (44.3) | 0.744 (44.9) | 0.742 (43.4) | 0.734 (43.2) | 0.743 (44.1) | 0.734 (43.5) | 0.743 (43.3) |
| CRIX | 0.903 (69.4) | 0.528 (20.9) | 0.519 (20.1) | 0.515 (19.6) | 0.506 (19.4) | 0.515 (19.7) | 0.497 (18.9) | 0.521 (19.8) |
| MVDA25 | 0.359 (15.4) | 0.495 (24.1) | 0.509 (24.6) | 0.501 (23.7) | 0.504 (24.2) | 0.508 (24.4) | 0.504 (24.3) | 0.504 (23.8) |
| ETH | | | | | | | | |
| CCI30 | 0.501 (13.1) | 1.008 (37.3) | 1.020 (37.4) | 1.012 (37.7) | 1.012 (36.1) | 1.023 (36.0) | 0.998 (36.3) | 1.021 (37.8) |
| CRIX | 1.041 (33.6) | 0.513 (12.0) | 0.502 (11.6) | 0.489 (11.4) | 0.490 (11.2) | 0.498 (11.2) | 0.471 (10.9) | 0.510 (11.8) |
| MVDA25 | 0.568 (16.8) | 0.763 (25.3) | 0.778 (25.6) | 0.757 (25.0) | 0.778 (25.4) | 0.777 (24.8) | 0.760 (25.0) | 0.772 (25.5) |

Notes: Market betas with corresponding t-statistics in parentheses of daily returns on BTC (upper panel) and ETH (lower panel) prices from CG, CM and CC, and from Bitfinex, Coinbase, Gemini, Kraken and Poloniex. The market factor is the return on either the CCI30, the CRIX or the MVDA25 crypto market index. The sample period is 1 April 2016–31 March 2019 for BTC and 1 July 2016–31 March 2019 for ETH. Parameters of interest are highlighted in blue and red.

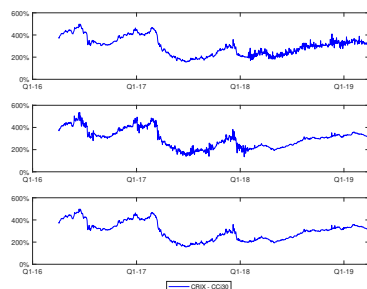
CoinGecko Problems

CG – CC and CM – CC price spreads relative to CC's daily price for BTC (left-hand graphs) and ETH (right-hand graphs), using CG price data as is (upper), lagged by one day (middle), and as until 29 January 2018 and lagged from 30 January 2018 (lower graphs).



Spillover to CRIX

CRIX – CCI30 spread relative to CCI30, using CRIX daily data as is (upper graph), lagged by one day (middle graph), and lagged starting from 30 January 2018 (lower graph).



GARCH Models

Generalised Autoregressive Conditional Heteroscedasticity
Bollerslev (1986)

- Crypto asset returns require two sources of asymmetry – i.e. volatility response and innovations and a regime-switching setting

Skew Student *t* Asymmetric Markov Switching GARCH:

$$\sigma_{it}^2 = \omega_i + (\alpha_i + \gamma_i I_{\{\varepsilon_{t-1} < 0\}}) \varepsilon_{t-1}^2 + \beta_i \sigma_{it-1}^2 \text{ where } \varepsilon_t \sim t_{\eta_i, \xi_i} \text{ and } i = 1, 2.$$

Unconditional steady-state volatility of each regime:

$$UV_i = \sqrt{\frac{365 \omega_i}{1 - \alpha_i - 0.5 \gamma_i - \beta_i}}$$

Unconditional state transition probability matrix:

$$\mathbf{\Pi} = \begin{pmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{pmatrix},$$

where $p_{ij} = P(s_t = j | s_{t-1} = i)$.

Skew Student t Asymmetric Markov Switching GARCH

Markov switching GJR-GARCH on BTC daily returns from CG, CM and CC and from the Bitstamp and Kraken CEXs. Estimation using MCMC. Sample period is 1 September 2013 – 31 March 2019.

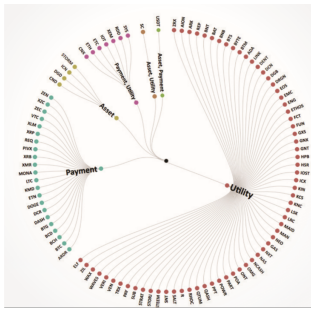
| | CG | CM | CC | Bitstamp | Kraken |
|-----------------------------|--------|--------|--------|----------|--------|
| Low Volatility State | | | | | |
| ω_1 | 0.145 | 0.007 | 0.197 | 0.036 | 0.011 |
| α_1 | 0.147 | 0.052 | 0.156 | 0.070 | 0.100 |
| γ_1 | -0.067 | -0.019 | -0.097 | -0.006 | -0.074 |
| β_1 | 0.865 | 0.953 | 0.858 | 0.922 | 0.917 |
| η_1 | 2.948 | 2.396 | 2.873 | 2.832 | 3.057 |
| ξ_1 | 1.013 | 1.046 | 0.998 | 1.028 | 1.100 |
| p_{11} | 0.94 | 0.96 | 0.98 | 0.98 | 0.86 |
| UV_1 | 49.57 | 21.45 | 45.70 | 36.32 | 14.22 |

Skew Student t Asymmetric Markov Switching GARCH

Markov switching GJR-GARCH on BTC daily returns from CG, CM and CC and from the Bitstamp and Kraken CEXs. Sample period is 1 September 2013 – 31 March 2019.

| | CG | CM | CC | Bitstamp | Kraken |
|------------------------------|--------|--------|--------|----------|--------|
| High Volatility State | | | | | |
| ω_2 | 30.442 | 2.377 | 4.599 | 24.312 | 1.828 |
| α_2 | 0.003 | 0.240 | 0.067 | 0.231 | 0.022 |
| γ_2 | 0.297 | -0.055 | 0.204 | 0.311 | 0.168 |
| β_2 | 0.009 | 0.767 | 0.682 | 0.308 | 0.880 |
| η_2 | 51.933 | 4.172 | 4.165 | 3.131 | 65.485 |
| ξ_2 | 0.710 | 0.865 | 0.937 | 0.854 | 0.906 |
| p_{22} | 0.77 | 0.95 | 0.97 | 0.95 | 0.60 |
| UV_2 | 115.07 | 204.41 | 106.27 | 170.28 | 216.24 |

4. Initial Coin Offerings



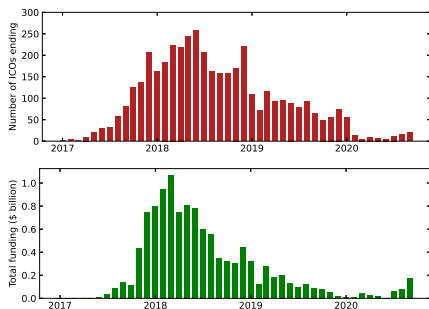
Evolution of ICOs

Data Sources

Alexander C. and M. Dakos (2021) The Changing Face of Initial Coin Offerings *In Prep.*

- Primary data source: [ICObench](#)
- Other ICO rating websites used: [ICOdata](#), [TokenData](#), [ICODrops](#), [ICOrating](#) and [Neironix](#), [ICOholder](#), [Cryptocompare](#), [Smith and Crown](#), [ICOMarketdata](#), [ICOSTats](#), [Coincodex](#), [Cryptodiffer](#) and [Cryptorank](#).
- Initial sample of 4,152 ending before 31 Dec 2019
- Reduced to 1,215 with data on amount raised, price, supply, distribution, team, etc..
- Some large ICOs such as EOS, TON and LEO excluded
- Now extending to end 2020

Our Sample



Number of ICOs ending (red) and USD total amount raised (green)
Total amount raised ~ \$12 billion

| Authors | Montez (2016a) | Montez (2016b)* | Bourdeloup et al. (2018)** | Aste and Exler (2020) | Agarwal et al. (2019) | Albrecht et al. (2019) | Borckes and Valasek (2019) | Chen (2019) | Fisch (2019) | Lyandres et al. (2019) | Amidon and Schweizer (2018) | Blöchl (2018)* | Bourreau et al. (2018) | Lee et al. (2018)* |
|----------------|----------------|-----------------|----------------------------|-----------------------|-----------------------|------------------------|----------------------------|-------------|--------------|------------------------|-----------------------------|----------------|------------------------|--------------------|
| Data start | 8/15 | 8/15 | 8/15 | 4/17 | 1/15 | 1/17 | 1/13 | 1/15 | 3/16 | 1/13 | 1/15 | 1/14 | 4/14 | 1/16 |
| Data end | 7/18 | 4/18 | 12/17 | 10/18 | 9/18 | 3/18 | 9/17 | 3/18 | 3/18 | 11/18 | 3/18 | 12/17 | 2/18 | 5/18 |
| N | 495 | 132 | 630 | 151 | 853 | 522 | 178 | 479 | 423 | 980 | 214 | 670 | 200 | 727 |
| Price | | | | | | | | | | | | | | |
| Supply | + | + | | | | | | | + | + | | | | |
| GitHub | | + | | | + | | | | o | o | | | o | |
| Whitepaper | | | o | | o | | | | o | o | | | | |
| Presale | - | + | | | | | | | o | + | o | | | - |
| Rating | + | | | | + | + | | | | | | | + | + |
| Team size | | + | + | + | | | | + | | + | + | o | + | |
| # Advisors | | | o | | | | | | | o | | | | |
| ETH | + | | | | | | | o | | | + | | | |
| Bonus | | o | | | | | | | | o | | o | | |
| Distribution | | o | | | | | | | o | - | - | o | - | |
| Duration | - | - | o | | | | | | - | - | | o | | |
| R ² | 0.23 | 0.18 | 0.23 | 0.38 | 0.18 | 0.37 | 0.30 | 0.22 | 0.42 | 0.39 | 0.28 | 0.14 | 0.28 | 0.03 |

Binary Variables Considered – but not Significant

- **Pre-Sale:** 1 = Private sale prior to the main ICO start
- **Github:** 1 = Venture had active Github profile at start of ICO
- **Twitter:** 1 = Twitter account active at time of ICO start
- **Whitepaper:** 1 = Whitepaper on ICObench
- **Bonus:** 1 = scheme for rewarding early ICO investors

Determinants of Success

| | ICO boom (Jan 2017 - Jun 2018) | | | Post-boom (Jul 2018 - Dec 2019) | | | | |
|-------------------------|--------------------------------|-----------|------------|---------------------------------|-----------|------------|-----------|---------|
| | (i) Basic | (ii) Full | (iii) Full | (i) Basic | (ii) Full | (iii) Full | | |
| Constant | -0.959*** | (-3.91) | -0.961*** | (-3.45) | -0.219 | (-0.96) | 0.110 | (0.38) |
| Log Target Cap | 0.260*** | (4.67) | 0.269*** | (5.14) | 0.361*** | (9.16) | 0.347*** | (8.40) |
| Rating | 0.389*** | (5.99) | 0.350*** | (5.33) | 0.089 | (1.39) | 0.100 | (1.51) |
| Team Size | 0.022*** | (4.14) | 0.022*** | (3.86) | 0.016*** | (2.94) | 0.017*** | (2.92) |
| ETH price | 0.174*** | (3.90) | 0.172*** | (3.82) | 0.164*** | (2.74) | 0.164*** | (2.67) |
| Tax Haven | 0.162** | (2.22) | 0.166** | (2.26) | 0.202*** | (2.82) | 0.187** | (2.49) |
| % Distributed in ICO | -0.150*** | (-3.75) | -0.152*** | (-3.64) | -0.019 | (-0.47) | -0.034 | (-0.85) |
| Log Duration | -0.150*** | (-4.65) | -0.166*** | (-4.95) | -0.070** | (-2.57) | -0.082*** | (-2.73) |
| Observations | 589 | | 589 | | 626 | | 626 | |
| Adjusted R ² | 0.282 | | 0.290 | | 0.198 | | 0.200 | |

Dependent variable: **log amount raised**

Regression (ii) includes control variables and industry fixed effects (e.g. KYC, Accepts BTC, IEO, etc.)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, t-statistics in parentheses

5. Price Discovery

Alexander, C. and D. Heck (2020) Price Discovery in Bitcoin: The Impact of Unregulated Markets. *Journal of Financial Stability* 50, 1-18.

Alexander, C., Choi, J., Massie, H. and S. Sohn (2020) Price Discovery and Microstructure in Ether Spot and Derivatives Markets. *International Review of Financial Analysis*, 71

Alexander C., Choi, J., Park, H., and S. Sohn (2019) BitMEX Bitcoin Derivatives: Price Discovery, Informational Efficiency and Hedging Effectiveness. *Journal of Futures Markets*, 40(1) 23-43

Alexander and Heck (2020)

Multidimensional price discovery analysis on bitcoin spot and futures
Minute-level data from 21 exchanges

| Futures | Perpetuals | Spot |
|-----------------------|-----------------------|--------------------------|
| Bakt ^{Sept} | BitMEX | BinanceUS ^{Oct} |
| CME | Deribit | Bitfinex |
| BitMEX | Kraken ^{Oct} | Bitstamp |
| Deribit | OKEx ^{July} | Bittrex |
| Huobi ^{July} | | Coinbase |
| Kraken ^{Oct} | | Exmo |
| OKEx | | Gemini |
| | | itBit |
| | | Kraken |
| | | OKCoin |

We exclude Binance because almost all its trading is on tether perpetuals

Binance Exchange



Dogecoin Perpetual

Where are the most Speculative Trades?

↓ average holding period ⇒ ↑ in speculative activity

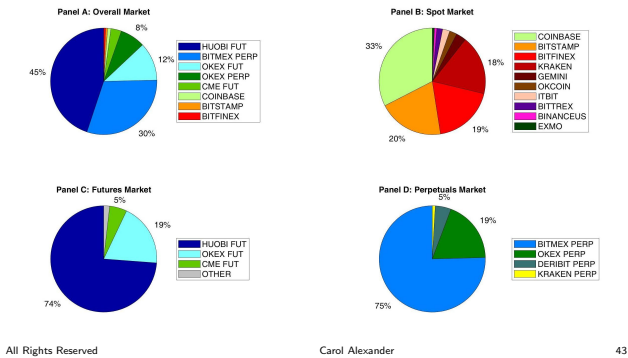
Average Holding Period (hours)

| | Perpetuals | | | Futures | | | |
|-----------|------------|---------|-------|---------|---------|-------|--------|
| | BitMEX | Deribit | OKEx | BitMEX | Deribit | Huobi | OKEx |
| September | 20.25 | 25.65 | 25.44 | 423.49 | 315.01 | 32.13 | 107.59 |
| October | 18.80 | 25.08 | 19.53 | 277.96 | 225.44 | 7.28 | 36.85 |
| November | 19.33 | 24.95 | 17.78 | 366.50 | 241.71 | 6.29 | 28.74 |
| December | 21.64 | 41.36 | 13.95 | 628.12 | 385.26 | 20.83 | 56.55 |
| January | 17.61 | 35.35 | 17.06 | 402.81 | 345.69 | 7.61 | 37.66 |

$$\text{Average holding period} = \frac{\text{Open Interest}}{\frac{1}{2} \text{Volume}}$$

Relative Volumes

Data from 1 April 2019 to 31 January 2020



Futures Contract Specifications

Table 1 Futures Specifications

| Contracts | Regulated Futures | | | | Unregulated Futures | | |
|--------------------|-------------------|------------------------------|-----------------|------------------|-----------------------------------|--------------------------------|-----------------------------------|
| | CME | Bakkt | BitMEX | Deribit | Huobi | Kraken | OKEx |
| Contract Size | 5 XBT Monthly | 1 XBT Daily, 1 XBT Quarterly | 1 USD Quarterly | 10 USD Quarterly | 100 USD Weekly, 100 USD Quarterly | 1 USD Monthly, 1 USD Quarterly | 100 USD Weekly, 100 USD Quarterly |
| Frequency | Monthly | Daily, Quarterly | Quarterly | Quarterly | Weekly, Quarterly | Monthly, Quarterly | Weekly, Quarterly |
| Margin Requirement | 37% | 37% | 1% | 1% | 1% | 2%-6%* | 10% |
| Settlement | Cash in USD | Physical | Cash in XBT | Cash in XBT | Cash in XBT | Cash in XBT | Cash in XBT |
| Trading Days | Weekdays | Weekdays | 24/7 | 24/7 | 24/7 | 24/7 | 24/7 |
| Delivery Date | Last Friday | 3rd Friday | Last Friday | Last Friday | Last Friday | Last Friday | Last Friday |
| Fees (maker/taker) | \$1.25 | \$1.25 | -2.5/7.5 | -2/5 | 2/3** | -2/7.5 | 2/5** |

Note: The table shows the main specifications of the quarterly futures contracts included in our analysis. Except for CME and Bakkt, fees are reported in basis points. *Kraken is the only exchange that distinguishes between margins for professional and retail clients. The former face margin requirements of 2-6%, while the latter have to deposit 50% as initial margin. **Huobi and OKEx do not offer maker rebates for ordinary users, but for VIP investors with a 30-day trading volume of at least \$500m or 100,000 XBT, respectively.

Measures

Generalized Information Share (GIS) for Product X

- When new information arrives to the network, what proportion of the total price innovation originates on product X?

Impulse Response of Product X

- When a price jump occurs on a leading product, how long does a following product take to adjust to the new market price?
- What happens when a jump occurs on a following exchange?

Procedure

- Various n -dimensional vector error correction models (VECM)
- Five Systems of traded BTC prices:
 - Spot ($n = 10$)
 - Perpetuals ($n = 4$)
 - Futures (reg. $n = 2$, unreg. $n = 5$)
 - Main ($n = 8$)
- Day-by-day analysis of minute-level traded prices → daily time series of GIS for each exchange in the system
- Exponential smoothing of GIS aids visual displays
- Robustness checks: 5-min and 15-min frequencies and different information measures

Vector Autoregression Models

Let \mathbf{p}_t be the $n \times 1$ vector of cointegrated log prices at time t and let $z_t = \beta^T \mathbf{p}_t$ denote their deviations from long-run equilibrium. Then the VECM is:

$$\Delta \mathbf{p}_t = \alpha + \sum_{i=1}^{q-1} \Gamma_i \Delta \mathbf{p}_{t-i} + \delta z_{t-1} + \mathbf{e}_t,$$

where \mathbf{e}_t are serially uncorrelated innovations with zero mean and covariance matrix Ω and δ captures reactions to transitory equilibrium deviations. Inverting and integrating gives:

$$\mathbf{p}_t = \mathbf{p}_0 + \Psi(1) \sum_{j=1}^t \mathbf{e}_j + \Psi^*(L) \mathbf{e}_t$$

where $\Psi(1)$ i.e. the sum of the MA coefficients in the inversion of the AR, has identical rows which we denote ψ . Then the scalar $\psi \mathbf{e}_t$ is the **common efficient price** and it has variance $\psi \Omega \psi^T$

Information Shares

The Hasbrouck (1995) **information share** of each market, i.e. its relative contribution to the variance of the common efficient price, is:

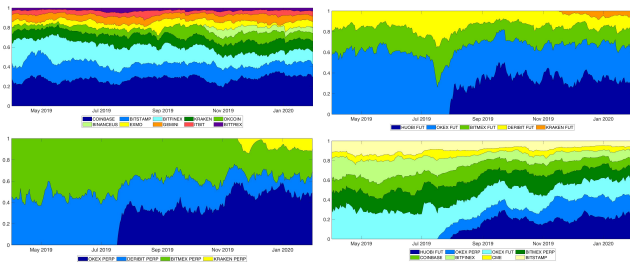
$$IS_i = \frac{(\psi \mathbf{M})_i^2}{\psi \Omega \psi^T} \text{ for } i = 1, \dots, N,$$

where \mathbf{M} is the lower triangular matrix of the Cholesky decomposition of Ω and $(\psi \mathbf{M})_i$ is the i -th entry of $\psi \mathbf{M}$.

Various improvements of the IS have been proposed for different reasons – we use the **generalised information share** of Lien and Shrestha (2015)

We also check robustness with the **component share** of Gonzalo and Granger (1995)

Results



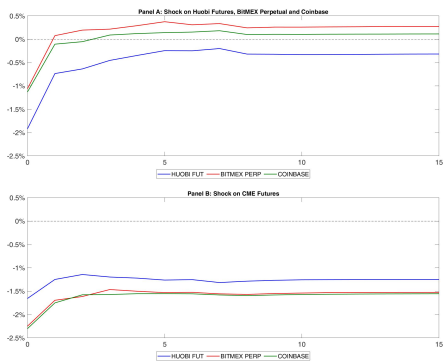
Impulse Responses to/from CME Futures

- How does CME react to price jumps on an unregulated exchange?
- How do the unregulated exchanges react to price jumps on CME?
- Two-dimensional VECMs on all transaction data for January 2020
- Spread measured relative to the CME price – i.e.

$$\frac{p_{cme} - p_{unreg}}{p_{cme}}$$

- Next two graphs show the **expected spread after a shock**

Convergence to Equilibrium Price after Shock



Thank you for your attention

Any questions?