MSc Business Analytics

Financial Modelling and Analysis

Chapter 5.2. Finance based on blockchain technologies. Cryptocurrency as an Asset Class

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What will we be speaking about?

- Does cryptocurrency have a place in the portfolio of an investor?
  - From a theory perspective
  - From a data perspective (return, volatility)
  - Review of Portfolio Theory from the point of view of cryptos

Some old quotes

- “A fraud, worse than tulip bulbs” — Jamie Dimon, JP Morgan CEO on September 12, 2017
- “Probably rat poison squared” — Warren Buffet, Berkshire Hathaway CEO on May 5, 2018

Two Views of Cryptocurrency as Part of a Portfolio

- View 1: Traditional finance, from a theory perspective
- View 2: Traditional finance, from a data perspective

View 1: Traditional Finance - Theory Perspective

- The Capital Asset Pricing Model (CAPM) is one of the great achievements of finance, and still the benchmark theory for expected returns
- CAPM — **investors should hold risky securities according to market weighted values**
- What does the CAPM say about crypto?
  - **One should hold zero cryptocurrency**, in general
  - **Cash, or currency, has transaction value, but has no underlying value** (such as debt or equity in a company) - it is simply a medium of exchange
  - **CAPM would say you shouldn’t really hold any currency in your portfolio** (hold as little as possible for transaction needs)

View 1: Traditional Finance - Theory Perspective

- **Gordon Growth Model**
  - The benchmark method for valuing companies
  - Idea: perhaps if one could value cryptocurrency using the Gordon Growth
  - Model, one could decide if crypto was under or over-valued
  - **P=D/(r-g)**, D-dividends that grow every year at a rate g, and the expected return on the asset is r.
  - Values companies based on their dividends, and obviously currency pays no dividends

View 2: Traditional Finance - Data Perspective

- An alternate view: Construct returns on cryptocurrency
- Examine the empirical properties of these returns
- Treat these returns as if they were returns on a traditional investment and ask:
  - If we saw an investment with returns like these, would we want to hold it as part of our portfolio?

View 2: Traditional Finance - Data Perspective

- Both View 1 and View 2 are traditional finance viewpoints
- They may or may not yield opposite results (we will see)
- They each have drawbacks
  - View 1 (Theoretical): What if we are missing something important in our assumptions?
  - View 2 (Empirical): There may be serious limitations to the data
- Is there a third view?

Dollar-to-BTC Exchange Rate, Along With Volume

Dollar-to-BTC Exchange Rate, Along With Active Addresses

- Recall that an address is a user of Bitcoin

Dollar-to-ETH Exchange Rate, Along With Volume

First impression

- Sometimes **prices track volume closely** (especially for bitcoin)
- **Prices track active addresses to some extent**
- Active addresses have stabilized
- However, many cryptocurrencies have failed, the biggest ones
  - *Ethereum's DAO* ($168 million of investment into it, issues due to a hacker attack)
  - *Dogecoin* (The success was short-lived when its founder took an unexpected turn and shut down the exchange. After the collapse of the exchange and disappearance of funds, the story of Dogecoin comes to an end)
  - *PayCoin* (the crypto came tumbling down when most of the promises made by the founders failed to materialize)
  - Terra (luna)…

Data Driven Approach

- Basic price patterns
- Defining the return to investing in crypto
  - What is the average return to investing in crypto?
  - What are the risks?

Returns

- Cryptocurrency is a store of value, and as such, it is an asset
- We will refer to the price of bitcoin as the number of dollars it takes to buy one bitcoin
- Consider the strategy:
  – Purchase one bitcoin today
  – Tomorrow, exchange that bitcoin for dollars
  – What is the return on this strategy?

Year	Bitcoin, Return (%)	SPDR Gold Shares (GLD) Return (%)
2010	9,900	29.27
2011	1,473	9.57
2012	186	6.6
2013	5,507	-28.33
2014	**-58**	-2.19
2015	35	-10.67
2016	125	8.03
2017	1,331	12.81
2018	**-73**	-1.94
2019	95	17.86
2020	301	24.81
2021	90	-4.15
2022	**-81.02**	-3.21%

Bitcoin has an average annual return of 1,576% and a total return of 18,912% from 2010 to 2021.

Means Versus Medians

- Reported were statistical averages (means)
  - Technically: you sum up the daily returns and divide by the length of the sample period
- This is (usually) the typical estimator of what you are truly expected to earn
- However, your returns on a day-to-day basis could look very different
- Median for log Bitcoin return = $0.0002 < 0.0003$ (Since 2019)
  - the data are "skewed to the right", returns are positively skewed, with a longer tail of high scores pushing the mean up more than the median.)
  - It highly depends on the time window (higher skewness in the earlier period)
- Extending the window will change the situation to opposite!

Top 100 cryptos by capitalization (1 year ago)

- "BTC“
- "ETH“
- "BCH“
- "LTC“
- "XRP“
- "BSV“
- "EOS“
- "XLM“
- "ADA“
- "YFI“
- "LINK“
- "TRX“
- "USDT“
- "ETC“
- "IOST“
- "DOT“
- "BUSD“
- "ZEC“
- "UNI“
- "BNB“
- "NEO“
- "ATOM“
- "DOGE“
- "SUSHI“
- "DASH“
- "ZRX“
- "MIOTA“
- "OMG“
- "BAND“
- "USDC“
- "VET“
- "LRC“
- "XMR“
- "MKR“
- "QTUM“
- "ONT“
- "XTZ“
- "THETA
- "OKB“
- "ALGO“
- "SXP“
- "ZIL“
- "HBAR“
- "XEM“
- "RSR“
- "AVAX“
- "CTXC“
- "NANO“
- "SNX"
- "CVC“
- "NEAR“
- "HT"
- "AAVE“
- "CRV“
- "SRM“
- "SOLAN"
- "KNC"
- "WAVES"
- "ICX"
- "CRO"
- "BAT"
- "EGLD"
- "GRT"
- "ENJ"
- "WBTC"
- "STORJ"
- "REN"
- "PAY"
- "MANA"
- "KLAY"
- "DNT"
- "KSM"
- "COMP"
- "KAVA"
- "FIL"
- "VGX"
- "MCO"
- "BTG"
- "TOMO"
- "SNT"
- "FTT"
- "BTM“
- "GTO"
- "TRB"
- "DAI"
- "MATIC"
- "ONE"
- "ALPHA"
- "BAL"
- "ABBC"
- "SC"
- "PAX"
- "TUSD"
- "XVG"
- "RVN"
- "LUNA"
- "OCEAN"
- "ELF"
- "TRUE"
- "DCR"

Top 100 cryptos by capitalization (2022)

- "BITCOIN“
- "WRAPPED BITCOIN"
- "HUOBI BTC"
- "ETHEREUM“
- "LIDO STAKED ETHER “
- "MAKER "
- "BINANCE COIN "
- "BITCOIN CASH “
- "KUSAMA “
- "MONERO "
- "AAVE"
- "ELROND“
- "LITECOIN "
- "SOLANA "
- "QUANT “
- "DASH “
- "ZCASH"
- "BITCOIN SV "
- "AVALANCHE“
- "AXIE INFINITY“
- "CETH“
- "TERRA“
- "FTX TOKEN“
- "ARWEAVE“
- "HELIUM“
- "COSMOS“
- "CONVEX FINANCE“
- "ETHEREUM CLASSIC"
- "OKB“
- "\nFILECOIN“
- "NEO“
- "INTERNET COMPUTER“
- "POLKADOT“
- "KUCOIN TOKEN“
- "CHAINLINK“
- "UNISWAP“
- "NEAR“
- "BITKUB COIN“
- "HUOBI TOKEN“
- "WAVES“
- "PANCAKESWAP“
- "OSMOSIS“
- "GATETOKEN“
- "FLOW“
- "KADENA"
- "SYNTHETIX NETWORK TOKEN“
- "THE SANDBOX"
- "THORCHAIN“
- "LEO TOKEN“
- "TEZOS“
- "CURVE DAO TOKEN“
- "CELO“
- "THETA NETWORK"
- "DECENTRALAND"
- "CELSIUS NETWORK"
- "EOS"
- "FANTOM"
- "NEXO“
- "ENJIN COIN“
- "POLYGON“
- "STACKS"
- "POCKET NETWORK"
- "KLAYTN“
- "CARDANO"
- "PAX DOLLAR"
- "TRUEUSD"
- "FRAX"
- "DAI" "TERRAUSD“
- "BINANCE USD"
- "USD COIN"
- "TETHER“
- "MAGIC INTERNET MONEY“
- "LOOPRING"
- "ALGORAND"
- "BASIC ATTENTION TOKEN“
- "IOTA“
- "XRP“
- "CRYPTO.COM COIN“
- "THE GRAPH“
- "OASIS NETWORK"
- "HEDERA“
- "STELLAR“
- "GALA“
- "HARMONY“
- "CHILIZ“
- "THETA FUEL“
- "RADIX"
- "DOGECOIN“
- "NEM"
- "TRON“
- "VECHAIN“
- "AMP"
- "CUSDC“
- "CDAI"
- "ECOMI“
- "BITTORRENT"
- "SAFEMOON“
- "ECASH"
- "SHIBA INU"

Top 100 cryptos by capitalization

- **Top by capitalization**

crypto	meanPrice	meanReturn	medianReturn	sdReturn	name
BTC	11411.27	0.003316	0.003474	0.04519	Bitcoin
ETH	313.1222	0.003687	0.0031	0.059914	Ethereum
BCH	269.1448	-4.81E-05	0.001385	0.06548	Bitcoin Cash
LTC	57.60833	0.001845	0.002672	0.056815	Litecoin
XRP	0.254945	-0.00115	0.002071	0.066873	XRP
BSV	186.8433	-0.00132	0.00036	0.075555	Bitcoin SV

- **Top 6 by mean return**

crypto	meanPrice	meanReturn	medianReturn	sdReturn	name
ALPHA	0.152543	0.018156	0.012847	0.110712	Alpha Finance Lab
KSM	20.91312	0.007382	0.001204	0.095099	Kusama
YFI	20279.08	0.006793	-0.01053	0.10849	yearn.finance
DOT	5.119528	0.005651	0.000353	0.07199	Polkadot
THETA	0.385304	0.005107	0.006369	0.080488	Theta
AAVE	67.28692	0.00509	0.003488	0.084573	Aave

- **Top 6 by SD of the return**

crypto	meanPrice	meanReturn	medianReturn	sdReturn	name
ONE	0.004869	-0.15521	0.003241	1.145168	Harmony
GRT	0.396691	-0.01327	-0.01986	0.218817	The Graph
VGX	0.088372	-0.00769	-0.00232	0.194884	Voyager Token
SUSHI	1.826177	-0.01701	0	0.175844	Sushi
IOST	0.0055	-0.00871	0	0.140964	IOS token
DNT	0.015123	-0.00161	-0.003	0.129238	district0x

Top 100 cryptos by capitalization

- Bottom 6 by SD of the return (stablecoins)

crypto	meanPrice	meanReturn	medianReturn	sdReturn	name
DAI	1.008642	-2.10E-05	0	0.005207	Multi Collateral Dai
USDT	1.000793	-9.49E-06	0	0.001992	Tether
PAX	1.000409	-1.19E-05	0	0.001973	Paxos Standard
USDC	1.000337	-6.03E-06	0	0.00143	USD Coin
TUSD	1.000528	-9.98E-06	0	0.001392	True USD
BUSD	1.000441	-8.32E-06	0	0.001279	BUSD

View 2: Traditional finance, from an estimates perspective

- **The CAPM (Capital Asset Pricing Model) is a way to think both about the risk of an investment and the expected return**.
- Some benchmark is usually specified, such as the S&P 500 or the world stock market, and we measure how sensitive the asset is to movements in the "market".
- For example, **if the S&P drops 10% and an asset in question plummets 30%, this asset is "risky" and we say the "beta" is approximately 3.0.**
- This asset should also have a high expected return (low price) to compensate people for bearing such risk.
- We can use this model for any asset return. For example, you could look at any FX rate or bond return.
- To use the CAPM, first specify the benchmark (world indexes), and then sample bitcoin prices (from a liquid exchange, coinbase, for instance).
- **The beta factor is an indicator of expected changes in the return on a particular portfolio or individual security in response to the behaviour of the market as a whole:**

$$\mathrm{E[R]=RFR+b}(E[R\mathrm{m}] - RFR)$$

- The beta coefficient can be interpreted as follows:
  - **β =1** exactly as volatile as the market
  - **β >1** more volatile than the market (Assets with a higher beta - more inherent risk- demand a higher expected return)
  - **β <1>0** less volatile than the market
  - **β =0** uncorrelated to the market
  - **β <0** negatively correlated to the market

View 2: Traditional finance, from an estimates perspective

CAMP beta (lowest)	index
-0.137291363	DRAMeXchange.DXI.Index...PRICE.INDEX
0.007599901	Baltic.Exchange.Dry.Index..BDI....PRICE.INDEX
0.076962831	KARACHI.SE.100...PRICE.INDEX
0.117488628	PHILIPPINE.SE.I.PSEi....PRICE.INDEX
0.124034742	S.P.MERVAL.INDEX...PRICE.INDEX

CAMP beta (highest)	index
0.941767161	FTSE.JSE.ALL.SHARE...PRICE.INDEX
0.786935905	MSCI.EAFE.U....PRICE.INDEX
0.776570018	MDAX.FRANKFURT...PRICE.INDEX
0.771331368	OMX.HELSINKI..OMXH....PRICE.INDEX
0.744760063	WARSAW.GENERAL.INDEX...TOT.RETURN.IND

- In general 78 out of 79 indexes beta >0;
- In 1case beta<1; (DRAMeXchange.DXI.Index)

Volatility

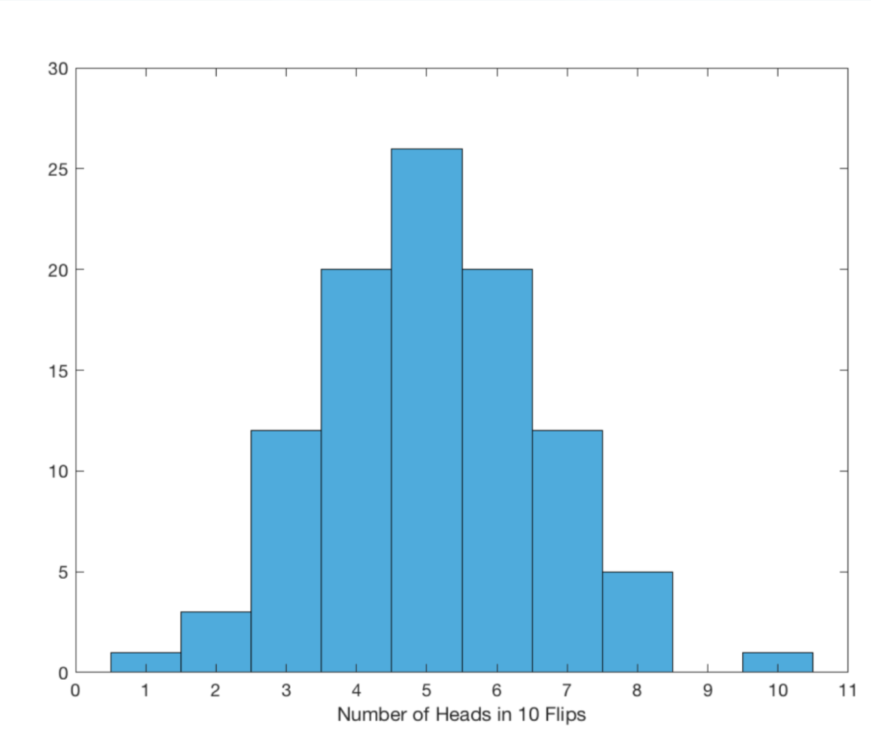
- **Volatility measures risk** (assuming that return is generally normally distributed)
  - For example: log returns on Bitcoin have a standard deviation of 0.2%, and a mean of 0.39% (before 2021)
- If Bitcoin returns were normally distributed, 95% of returns would fall between 2 standard deviations above and below the mean (0.39%+/-2*0.2%)
- However, the normal distribution does not describe Bitcoin very well
- Most returns are more concentrated than our volatility discussion suggests
- Also, there are outliers
- A normal distribution would imply a return of > 160% as statistically impossible.
  - 160% of Bitcoin return was observed on some days
  - Thus, that did happen!

Caveats

- This discussion does not assume transaction costs, which can be substantial
  - Example: a $10 purchase of bitcoin on Coinbase yields only $8.50 worth of the coin
- Survivor bias

Survivor Bias

- If one flipped 100 coins ten times
- Here is a histogram describing the number of heads
- Now suppose I look only at the number of heads for the top 3 or top 5
  - These are 7, 8, and 10
- Should I conclude that flipping a coin almost always yields heads?
  - Of course not!
- It is an artifact - I decided to pick the top 3 or the top 5
- The focus on the selective cryptocurrencies has the same concern



So…

- Prices of cryptocurrency are volatile
- Active addresses have grown, and prices seem to rise with them
- Prices and volumes look like to be correlated
- Returns subject to survivor bias (we cannot generalize for all cryptos)

REVIEW OF PORTFOLIO THEORY

Background

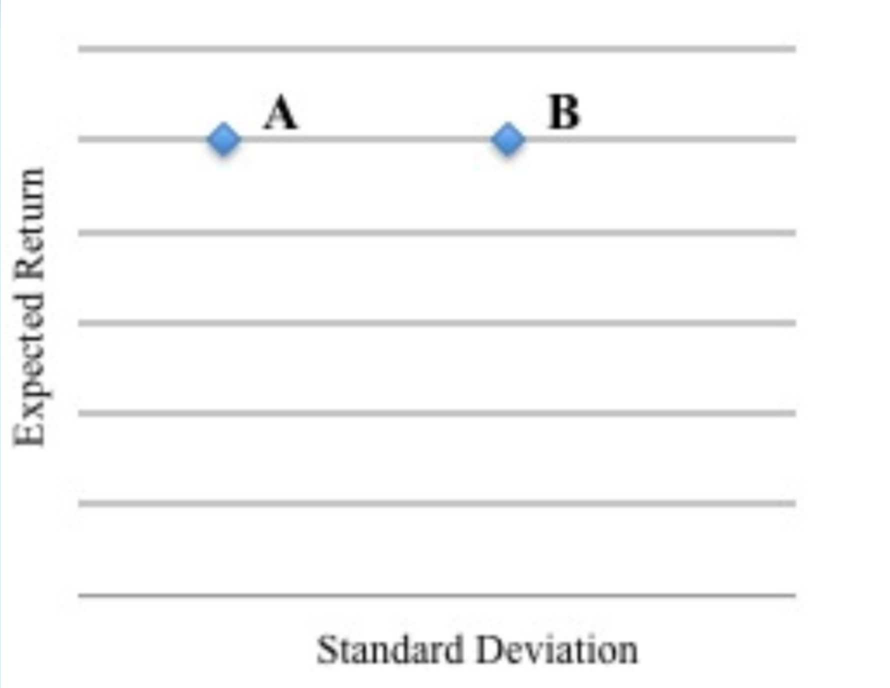
- Portfolio theory developed by Markowitz (1952)
- This is still benchmark portfolio theory
- It does require an approximation — **that returns are normally distributed!**
- However, the most important insight from this theory, that there are gains from diversification, transcends the assumption of normally distributed returns
- We will also review the Capital Asset Pricing Model of Sharpe (1962)

Assumptions of Portfolio Theory

- Investors prefer more to less
- Investors are risk averse
- Returns are normally distributed

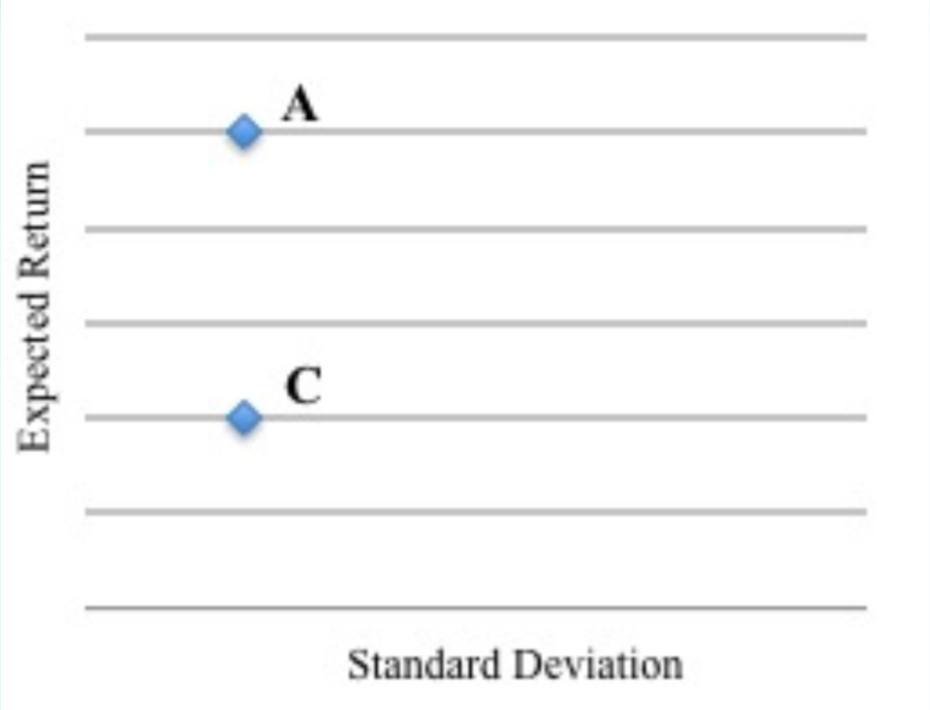
Mean-Standard Deviation Diagram

- Between points A and B, which is preferred?
  - A and B have the same mean
  - A has a lower standard deviation than B
  - **A** dominates B



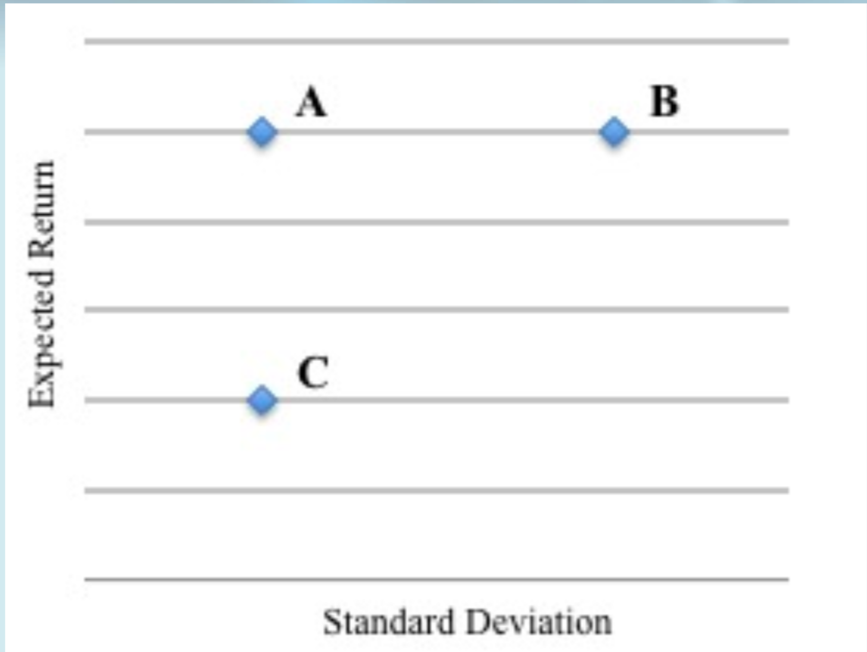
Mean-Standard Deviation Diagram

- Between points A and C, which is preferred?
  - A and C have equal standard deviations
  - A has a higher mean
  - **A** dominates C



Mean-Standard Deviation Diagram

- What about B and C?
- Neither dominates the other

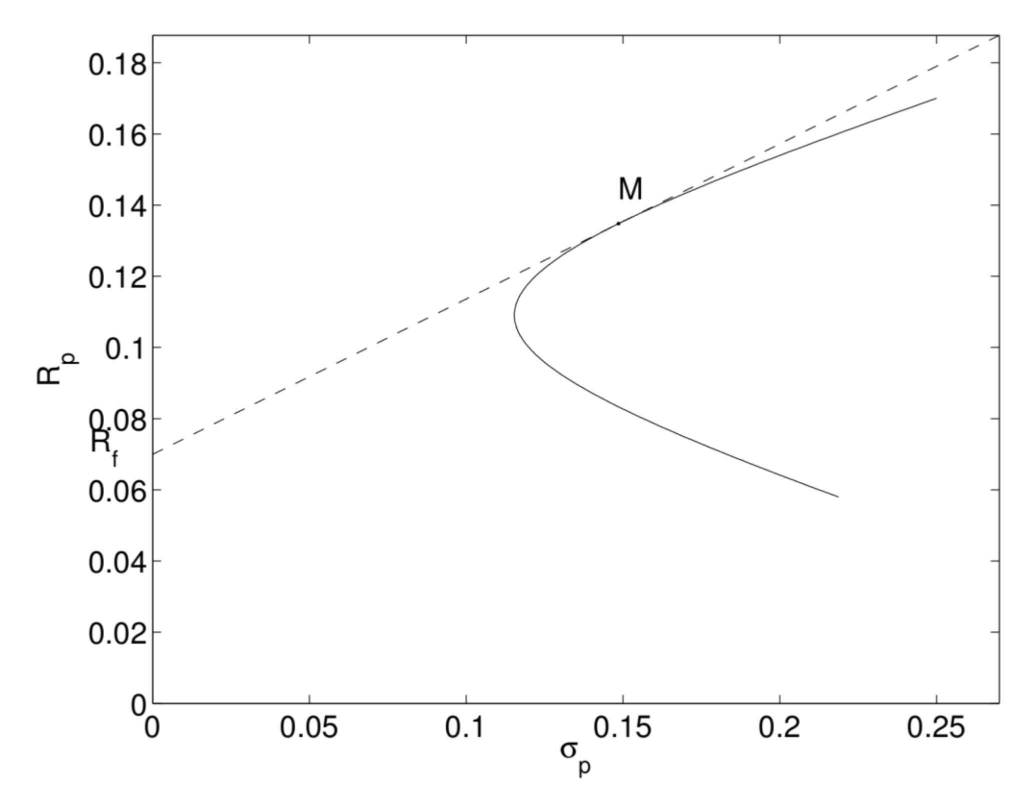


Mean-Standard Deviation Diagram

- Markowitz showed that the set of all risky assets lie inside of a sideways "U"
  - This sideways "U" is called the risky asset frontier
- By combining risky assets cleverly, you can get to the top part of the frontier (called the efficient frontier)

The tangency portfolio

- Now introduce a riskless asset (like a Treasury bill)
- The tangency line from the riskless asset to the frontier tells you the best possible risky asset portfolio
- The tangency portfolio has the highest slope possible
- Any portfolio with a lower slope will be sub-optimal and inefficient
- Any portfolios with higher slope cannot be attainable
- This slope: **(E[R] – RFR)/σ** is called the Sharpe ratio
- The line from the risk-free rate to the tangency portfolio is called the capital allocation line



The Mutual Fund Theorem

The portfolio allocation problem can be divided into two steps

1. Determine the tangency portfolio $\Rightarrow$ this is the optimal combination of the risky assets.
2. Determine where you want to be on the capital allocation line

Consequences of the Mutual Fund Theorem

- If everyone holds the same portfolio, then the market portfolio (which is the weighted average of everyone's portfolio) is the best possible portfolio

- Namely, **the market portfolio is efficient**

Consequences of the Mutual Fund Theorem

- Due to Sharpe (1964)
  - Called the Capital Asset Pricing Model (CAPM)
- **The market portfolio – the portfolio that holds assets according to their market weights – is efficient**
- **The market portfolio has the highest Sharpe ratio possible**
- Expected returns on assets are determined by their βs with respect to the market portfolio:
- where

$$E[\mathrm{Ri}] = RFR + \beta(E[\mathrm{Rm}] - RFR)$$

$$\beta = Cov(\mathrm{Ri}, \mathrm{Rm})/Var(\mathrm{Rm})$$

So: Asset Allocation with Cryptocurrency

- The theoretical view is simple:
  - Because cryptocurrency has no intrinsic value and pays no dividends, it should not be part of the optimal portfolio
  - Developing the empirical view we found that
    - Cryptocurrencies have high average returns
    - The standard deviation (risk) is also very high
    - Returns are positively skewed
    - Betas with the majority of the indexes are less than one

Sharpe Ratio

- The Sharpe ratio is one way to adjust for the risk of an asset
  - It is named for Bill Sharpe, the Nobel Prize winning economist and inventor of the CAPM
- The Sharpe ratio is the slope of the capital allocation line

Sharpe ratio = (Expected return – Risk free rate)/SD of return

- It tells you the extra return you receive per unit of standard deviation

Sharpe Ratio

- Let's use the statistics we have already calculated to compute the Sharpe ratio on some major cryptocurrencies
- Because these are daily returns, and the interest rate is so low, we will use a risk-free rate of zero
- Thus we compute:

Sharpe ratio = Expected return/SD of return

Sharpe Ratio

- Some caveats:
  - Recall: the return tells you your percent gain on a strategy that exchanges dollars for cryptocurrency, and then converts the cryptocurrency back to dollars
  - It assumes no trading costs
  - It uses average returns - the Sharpe ratio on a portfolio could be high, even if you lose money on most days
  - Recall survivor bias

Sharpe Ratio

- Bitcoin
  - Average daily return = 0.00362,
  - Standard deviation = 0.037⇒
  - Daily Sharpe ratio on Bitcoin = 0.00362 /0.037 = **0.097**
- Ethereum
  - Average daily return = 0.003686526, Standard deviation = 0.0599 ⇒
- Sharpe ratio on Ether = 0.00369/ 0.0599 = **0.0615**
- Litecoin
  - Average daily return = 0.001845445, Standard deviation = 0.05681539 ⇒
  - Sharpe ratio on Litecoin = 0.00184/0.0568 = **0.0325**
- As a comparison, Sharpe ratio on the S&P 500 composite = **0.038**

Another Measure: Alpha

- What is the alpha on an asset?
  - **Alpha measures abnormal return**
- According to the Capital Asset Pricing Model (CAPM) – for any asset with return R:

$$\mathbf{E[R]=RFR+b(}E[R\mathbf{m}] - RFR\mathbf{)}$$

- for RFR = the risk-free rate (Tbill return)
- Rm is the return on the aggregate stock market (the S&P 500 comes close)

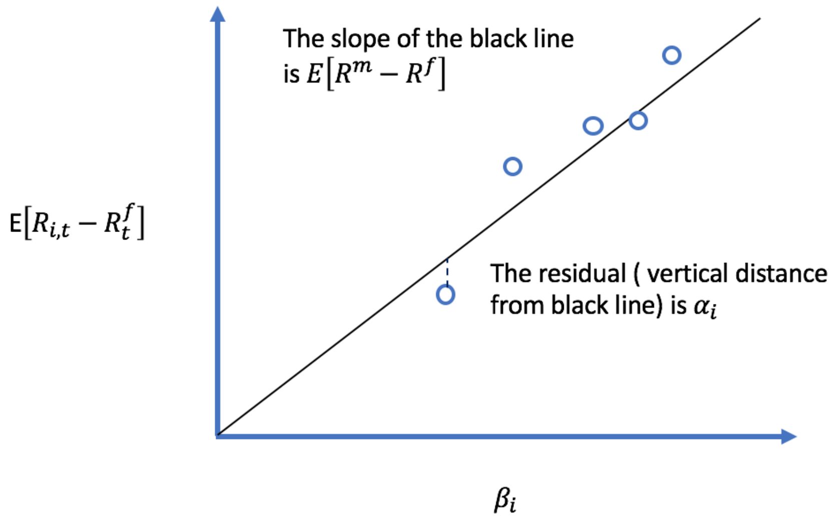
$$\beta = Cov(R\text{i}, R\text{m})/Var(R\text{m})$$

- This measures how much an asset moves when the market moves
- **What is the alpha (α) on a security return?**
- **It is the part of the return that the CAPM does not explain:**

$$\mathbf{\alpha = E[R]\text{-}(RFR+b(}E[R\mathbf{m}] - RFR\mathbf{))}$$

- According to the CAPM, **α should be zero**
- We might measure a positive α, but this — according to the CAPM —should be simply statistical noise (or survivor bias)

Cross-sectional implications of the time series regression



(This is made up data, as if the CAPM actually worked…)

- The intercepts αi in time-series regressions are residuals in the cross-sectional regression.
- Each blue circle represents a different security/portfolio.
- For each return series i, the estimated αi from a time series regression is the vertical distance to the black line.
- If the CAPM were true, all those αi would be zero and every security would be on that line.

Daily Alphas on Cryptocurrency

- Bitcoin: 0.004
- Ether: 0.003
- Litecoin: 0.0004
- Mean alpha for the main indexes = 0.00027 (transforming from ln scale will give us ~1%)
- SO: **Alpha refers to excess returns earned on an investment above the benchmark return**
- **An alpha of one (the baseline value is zero) shows that the return on the investment during a specified time frame outperformed the overall market average by 1%.**
- Thus, our alphas represent a percentage that reflects how an investment performed relative to a benchmark index.

Which Measure: α or Sharpe Ratio?

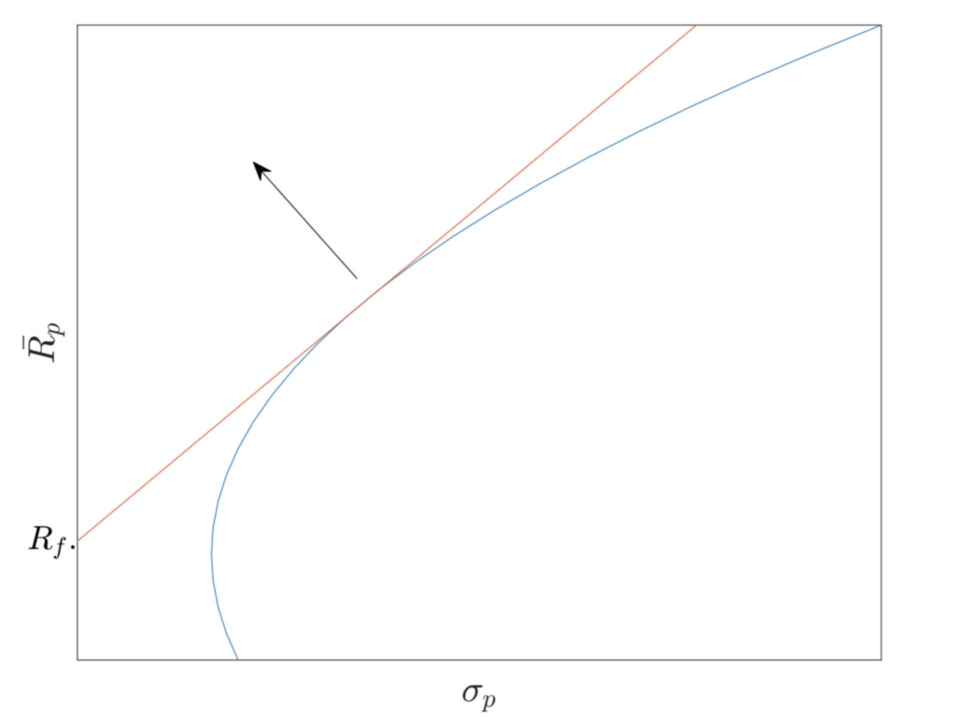
- It makes a difference!
- **Cryptocurrency look better in terms of α**
- Why?

Recall Portfolio Theory

- Investors should seek out the highest Sharpe ratio portfolio
- The Sharpe ratio is an intuitive measure of risk and return on an asset
- **But it is not the most useful measure, because it does not take into account covariance**
  - **Crypto had a low covariance with the market**
  - After the introduction of bitcoin futures, these markets became more connected
- But still, a lower covariance with the traditional financial market makes cryptos' returns more impressive

The Investment Opportunity Set With a Positive α Investment

- Note: **a positive α investment shifts the opportunity set outward, creating a higher Sharpe ratio on the portfolio**



The Importance of Covariance

- **The return on the top cryptocurrencies has been high**
  - This may in part reflect a resolution of the risk of these currencies, and so might be unlikely to be repeated
- The covariance with the market and the associated beta is less likely to be mismeasured
- The beta of top100 cryptocurrencies is about 0.5 (0.489)
- This beta is important: **if it is low, then cryptocurrency has value as a hedge**
- How to think about this beta?

A Simple Model of the Price of Bitcoin, recall

- Gordon Growth Model
- If an asset pays dividends that grow every year at a rate g, and the expected return on the asset is r, then

$$P=D/(r-g)$$

where D is next year's dividends

- strictly speaking, according to this formula, crypto's price should be exactly zero all the time, because it pays no dividends (recall the first module)
- This is the theoretical view

A Simple Model of the Price of Bitcoin

- However, **if Bitcoin should be useful someday as medium of exchange, then the "dividend" reflects the convenience of exchange**
- For example, many people have bank accounts, even though the rate paid by bank accounts is often below the Treasury Bill rate, which is in turn below the rate on AAA Corporate Bonds

Pricing and Covariance

- What does the pricing formula tell us about the covariance?
  - **The greater the economic activity, the greater the demand for currency**
  - Also, **both cryptocurrency and the aggregate market depend positively on technological innovation**
- Both of these would argue for positive covariance and high betas – **the better the economy does, the more demand there is likely to be for cryptocurrency, the more likely crypto will be used as a medium of exchange, the greater the price**

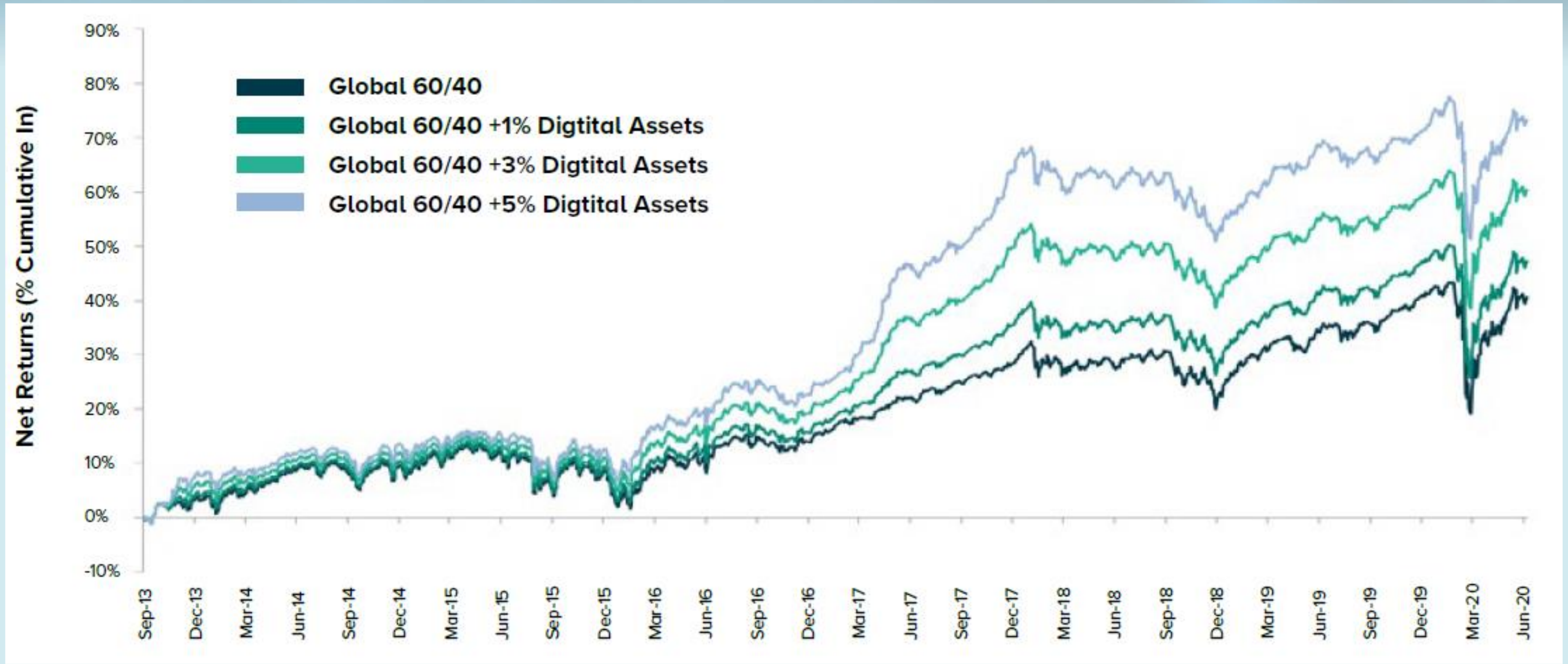
Pricing and Covariance

- However, when is it likely that cryptocurrency will become a medium of exchange?
  - Related: when might cryptocurrency be appealing as a store of value?
    - **During very bad economic times!**
- This will push the covariance and the beta lower
- **It is likely that the beta of ≈ 0.5 reflects these two forces**
- Crypto possibly has a role in a portfolio as a hedging security

Conclusions

- Cryptocurrency returns imply Sharpe ratios often close to those of the market
- They have positive αs (abnormal returns) $\Rightarrow$ suggests they might be a good investment
- But this does not take into account survivor bias and transaction costs
- Traditional theory says: do not hold cryptocurrency
- But traditional theory says: do not hold money of any kind
- Crypto's role as a hedge against bad economic times makes it intriguing as an investment
- Needed: a quantitative theory of cryptocurrency to take this into account

Simulated portfolio performance with digital currency exposure



Hypothetical portfolios that look at both a traditional allocation (60% stocks/40% bonds) and a series of updated allocations with varying levels of digital currency exposure (source: Grayscale Investments, LLC)

Simulated portfolio performance with digital currency exposure

September 24, 2013 through June 30, 2020				
Portfolio	Global 60/40	Global 60/40 +1% Digital Assets	Global 60/40 +3% Digital Assets	Global 60/40 +5% Digital Assets
Total Return (Cumulative)	50.0%	60.3%	82.8%	108.2%
Total Return (Annualized)	6.2%	7.3%	9.4%	11.6%
Risk (Annualized Std Dev)	10.4%	10.5%	10.7%	11.1%
Sharpe Ratio	0.52	0.62	0.80	0.96
Change in Annualized Return	--	1.1%	3.2%	5.3%
Change in Annualized Risk	--	0.0%	0.3%	0.7%
Ratio Improvement	--	19.2%	55.2%	86.6%

Hypothetical portfolios that look at both a traditional allocation (60% stocks/40% bonds) and a series of updated allocations with varying levels of digital currency exposure (source: Grayscale Investments, LLC)

The present and future of cryptocurrency and crypto assets

What will we be speaking about?

- General overview of the cryptocurrency market
- Who can prefer crypto-currencies more?
- Recent dynamics
- Centralized vs decentralized exchanges
- Introduction of futures
- Post-introduction-of-bitcoin-futures period
  - Hedging against economic uncertainty
  - Hedging against inflation
  - Portfolio optimization
- Cryptocurrency market and black-swan events (COVID, war)
  - Persistence cryptocurrency vs traditional markets
  - Bubbling during COVID19
  - Herding in COVID
  - Sport (football) vs crypto
  - Stablecoins
- Trust and adoption
- Cryptocurrency during the war
- Cybercrime

It’s all about perception: crypto optimists vs crypto pessimists

- **Crypto optimists** argue that cryptocurrency is the most effective means to transfer assets across long distances without the need for a third party.
- **Crypto pessimists** argue that cryptocurrencies possess no real value, can be used as a means in illegal activities and have significant negative effect on environment (PoW) .
- But, despite the issues, **> 22 000 different cryptocurrencies and tokens** that are traded.

Who do prefer crypto-currencies more?

- Cryptocurrency is mostly popular with young adults (*Pew Research*). Cryptocurrencies are used by
  - **31%** of people ages **18 to 29**,
  - 21% of people ages 30 to 49,
  - 8% of people ages 50 to 64 and
  - 3% of people age 65 or over.
- Income status does not appear to have an effect on cryptocurrency use/adoption.
- Gender matters: 22% of men vs 10% of women.

- **Long-term holding in Bitcoin increased by approximately 16%** over 2021, while short-term holding supply declined by around 32%.
  - This "macro consolidation" has increased **optimism in the Bitcoin**.

Recent dynamics

- We find that **while bullish UK, Euro and Japanese Bitcoin markets facilitate hedging against inflation by offering higher returns, the USD Bitcoin market performs worse with inflation**. (*Matkovskyy, R., Jalan, A. 2020. Can Bitcoin be an inflation hedge? Evidence from a quantile-on-quantile model. Economic Review, 7, 1024-1041*)
  - In general, our results indicate an **asymmetric relationship between inflation, both realized and unexpected, and alternative investments such as the Bitcoin market** We analyze the ability of the top 10 cryptocurrencies in enhancing portfolio returns of the 10 worst-performing stocks in the S&P600, S&P400 and S&P100 indexes, to match those of the 10 best-performing stocks therein.
  - We apply a probabilistic utility approach with different random walk Metropolis algorithms and time horizons (from 5 to 250 days).
  - We find that **addition of cryptocurrencies to traditional stock portfolios adds value in terms of enhancing returns (***Matkovskyy, R., Jalan, A., Dowling, M., Bouraoui, T. 2020. From bottom ten to top ten: the role of cryptocurrencies in enhancing portfolio return of poorly performing stocks. Finance Research letters, 101405*)
- **Shocks in economic policy reduces volatility in USD, euro, GBP and JPY bitcoin markets but increase in NASDAQ,S&P500, Euronext100, FTSE100** (*Matkovskyy, R., Jalan, A. and Dowling, M. 2021. Effects of economic policy uncertainty shocks on the interdependence between cryptocurrency and financial markets. Quarterly Review of Economics and Finance 77*)
- Nevertheless, during COVID19 we find **strong potential for mean reversion in equity markets even at high levels of shocks while cryptocurrencies turn out to be the riskiest in the long-term, with a more than 50% decline in value coupled with high degrees of persistence** (*Yarovaya, L., Matkovskyy, R., and Jalan, A. 2022. The COVID-19 black swan crisis: Reaction and recovery of various financial markets. Research in International Business and Finance 59, 101521*)
  - Our results put to question the safe-haven characteristics of the newly popular Bitcoin
- We also find that during the COVID-19 pandemic, **gold-backed cryptocurrencies were susceptible to volatility transmitted from gold markets**.
  - **Our results indicate that for the selected gold-backed cryptocurrencies, their volatility, and as a consequence, risks associated with volatility, remained comparable to the Bitcoin** (*Jalan, A., Matkovskyy, R., and Yarovaya, L. 2021. Shiny crypto assets: A systemic look at gold-backed cryptocurrencies during the COVID-19 pandemic. International Review of Financial Analysis 78, 101958*)
- While there are several strong theoretical reasons to observe the "black swan" effect on cryptocurrency herding, our results suggest **a low propensity to herd and that COVID-19 does not amplify herding in cryptocurrency markets**. (*Yarovaya, L., Matkovskyy, R., Jalan, A. (2021). "The effects of a "black swan" event (COVID-19) on herding behavior in cryptocurrency markets". Journal of International Financial Markets, Institutions and Money, 75, 101321*)
  - **These findings contradict the popular belief that herding is stronger during times of heightened uncertainty and highlight the dominance of informed and probably institutional investors in the crypto market**.
- We analyze the efficacy of cryptocurrencies as diversifiers in mitigating the dampening effects of COVID-19 on football clubs' equities performance.
  - **Results indicate that cryptos remain ineffective as diversifiers in uncertain times such as the COVID-19** (***Matkovskyy, R. and Jalan, A. 2022. Football vs Cryptos: Which Scores the Goal During COVID-19? http://dx.doi.org/10.2139/ssrn.4017746***)

CENTRALIZED VS DECENTRALIZED EXCHANGES

Matkovskyy, R. (2019), Centralized and decentralized Bitcoin markets: Euro vs. USD vs GBP. Quarterly Review of Economics and Finance 71, 270–279, https://doi.org/10.1016/j.qref.2018.09.005

Centralized vs decentralized exchanges

- Centralized bitcoin exchanges include intermediaries such as companies that act as a proxy in order to facilitate trading.
- Unlike centralized exchanges, the decentralized market is a person-to-person (P2P) bitcoin trading site that allows users to post advertisements indicating exchange rates and payment methods for buying or selling bitcoins without disclosing their identities [e.g. LocalBitcoins]
- Trading in the decentralized bitcoin markets has disadvantages, because the centralized exchanges offer significantly better trading functionalities.
- But the major centralized exchanges are not immune to difficulties and have experienced delays and technical difficulties in transactions.

Centralized vs decentralized exchanges, cont.

- Tools: the generalized autoregressive conditional heteroskedasticity (GARCH) model (on the residuals from the autoregressive–moving-average [ARMA] models), a multivariate exponentially weighted moving average (EWMA) for the covariance matrix, and a multivariate model based on copulas that uses the residuals of the ARMA-GARCH process.
- The results showed that the **decentralized bitcoin exchange has higher volatility than the centralized markets**.
- In the centralized markets, **volatility increased as prices jumped, but that was not the case in the decentralized exchanges**.
  - The volatility analysis results are contrary to the conventional leverage reason that market drops cause volatility.
  - Thus, **bitcoin price increases cause an increase in risk because a greater dispersion of returns around the mean causes a larger drop in the compound return.**
- **The centralized bitcoin markets demonstrated a higher left tail dependence that is in line with the general pattern in the "traditional" financial markets that are more extreme dependent in downturns**.
- Having long tails, the **decentralized bitcoin market does not show a strong pattern of extreme (tail) dependency**.
- **The decentralized bitcoin market is more interdependent**.
- Thus, a price setting in the P2P bitcoin markets is not correlated over time or across markets. Correlation between markets is not stable over time and is higher for the centralized exchanges.

INTRODUCTION OF BITCOIN FUTURES

Jalan, A., Matkovskyy, R. and Urquhart, A. (2021). What effect did the introduction of Bitcoin futures have on the Bitcoin spot market? The European Journal of Finance, 27(13), 1251-1281, https://doi.org/10.1080/1351847X.2020.1869992

Introduction of futures

- With the introduction of Bitcoin futures on the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME), investors could now speculate on falling prices (“go short”) and interestingly, according to Robert Shiller, it was exactly this lack of being able to go short which was responsible for the Bitcoin pricing bubble in 2017 (Shiller 2017).
- So, what was the effect of this introduction?

Introduction of futures, variables of interest

$$r_t = (InP_t - InP_{t-1}) \times 100$$

Where r_t is the daily return on day *t* and P_t and P_{t-1} are the prices at day *t* and day *t-1*

- Realized variance (RV), is defined any given day *t* as the sum of the squared intraday returns $r_{t,j}$ at a given sampling frequency *1/M*

$$RV_{t,M} = \sum_{j=1}^{M} r_{t,j}^2$$

where *M* is the number of intervals in the trading day. We choose hourly data because for any higher frequency, we observe lack of liquidity.

- Realized volatility is calculated by applying the median realized volatility, medRV, of Andersen et al. (2012).
- This approach has better efficiency properties than other formalizations for volatility and displays better finite-sample robustness to jumps and small returns.

$$medRV_t = \frac{\pi}{6 - 4\sqrt{3} + \pi}\left(\frac{M}{M-2}\right)\sum_{i=2}^{M-1} med(|r_{t,i-1}|, |r_{t,i}|, |r_{t,i+1}|)^2$$

The MedRV allows the impact of jumps to completely vanish except in the case of two consecutive jumps and it is robust to the occurrence of zero returns

Introduction of futures, variables of interest

- For the purpose of checking robustness we also calculated the time-varying GARCH models (tGARCH, GARCH-in-mean etc.) volatility that are a standard instrument in volatility estimation and the time dependent variance as the stochastic volatility with student-t errors and leverage, that provide more sophisticated framework for volatility estimates.
- We also measure realised skewness and kurtosis as in Amaya et al. (2011):

$$RSkewness_t = \frac{\sqrt{N}\sum_{i=1}^{N}(r_{t,i})^3}{RV_t^{3/2}}$$

$$RKurtosis_t = \frac{\sqrt{N}\sum_{i=1}^{N}(r_{t,i})^4}{RV_t^2}$$

- These two measures enable us to study the normality of returns and determine the negative or positive skewness as well as the excess kurtosis of Bitcoin returns

Introduction of futures, variables of interest

- Liquidity measurement is important given the role of liquidity in affecting market functioning.
  - For instance, Korn et al. (2019), formalizing the derivative hedge theory of Cho and Engle (1999), show that spot market illiquidity is not shifted in a one-to-one fashion to the futures market.
  - Instead, it interacts with price risk, liquidity risk, and the risk aversion of the market maker.

- Two measures of Bitcoin market liquidity are used - the high-low range (HLR) following Chung and Zhang (2014) and the volatility over volume (VoV) index developed by Fong et al. (2017). The high-low range (HLR) is computed by adjusting the Chung and Zhang (2014) measure by replacing bid and ask prices with the high and low prices, such that:

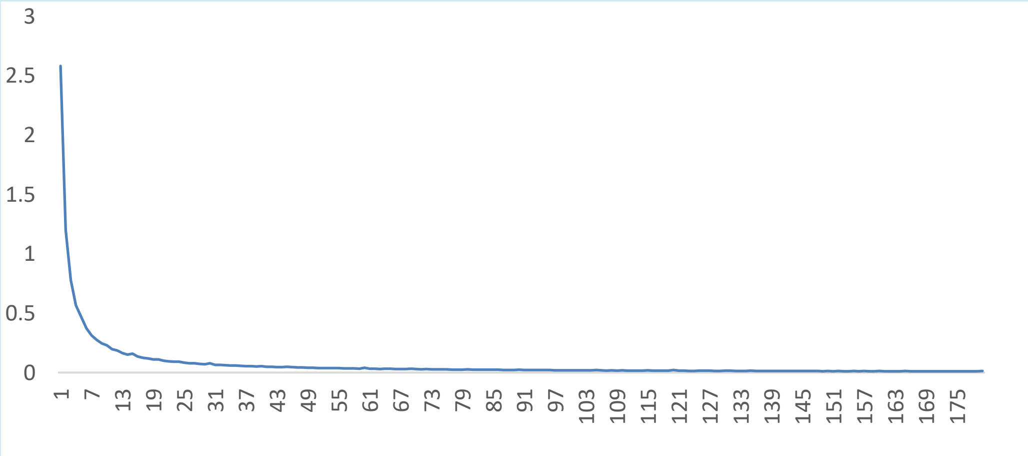
$$HLR_t = \frac{H_t - L_t}{0.5\,(H_t + L_t)}$$

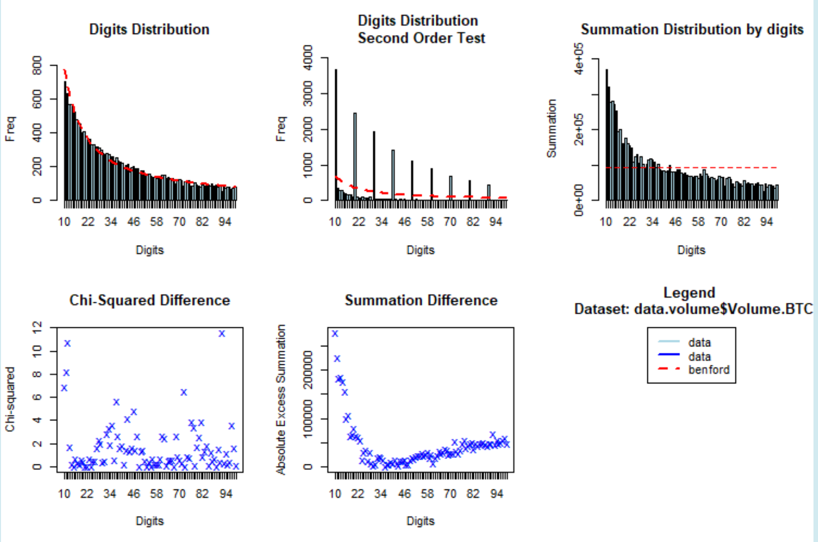
- The volatility over volume (VoV) index (Fong et al. 2017) is defined as:

$$VoV_t = \frac{\ln\left({}^{H_t}/_{L_t}\right)}{\sqrt{volume}}$$

Introduction of futures, variables of interest

- To ensure the validity of our liquidity measures that use reported Bitcoin trading volumes, we check for potential anomalies in trading volumes using Benford's law, a well-documented technique in fraud detection.
- The Law argues that numbers in a series consistently follow a pattern with low digits occurring more frequently in initial positions than larger digits.
- Given its efficacy in detecting anomalies in almost any series of numbers, the Law has been applied to a variety of settings, ranging from natural sciences (see for instance, Sambridge et al., 2010) to auditing (Drake and Nigrini, 2000) and accounting (Papanikolaou and Grammatikos, 2020).

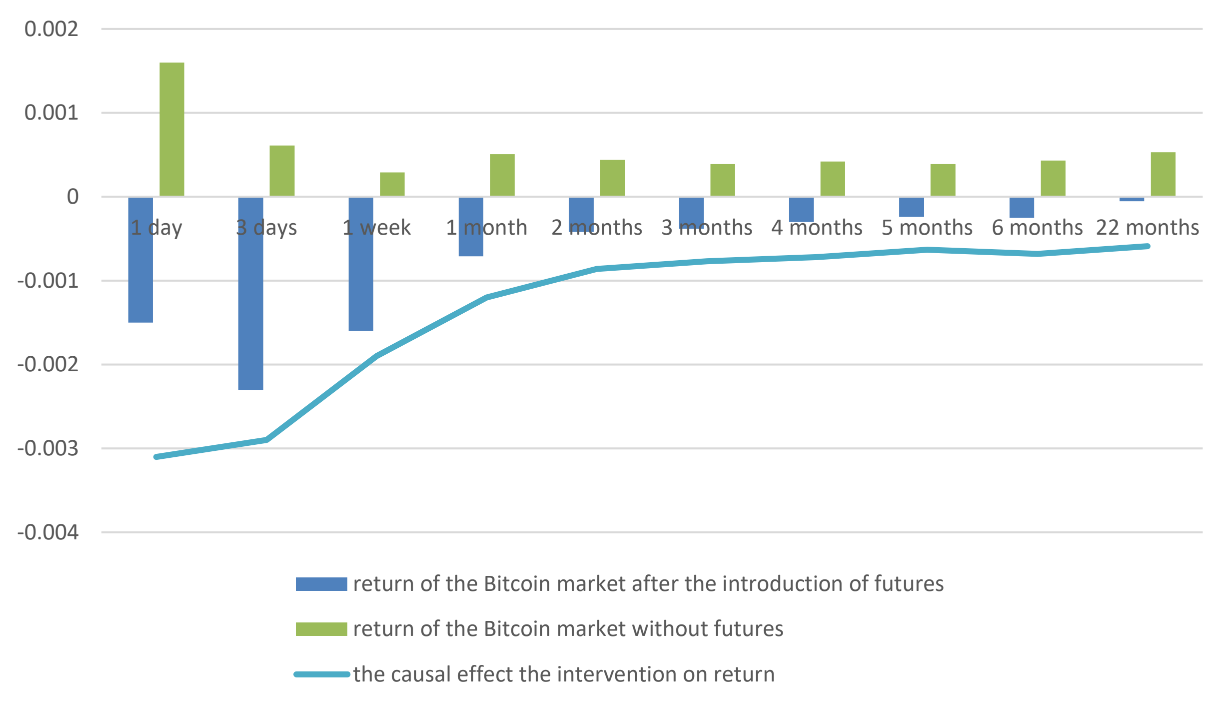




Introduction of futures, Methodology

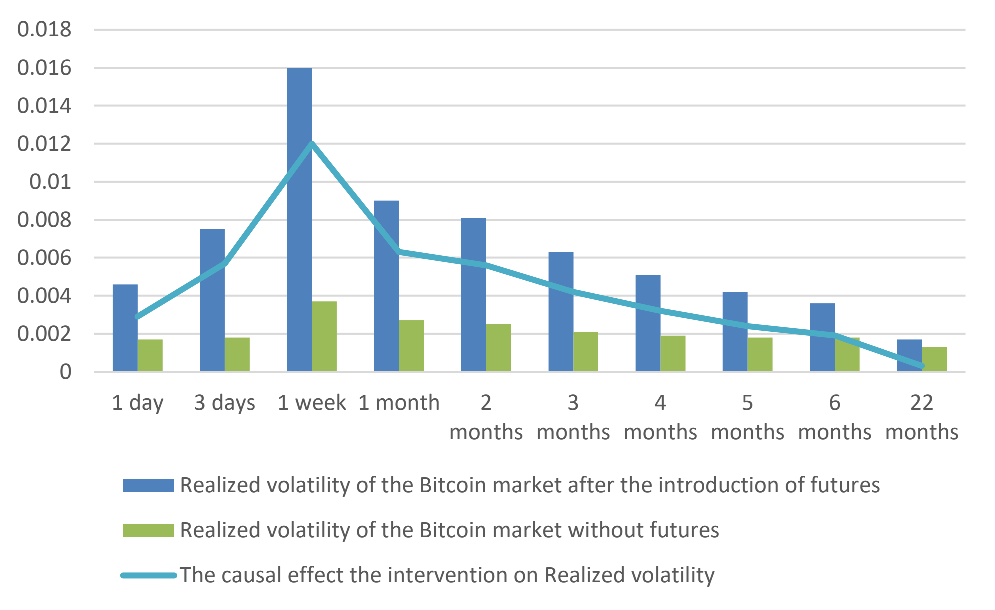
- In this study we quantify the impact of a discrete event (a treatment), i.e., the introduction of bitcoin futures on the Bitcoin spot market.
- **The causal impact of an event is the difference between the observed value of the response variable and the unobserved value that would have been obtained had the intervention not taken place** (Brodersen et al. 2015; Claveau 2012; Hoover 2012; Antonakis et al. 2010).
- We use several sources of information to quantify the causal effect of the launch of bitcoin futures.
  - First, **the behaviour of Bitcoin spot market itself**, **prior to the introduction of futures**.
  - Second, **the behaviour of potential control variables**, that are not directly affected by the intervention but are correlated with the variable of interest and were predictive of the target series prior to the intervention (for instance, return series for other cryptocurrencies).
  - We also assume, that the correlation between the Bitcoin spot market and the control series continued after the launch of Bitcoin futures.
- In our model, we **use Bitcoin return, variance, volatility, skewness, kurtosis and liquidity as the treatment variables, y's, and the ones of Ethereum and Litecoin as controls**.
- Ethereum and Litecoin are chosen due to their correlation with bitcoin and absence of bitcoin futures effect on their efficiency
- Following Brodersen et al. (2015) we built a diffusion-regression (state-space) structural time-series model, where one component of state is a regression that prevents an inflexible commitment to a particular control variables implemented by integrating a posterior uncertainty regarding influence of selected predictors as well as an uncertainty about which predictors to include.
- The pre-intervention period starts on 1st July 2017 due to data availability and continues till 18th December 2017, which is treated as the day of the event or intervention

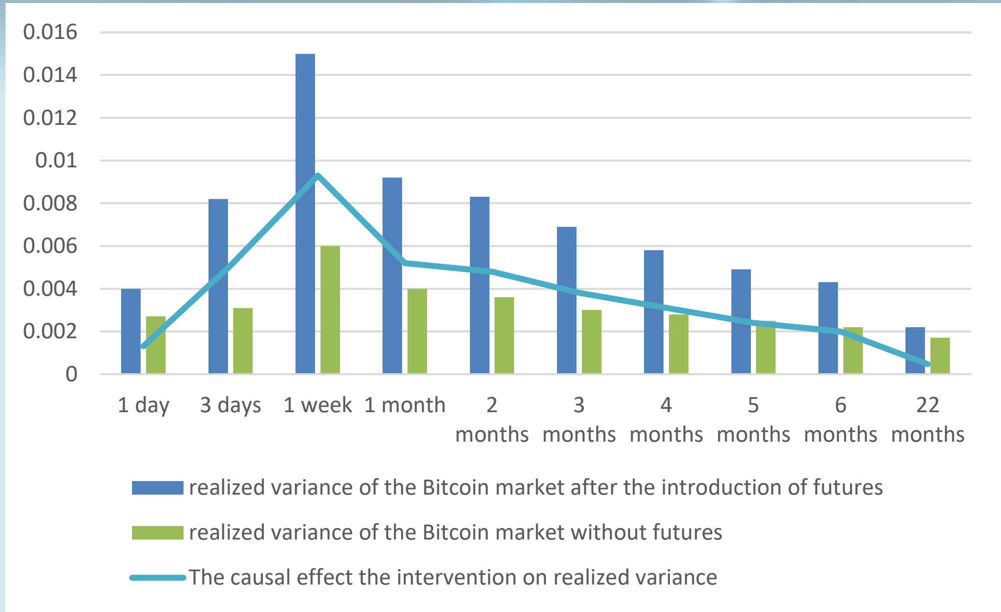
Introduction of futures, Results



Dynamics of the USD Bitcoin spot market return with and without the introduction of Bitcoin futures (the y-axis values represent accumulative return of the Bitcoin spot market).

Introduction of futures, results

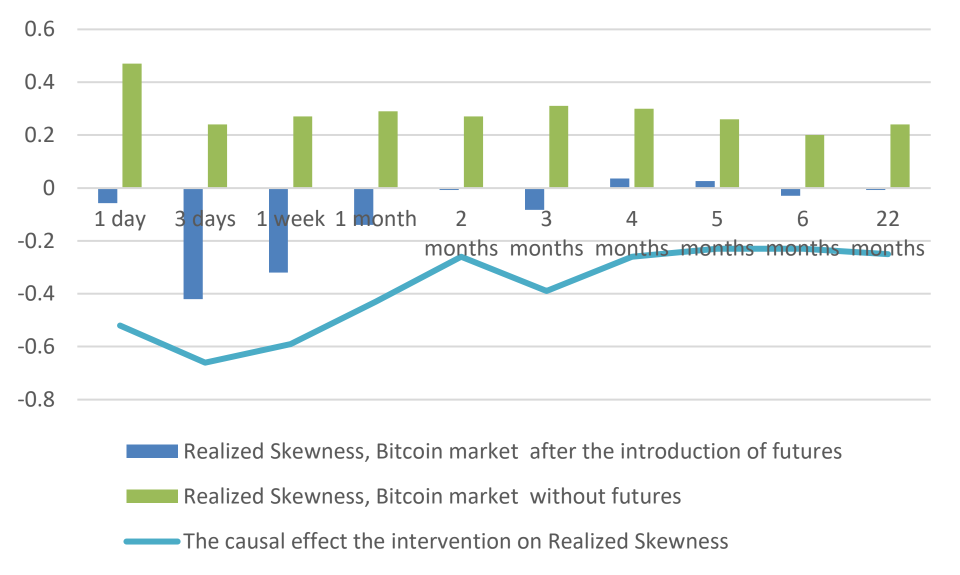




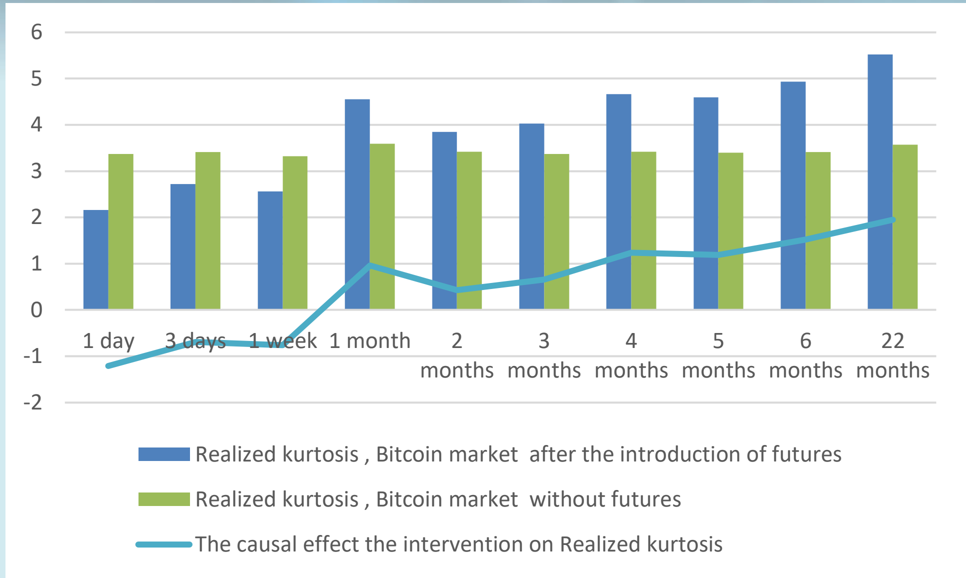
Dynamics of the realized volatility of the USD Bitcoin spot market return with and without the introduction of the Bitcoin futures (the y-axis values represent accumulative realized volatility of the Bitcoin spot market)

Dynamics of the realized variance of the USD Bitcoin spot market return with and without the introduction of the Bitcoin futures (the y-axis values represent accumulative realized variance of the Bitcoin spot market)

Introduction of futures, results

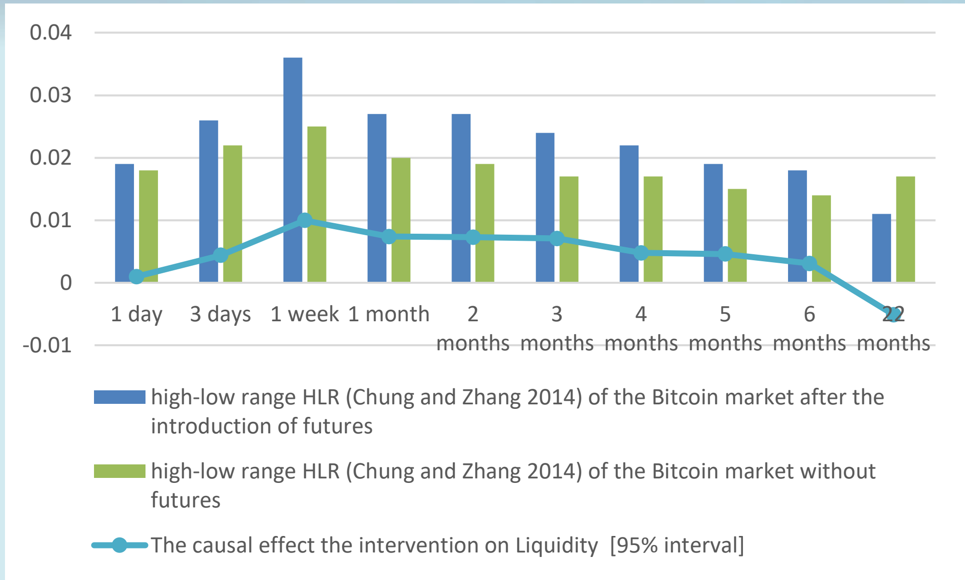


Dynamics of the realized skewness of the USD Bitcoin spot market return with and without the introduction of the Bitcoin futures (the y-axis values represent accumulative realized skewness of the Bitcoin spot market).

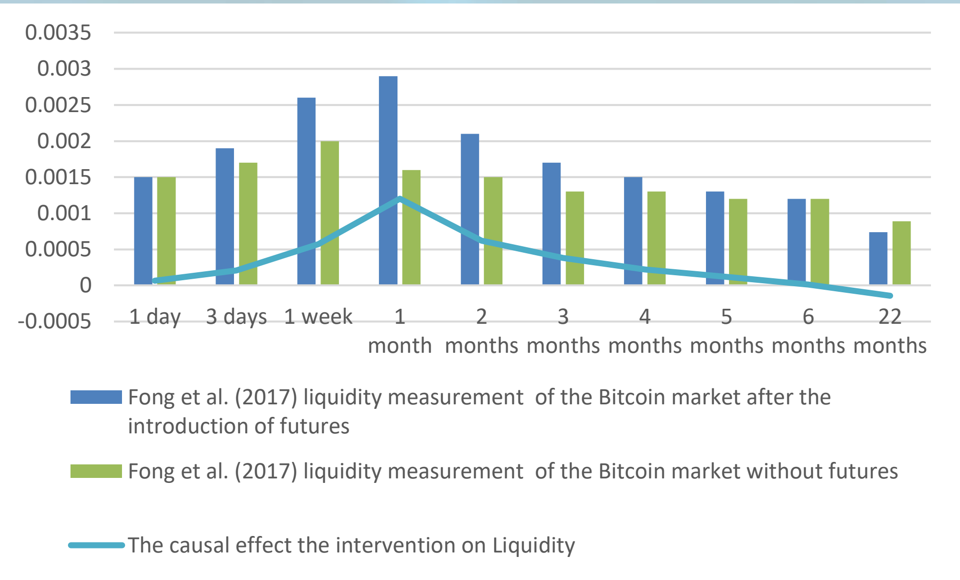


Dynamics of the realized kurtosis of the USD Bitcoin spot market return with and without the introduction of the Bitcoin futures (the y-axis values represent accumulative realized kurtosis of the Bitcoin spot market

Introduction of futures, results



Dynamics of the high-low range HLR (Chung and Zhang 2014) of the USD Bitcoin spot market with and without the introduction of Bitcoin futures (the y-axis values represent the accumulative high-low range HLR of the Bitcoin spot market)



Dynamics of the VoV index (Fong et al. 2017) of the USD Bitcoin spot market with and without the introduction of Bitcoin futures (the y-axis values represent the accumulative VoV index of the Bitcoin spot market)

POST-INTRODUCTION-OF-BITCOIN-FUTURES PERIOD

HEDGING AGAINST ECONOMIC UNCERTAINTY

Matkovskyy, R., Jalan, A. and Dowling, M. 2021. Effects of economic policy uncertainty shocks on the interdependence between cryptocurrency and financial markets. Quarterly Review of Economics and Finance 77, https://doi.org/10.1016/j.qref.2020.02.004

Hedging against economic uncertainty

- We analyse the effects of economic policy uncertainty (hereafter, EPU) on the relationship between Bitcoin and traditional financial markets, represented by five stock market indices – NASDAQ100, S&P500, Euronext100, FTSE100 and NIKKEI225.
- EPU is measured in terms of economic policy, monetary policy, financial regulation, taxation policy, and the news-based policy uncertainty index for the U.S., U.K., Europe and Japan .
- We estimate interdependence between traditional financial and Bitcoin markets and their reaction to selected policy shocks.

Economic policy uncertainty

- To capture policy-related economic uncertainty, we use the well established economic policy uncertainty index (hereafter, EPU), developed by Baker, Bloom and Davis (2016).
- This index shows a strong relationship with other measures of economic uncertainty, e.g., implied stock market volatility.
- We focus on EPU in terms of economic policy, monetary policy, financial regulation, taxation policy, and the news-based policy uncertainty index for the U.S., U.K., Europe and Japan.

Motivation and recent studies

- The substantial **negative impact of EPU on macro-economic conditions** is well documented.
  - For instance, **an increase in economic uncertainty negatively impacts aggregate investment, industrial production and employment rate** (Baker et al. 2016, Caldara et al. 2016, and Henzel & Rengel 2017).
- A stream of literature focused explicitly on policy uncertainty: Friedman (1968), Rodrik (1991), Higgs (1997) and Hassett and Metcalf (1999), among others, consider **the detrimental economic effects of monetary, fiscal, and regulatory policy uncertainty**.
- **EPU has an impact on financial markets** (e.g. Joets et al. 2016, Van Robays 2016, Bakas & Triantafyllou 2018), particularly :
  - **EPU causes an increase in stock-market turbulence** (Baker et al. 2016);
  - **Stock returns are negatively correlated with EPU innovation** (Chiang 2019);
  - **EPU causes a decrease in stock prices** (Antonakakis et al. 2013, Arouri et al. 2016, Kang & Ratti 2014) ;
  - **EPU must be accounted for in any forecasting of real economic activity** (Junttila & Vataja 2018);

Methodology

- As the first step, we use **multivariate EWMA models** for the covariance matrix *to study the volatility of returns* across selected markets.
- The *dynamics of volatility correlation* between Bitcoin and traditional financial markets is derived by means of **Spearman's rho**.
- *Volatility spill-overs* between the two types of the markets are measured using **the Diebold & Yilmaz (2012) spill-over index**.
- The *evolution of return interdependence* between Bitcoin and traditional markets is derived by means of **time-varying parameter copula models, i.e., GAS models with conditional multivariate Student–t distribution and time–varying scales and correlations** (Creal et al. 2011, 2013).
- The interdependence measures obtained are further used in **BVAR models with the Litterman/ Minnesota priors**
- We compute **nonlinear impulse responses with local projections** as in Ahmed and Cassou (2016).:
  - Reactions of Bitcoin markets to shocks are analysed in two different conditions, i.e., *a* ***high and low uncertainty in policy***.
  - For this purpose, the data is separated into two states by a **smooth transition function** as applied in Auerbach and Gorodnichenko (2012) and two regimes are distinguished: *high uncertainty (regime 1) and low uncertainty (regime 0)*.
  - Reaction is calculated to standard deviation shock. The time series are decomposed via the Hodrick-Prescott filter (Auerbach & Gorodnichenko, 2013).

Data

- The data set covers the daily close prices of the Bitcoin in Euro, US Dollar, Great Britain Pound, and the Japanese Yen in centralized Bitcoin markets of GDAX, Bitmap and BTCBOX and closing prices of the traditional financial market indices, namely the NASDAQ100, S&P500, Euronext100, FTSE100 and Nikkei225 over the period 27/04/2015 to 25/10/2018.
- The monthly economic policy uncertainty data comes from Baker et al. (2016) and www.policyuncertainty.com. These sources present uncertainty data in terms of the economic policies of **EU, the UK and the U.S**. They further decompose EPU into **monetary policy, taxes and financial regulation**.
- Data for EPU in Japan comes from Arbatli et al. (2017).

Bitcoin market volatility estimates

- We build multivariate EWMA models for the covariance matrix to demonstrate the volatility of returns across different markets.
- Among the many desirable properties EWMA has over traditional GARCH modelling is the greater weight it assigns to more recent observations.
- The EWMA model was first proposed in Riskmetrics (1996), where variances and covariances are as in the IGARCH-type models.
- In general, this model is of the form $\hat{\Sigma}_t = \lambda\hat{\Sigma}_{t-1} + (1-\lambda)\hat{a}_{t-1}\hat{a}'_{t-1}$, where $\hat{a}_t$ are residuals from the fitted ARMA-GARCH (selected based on the AIC/BIC values), and λ ($0<\lambda<1$) is the persistence parameter, which equals 0.96 for daily observations (Riskmetrics, 1996).

Market connectedness - Measures

- Because correlation is not linear and variance is not constant, *Spearman's rho* was applied to test stability of correlation over time between the pairs of the selected markets.
- Overall, **volatility correlation does not remain stable over time for the selected markets**.
- Analysing with respect to the timing of launch of Bitcoin futures, one finds that **volatility correlation (connectedness) increased post-launch of futures**.

Market connectedness measures - Diebold-Yilmaz (2012)

Diebold-Yilmaz (2012) spillover index BEFORE launching the bitcoin future, 28/04/2015-18/12/2017

	NASDAQ100	SP500	Euronext100	FTSE100	Nikkei225
Euro Bitcoin market	7.349752	23.47119	8.275186	9.604854	6.180715
USD Bitcoin market	7.170259	22.29784	7.827653	8.899147	5.889108
GBP Bitcoin market	7.648259	21.93905	6.154367	9.591231	4.637915
JPY Bitcoin market	6.203949	25.5413	10.786378	10.069221	9.024821

Diebold-Yilmaz (2012) spillover index AFTER launching the bitcoin future, 19/12/2017-25/10/2018

	NASDAQ100	SP500	Euronext100	FTSE100	Nikkei225
Euro Bitcoin market	20.33132	16.25472	14.52911	10.81164	11.14566
USD Bitcoin market	22.05493	16.6771	16.6973	11.681073	12.09834
GBP Bitcoin market	20.00429	15.59556	13.66286	9.775718	10.03893
JPY Bitcoin market	19.58768	17.22312	17.0784	12.167246	12.87671

- **The Diebold-Yilmaz (2012) spillover index measures the contribution of spillovers of volatility shocks across the selected markets to the total forecast error variance**.
- **The estimates reflect an increase in interconnectedness of Bitcoin and financial markets after the launch of Bitcoin futures, especially for the Bitcoin markets and NASDAQ100 & Nikkei225**.
- It is in line with the findings of Matkovskyy & Jalan (2019) who document that the contagion effect increased after the launch of Bitcoin futures and during bearish times.
- Interestingly, **the spillover effect between FTSE100 and GBP Bitcoin market does not increase, implying that these markets are rather isolated from the rest**.

Markets connectedness, GAS models

- **Interdependence between Bitcoin and traditional financial markets in terms of returns is less significant** and is summarised in Table below.
- Note: “+” and “-” mean positive and negative correlations in returns, respectively; “No corr.” indicates no correlation between the markets.

Bitcoin markets	NASDAQ	S&P500	Euronext100	FTSE100	Nikkei225
Bitcoin Euro	No corr.	+	+	+	-
Bitcoin USD	-	+	No corr.	+	-
Bitcoin GBP	-	+	-	+	-
Bitcoin JPY	+	+	+	+	+

- **The estimates show that, for example, Bitcoin USD and GBP markets have negative correlation with the NASDAQ and Nikkei markets that gives them a rather ‘diversification’ quality, while the Bitcoin JPY market is positively correlated with traditional financial markets.**

Reaction to shocks in economic policy

- The calculated interdependence measurements (volatility and interdependence in returns) are used in the Bayesian Vector Autoregressions (BVAR) models with the Litterman/Minnesota priors to quantify the responses of the Bitcoin and traditional financial markets as well their interdependence to different economic policy shocks.
- We calculated generalized IRFs, accumulative generalized IRFs and nonlinear impulse responses with local projections for high and low uncertainty in policy regimes.
- Table summarizes the effects of shocks in economic policy on the selected markets.

Reaction of volatility connectedness to shocks

- We *a priori* expect that shocks in policies mainly cause an increase in volatility of the respective market to which they relate.
- Even when we find this to be true for the traditional financial markets, Bitcoin markets reveal a rather different trend.
- **We find that shocks in the USA economic policy that lead to an increase in uncertainty cause a decrease in volatility in Bitcoin markets.**
- **US news-based policy uncertainty index proves this correlation.**
- **These results point out to the 'hedging' quality of Bitcoin markets, making them rather insulated from the negative effects of policy uncertainty.**
- Also, **an increase in Japanese economic uncertainty causes a reduction in volatility of the JPY Bitcoin market**.
- Overall, our results contradict those of Vidal-Tomás and Ibañez (2018) who document that Bitcoin remains unaffected by monetary policy news.
- Calculations of nonlinear impulse responses with local projections for high and low uncertainty in policy regimes reveal minor differences in volatility reaction across the two regimes**.**

Shocks to	Volatility in								
	USD Bitcoin market	Euro Bitcoin market	GBP Bitcoin market	JPY Bitcoin market	NASDAQ	S&P500	Euronext100	FTSE100	NIKKEI225
USA economic policy	-	-	-	-	+	+	+	+	-
USA monetary policy	+	+	+	+	+	+	-	+	-
USA financial regulation	+	+	+	+	+	+	+	+	+
USA taxes	+	+	+	+	+	+	+	+	+
US news-based policy uncertainty index	-	-	-	-	+	+	+	+	-
European news-based policy uncertainty index	- /+	- /+	- /+	- /+	+	+	+	+	+
UK economic policy uncertainty index	+	+	+	+	+	+	+	+	+
Japan economic policy uncertainty index	+	+	+	-	+	+	-	+	-

Reaction of return connectedness

- **Interdependence in terms of return mainly decreases due to shocks in the US economic policies**.
- **Connectedness of Euronext100, FTSE100, Nikkei225 and Bitcoin markets (especially of GBP Bitcoin market) also decreases** due to shocks in European, UK and Japanese economic policy uncertainty.
- **Shocks to USA taxes cause an increase in interdependence in returns**.
  - We *a priori* expect changes in tax policy to affect the interdependence in volatility between financial and Bitcoin markets.
  - **Taxes on capital gains made on sale of investments affect the perceived net return on investment by prospective and current investors.**
  - Therefore, **a change in tax regime or uncertainty therein is expected to create opportunities for tax arbitrage between traditional and cryptocurrency markets**.
  - This opportunity becomes more stark given the fact that unlike traditional financial securities such as stocks, bonds and commodities, both purchase and sale of Bitcoin is rather opaque. The same opacity in transactions makes it easier to avoid/ evade taxes on sale of Bitcoin.

Shocks to	Return-Interdependence between				
	NASDAQ and Bitcoin markets	S&P500 and Bitcoin markets	Euronext100 and Bitcoin markets	FTSE100 and Bitcoin markets	Nikkei225 and Bitcoin markets
USA economic policy	Increase	Decrease	Decrease	Decrease	Decrease (especially for GBP)
USA monetary policy	Increase /(Decrease for GBP)	Decrease	Decrease	Decrease	Decrease (especially for GBP)
USA financial regulation	Decrease	Decrease	Decrease	Decrease for GBP/Increase for euro	Decrease (especially for GBP)
USA taxes	Increase (Decrease for JPY)	Increase	Increase (for GBP) / Decrease (for euro)	Increase for GBP/ Decrease for euro	Increase (especially for GBP)
European news-based policy uncertainty index	Increase (for JPY) / Decrease (for GBP)	Increase (for JPY) / Decrease (for GBP and USD)	Decrease for euro and GBP	Decrease for euro and GBP	Decrease for GBP
UK economic policy uncertainty index	Increase (for JPY) / Decrease (for GBP)	Increase (for JPY) / Decrease (for GBP)	Decrease for euro and GBP	Decrease for euro and GBP	Decrease for GBP
Japan economic policy uncertainty index	Increase (for JPY) / Decrease (for GBP)	Increase (for JPY) / Decrease (for GBP and USD)	Decrease for euro and GBP	Decrease for euro and GBP	Decrease for GBP

Thus:

- **Volatility correlation between Bitcoin markets and traditional financial markets is higher than return-interdependence therein and is not stable over time**;
- Volatility-connectedness between Bitcoin and traditional financial markets increased post-launch of Bitcoin futures;
- Results clearly indicate a significant relationship between EPU and volatility in Bitcoin markets;
- Uncertainty shocks in U.S. economic policy are associated with a decrease in volatility in the Bitcoin markets;
- Shocks in economic policy in Japan appear to reduce volatility in the JPY Bitcoin market;
- Return-interdependence between Bitcoin and traditional financial markets decreases due to economic policy uncertainty shocks (EPU).
- The findings show investment attractiveness of bitcoin as a hedging tool against shocks in economic uncertainty in the USA economic policy.

HEDGING AGAINST INFLATION

Matkovskyy, R., Jalan, A. (2021). Can Bitcoin be an inflation hedge? Evidence from a quantile-on-quantile model, Economic review 7, 1024-1041, https://doi.org/10.3917/reco.pr2.0173

Hedging against inflation

- **Do we have the possibility to use the Bitcoin as a means to minimise the impact of the potential threat that inflation poses to investment returns and portfolio risk?**
- **Most articles document poor hedging capability of equities** (Fama and Schwert 1977; Modigliani and Cohn, 1979; Geske and Roll, 1983; Lee, 1992; Amihud, 1996; Crosby, 2001; Gallagher and Taylor, 2002; Boucher, 2006; Ang, Brière, and Signori, 2012; Parikh et al. 2019; etc).
- **Equities have become much less efficient in inflation-hedging over time** (Bampinas and Panagiotidis, 2016).

Hedging against inflation

- We apply the partial linear model:

$$Bitcoin_t = \beta^{\theta}(CPI_t) + \alpha^{\theta} Bitcoin_{t-1} + u_t^{\theta}$$

where $Bitcoin_t$ and CPI_t are first-differenced natural logarithm of Bitcoin prices and CPI index in a given country in period t, respectively, θ is the θth quantile of the conditional distribution of Bitcoin price-growth, u_t^{θ} is the error term with a zero θ-quantile.

- the results suggest that **during bullish times, Bitcoin markets in GBP and JPY can provide a hedge against the real loss of return caused by realized inflation**.
- The estimates show that the **Bitcoin can be considered a macro hedge against realized inflation in bullish euro, GBP and JPY markets** offering higher returns during periods of very high inflation.

PORTFOLIO OPTIMIZATION

Matkovskyy, R., Jalan, A., Dowling, M., Bouraoui, T. (2020). From bottom ten to top ten: the role of cryptocurrencies in enhancing portfolio return of poorly performing stocks. Finance Research letters, 101405, https://doi.org/10.1016/j.frl.2019.101405

Portfolio optimization

- **We analyze the role of the top 10 cryptocurrencies by capitalization in enhancing portfolio returns of the bottom 10 large, medium and small market cap S&P companies to match those of the top 10 performers in their respective indices.**
- This is motivated by the hedging and diversification properties of cryptocurrencies against traditional asset classes such as equities, currencies and commodities.
  - Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Bitcoin Cash (BCH), EOS, Litecoin (LTC), Binance Coin (BNB), Tether (USDT), Stellar and Cardano (ADA).
  - Traditional financial assets are represented by the equity S&P600, S&P400 and S&P100 indices, comprising small, medium and large capitalization companies, respectively.
- We apply the Probabilistic Utility (hereafter, PU) approach using different estimates, which is best-suited to the study because it: (i) is less sensitive to sample size than Maximization of Expected Utility (hereafter, MEU) and (ii) yields less concentrated portfolio solutions.
- To address the issue of uncertainty in parameter determination, we apply the Bayesian approach of Rossi et al. (2002). In this case, the parameters describing the distribution of the cryptocurrency and the selected equity indices are defined by the distributions themselves.
  - This approach allows for taking into account uncertainty that states explicitly the errors associated with the determination of the portfolio.

Portfolio optimization

- We find that the addition of cryptocurrencies to a portfolio of the worst-performing stocks in three different indices indeed helps improve performance in terms of returns.
- **The highest efficacy of cryptos in boosting returns is noted for small-cap stocks**.
- Moreover, for medium -cap companies the role of cryptocurrencies is much lower and diminishing over time.
- Except the BTC, ETH and LTC, no other cryptocurrency seems to maintain its efficacy in boosting stock returns in the longer time horizon.

CRYPTOCURRENCY MARKET AND BLACK-SWAN EVENTS (COVID, WAR)

PERSISTENCE CRYPTOCURRENCY VS TRADITIONAL MARKETS

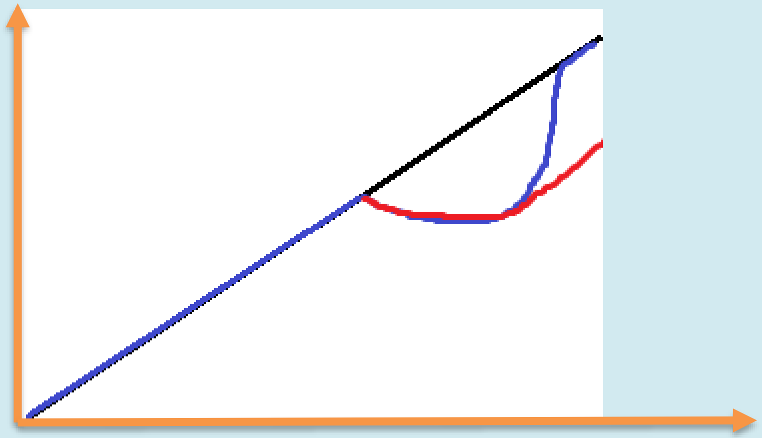
Yarovaya, L., Matkovskyy, R., and Jalan, A. (2022). The COVID-19 black swan crisis: Reaction and recovery of various financial markets. Research in International Business and Finance 59, 101521, https://doi.org/10.1016/j.ribaf.2021.101521

Persistence cryptocurrency vs traditional markets

- Persistence level is an important dynamic property of any timeseries that gives us an overview understanding of the series in question.
- **Persistence, is defined as “continuance of an effect after the cause is removed”.**
- If a series is given an external shock, the level of persistence would give us an idea as to what the impact of that shock will be on that series, will it soon revert to its mean path or will it be further pushed away from the mean path.
  - In case of a **highly persistence** series, **a shock to the series tends to persist for long and the series drifts away from its** historical mean path.
  - Opposite **is case of a series with low level of persistence**, post **a shock** to the series it has a tendency to get back to its historical mean path

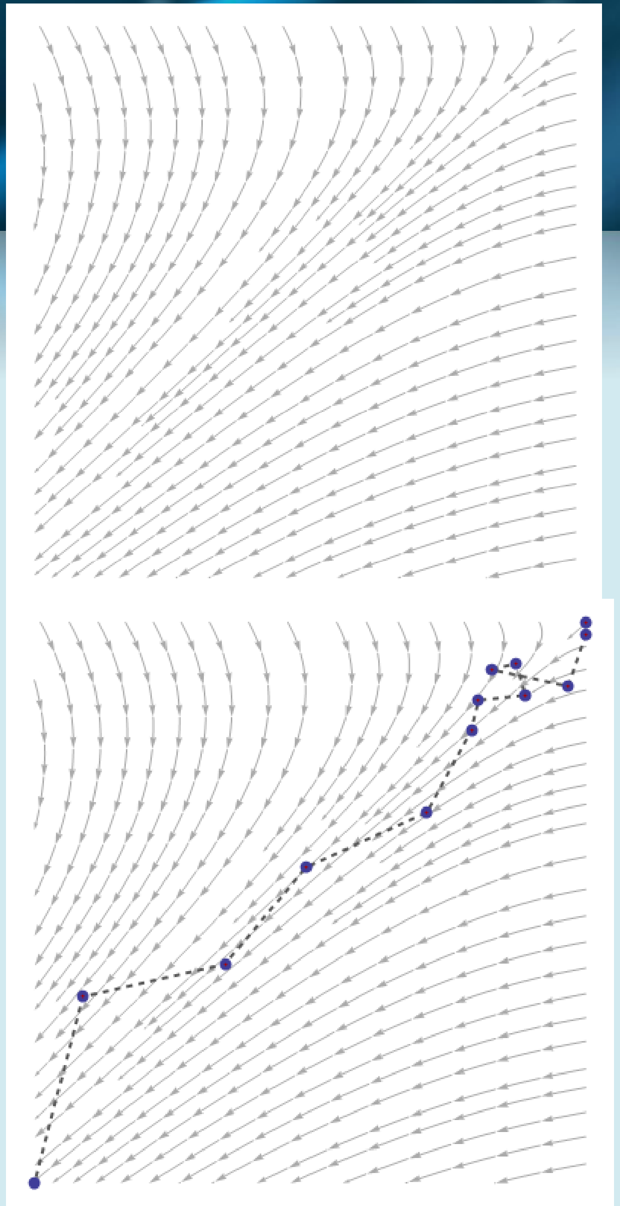
Persistence

- In a timeseries econometrics a persistence is intimately related to the concept of unit root.
- A possible unit root. The **red line** shows the drop in output and path of recovery if the time series **has a unit root**.
- **Blue** shows the recovery if there is **no unit root** and the series is trend-stationary.
- A unit root or a unit root process or a difference stationary process is a stochastic trend in a time series, sometimes called a "random walk with drift";
  - If a time series has a unit root, it shows a systematic pattern that is unpredictable.
- The reason why it's called a unit root is because of the mathematics behind the process.
  - At a basic level, a process can be written as a series of monomials (expressions with a single term). Each monomial corresponds to a root. If one of these roots is equal to 1, then that's a unit root.



Persistence

- Here is a picture of the flow along the surface of the water:
- The arrows show the direction of flow and are connected by streamlines.
- A cone, if your throw it to the water will tend to follow the streamline in which it falls.
- But it doesn't always do it the same way each time, even when it's dropped in the same place in the stream: random variations along its path, caused by turbulence in the water, wind, and other whims of nature kick it onto neighboring stream lines.



Here, the fir cone was dropped near the upper right corner. It more or less followed the stream lines--which converge and flow away down and to the left--but it took little detours along the way.

Table 1 Price dynamics in the main financial markets: pre-pandemic vs. pandemic

	Maximum in 2020 before a drop	Pandemic bottom date	Pandemic bottom value, USD	Decrease, %	The maximum after recovery, until 10/04/2020	Gain in value, %, until 10/04/2020
Cryptocurrencies						
Bitcoin	10371.33	12/03/2020	4857.1	-53.17	7370.11	151.74
ETH	286.27	12/03/2020	110.3	-61.47	173.36	157.17
LTC	83.31	12/03/2020	30.09	-63.88	46.58	154.80
Precious Metals						
Gold, Handy & Harman Base $/Troy Oz	1683.65	19/03/2020	1474.25	-12.44	1741	118.09
Platinum,Free Market $/troy oz	1025.7	19/03/2020	586.6	-42.81	747.2	127.38
Silver, Handy&Harman (NY) U$/Troy OZ	18.8	18/03/2020	12.13	-35.48	15.4	126.96
Palladium U$/Troy Ounce	2781	16/03/2020	1557	-44.01	2307	148.17
Rhodium CIF NWE U$/Ounce	394443	24/03/2020	178980	-54.62	313289	175.04
Iridium U$/Troy Oz	no effect					
Ruthenium CIF NWE U$/Ounce	no effect					
Osmium E/KG	11917	09/03/2020	11304	-5.14	11767	104.10
S&P GSCI Precious Metal Tot. Ret. - RETURN IND. (OFCL)	1958.16	18/03/2020	1680.94	-14.16	2010.33	119.60
Bonds						
BD BENCHMARK 10 YEAR DS GOVT. INDEX	199.977	19/03/2020	187.01	-6.48	193.838	103.65
US BENCHMARK 10 YEAR DS GOVT. INDEX	176.596	18/03/2020	166.057	-5.97	175.959	105.96
FR BENCHMARK 10 YEAR DS GOVT. INDEX	233.838	18/03/2020	219.567	-6.10	227.679	103.69
UK BENCHMARK 10 YEAR DS GOVT. INDEX	222.745	19/03/2020	210.373	-5.55	220.959	105.03
Indexes						
S&P 500 COMPOSITE	3386.15	23/03/2020	2237.4	-33.92	2789.82	124.69
DOW JONES INDUSTRIALS	29551.42	23/03/2020	18591.93	-37.09	23719.37	127.58
NIKKEI 225 STOCK AVERAGE	24083.51	19/03/2020	16552.83	-31.27	19345.77	116.87
DAX 30	13789	18/03/2020	8441.71	-38.78	10564.74	125.15
IBEX 35	10083.6	16/03/2020	6107.2	-39.43	7070.6	115.77
DOW JONES COMPOSITE 65 STOCK AVE	9710.01	23/03/2020	6100.31	-37.18	7804.73	127.94
NASDAQ COMPOSITE	9817.18	23/03/2020	6860.67	-30.12	8153.58	118.85
NASDAQ 100	9718.73	20/03/2020	6994.29	-28.03	8238.53	117.79
FTSE 100	7674.56	23/03/2020	4993.89	-34.93	5842.66	117.00
FTSE 250	21866	19/03/2020	12829.7	-41.33	16407.92	127.89
FRANCE CAC 40	6111.24	18/03/2020	3754.84	-38.56	4506.85	120.03
PORTUGAL PSI-20	5435.85	19/03/2020	3596.08	-33.85	4196.31	116.69
EURO STOXX	421.344	18/03/2020	261.534	-37.93	315.993	120.82
EURO STOXX 50	3865.177	18/03/2020	2385.823	-38.27	2892.794	121.25
ISRAEL TA 125	1684.12	23/03/2020	1105.95	-34.33	1312.52	118.68

Mean-reversion behavior

- Testing for a unit root at the different quantiles allows to define the existence of innovations of a certain magnitude, which reinforce the persistence of the asset prices considered in the study.
- The existence of a unit root implies that, shocks with a permanent effect are accumulated and build up a stochastic trend, causing a unit root nonstationary and non-mean-reverting.
- On the other hand, an autoregressive process becomes stationary and mean-reverting due to a shock that has a transitory effect and is offset by a future shock with the opposite sign.
- Therefore, the unit root test can be regarded as a test for non-stationarity and no mean reversion of the underlying time series.
- Yang and Zhao (2020) approach is used and compared to the one of Koenker and Xiao (2004).

Precious metals

Quantiles	YZt_{ks}	asymptotic critical values			YZt_{ks}	asymptotic critical values		
		1%	5%	10%		1%	5%	10%
	Gold				Platinum			
0.1	-3.0816***	-2.8363	-2.1671	-1.8075	0.95831	-2.8573	-2.1907	-1.8324
0.2	-3.9929***	-2.9911	-2.341	-1.9911	-3.1358***	-2.9801	-2.3289	-1.9782
0.3	-3.0633**	-3.1112	-2.4518	-2.1112	-3.5936***	-3.1813	-2.5397	-2.1997
0.4	-1.8201	-3.2309	-2.6074	-2.2695	-6.2449***	-3.2237	-2.5959	-2.2566
0.5	-0.493	-3.2602	-2.6543	-2.3224	-5.5168***	-3.1926	-2.5543	-2.2143
0.6	0.71413	-3.2654	-2.6626	-2.3317	-6.4845***	-3.1621	-2.5147	-2.1747
0.7	1.09894	-3.1957	-2.5583	-2.2183	-7.7407***	-3.0888	-2.4312	-2.0888
0.8	2.69236	-3.0246	-2.3719	-2.0246	-10.344***	-2.9931	-2.3428	-1.9931
0.9	2.884	-2.6658	-1.9925	-1.6325	-6.5663***	-2.6796	-2.0066	-1.6466
	Silver				Palladium			
0.1	-1.8035	-2.8741	-2.2097	-1.8524	-2.9916***	-2.6993	-2.0267	-1.6667
0.2	-2.2007*	-3.0794	-2.4225	-2.0794	-2.1233*	-3.055	-2.4	-2.055
0.3	-2.141	-3.1499	-2.4988	-2.1588	-2.3085*	-3.1654	-2.519	-2.179
0.4	-2.0553	-3.1676	-2.5219	-2.1819	-1.5031	-3.1674	-2.5216	-2.1816
0.5	-1.521	-3.1559	-2.5067	-2.1667	0.31785	-3.1709	-2.5262	-2.1862
0.6	-2.4422*	-3.1539	-2.5041	-2.1641	0.78756	-3.1415	-2.4879	-2.1479
0.7	-4.1684***	-3.0234	-2.3709	-2.0234	1.60891	-3.0552	-2.4001	-2.0552
0.8	-3.3548***	-3.0794	-2.4225	-2.0794	1.05596	-3.0072	-2.3559	-2.0072
0.9	-1.8462	-2.704	-2.0315	-1.6715	1.96546	-2.738	-2.0662	-1.7062

	Rhodium				Osmium			
0.1	-8.22***	-2.6042	-1.9297	-1.5697	-2.6076**	-2.8326	-2.1629	-1.8031
0.2	-4.3769***	-2.9091	-2.249	-1.894	-2.0426	-3.1256	-2.4673	-2.1273
0.3	-4.6879***	-2.9096	-2.2495	-1.8945	-2.7496**	-3.2519	-2.641	-2.3074
0.4	-1.713	-2.9429	-2.287	-1.934	-3.3045***	-3.2734	-2.6734	-2.3444
0.5	-0.1121	-2.9576	-2.3036	-1.9516	-3.9976***	-3.2817	-2.6817	-2.355
0.6	0.91914	-2.9638	-2.3105	-1.9589	-3.1504**	-3.258	-2.6508	-2.3184
0.7	0.53667	-3.0602	-2.4048	-2.0602	-1.9881	-3.2344	-2.6131	-2.276
0.8	0.98579	-3.0291	-2.3761	-2.0291	-1.3322	-3.1197	-2.4597	-2.1197
0.9	2.17492	-2.5045	-1.828	-1.468	-0.3624	-2.6422	-1.9685	-1.6085
	Iridium				GSCI			
0.1	0	-2.4161	-1.7378	-1.3778	-2.1305*	-2.9132	-2.2536	-1.8988
0.2	0	-2.5236	-1.8475	-1.4875	-4.5412***	-2.9507	-2.2957	-1.9433
0.3	0	-2.6618	-1.9885	-1.6285	-2.7076**	-3.0721	-2.4158	-2.0721
0.4	-25.587***	-2.3822	-1.7032	-1.3432	-1.9167	-3.1596	-2.5115	-2.1715
0.5	-44.433***	-2.3573	-1.6779	-1.3179	-0.8217	-3.1509	-2.5002	-2.1602
0.6	-24.629***	-2.3699	-1.6907	-1.3307	-0.7632	-3.138	-2.4833	-2.1433
0.7	-24.574***	-2.5502	-1.8746	-1.5146	1.47187	-3.1257	-2.4675	-2.1275
0.8	-6.1727***	-2.3459	-1.6663	-1.3063	0.50383	-2.9917	-2.3415	-1.9917
0.9	-3.7572***	-3.0558	-2.4007	-2.0558	2.50088	-2.8555	-2.1887	-1.8303

For all metals in the sample, significant values are highlighted in bold, indicating the presence of mean reversion, i.e. instances where the null hypothesis of a unit root is rejected, **implying that shocks are not accumulated**.

Equity indexes

Quantiles	YZt_{ks}	asymptotic critical values			YZt_{ks}	asymptotic critical values		
		1%	5%	10%		1%	5%	10%
	S&P500				DAX30			
0.1	0.18087	-2.6766	-2.0035	-1.6435	1.25379	-2.8185	-2.1483	-1.7883
0.2	-0.4172	-3.0073	-2.356	-2.0073	0.63817	-2.994	-2.3437	-1.994
0.3	-0.8185	-3.138	-2.4833	-2.1433	-0.77	-3.1333	-2.4772	-2.1372
0.4	-1.1819	-3.1898	-2.5508	-2.2108	-4.0163***	-3.2099	-2.5769	-2.2369
0.5	-1.9214	-3.2116	-2.5791	-2.2391	-4.1522***	-3.1794	-2.5372	-2.1972
0.6	-3.4305***	-3.1546	-2.505	-2.165	-3.9781***	-3.1109	-2.4516	-2.1109
0.7	-3.4974***	-3.0408	-2.3869	-2.0408	-3.038***	-2.9971	-2.3465	-1.9971
0.8	-3.7725**	-2.8862	-2.2233	-1.8668	-8.743***	-2.8254	-2.1553	-1.7953
0.9	-3.5004***	-2.5943	-1.9196	-1.5596	-13.311***	-2.4874	-1.8105	-1.4505
	DJ65				DJIndustr			
0.1	0.06029	-2.7634	-2.092	-1.732	-0.2967	-2.6365	-1.9627	-1.6027
0.2	-1.2809	-3.0073	-2.356	-2.0073	-1.6898	-3.03	-2.3769	-2.03
0.3	-1.127	-3.1184	-2.4585	-2.1184	-1.1937	-3.1201	-2.4602	-2.1202
0.4	-1.2063	-3.1748	-2.5313	-2.1913	-2.3088*	-3.1906	-2.5518	-2.2118
0.5	-7.2461***	-3.1321	-2.4757	-2.1357	-4.5453***	-3.1435	-2.4906	-2.1506
0.6	-9.8174***	-3.0692	-2.4132	-2.0692	-8.5191***	-3.0839	-2.4266	-2.0839
0.7	-10.54***	-2.9964	-2.3459	-1.9964	-8.4834***	-3.0103	-2.3587	-2.0103
0.8	-10.019***	-2.7803	-2.1094	-1.7494	-8.4132***	-2.8291	-2.1591	-1.7991
0.9	-9.3577***	-2.417	-1.7387	-1.3787	-9.1241***	-2.5994	-1.9248	-1.5648

	EuroStoxx				EuroStoxx50			
0.1	2.18359	-2.7003	-2.0277	-1.6677	2.36992	-2.7009	-2.0283	-1.6683
0.2	0.03536	-3.0087	-2.3573	-2.0087	1.10027	-2.9787	-2.3273	-1.9766
0.3	0.31933	-3.1543	-2.5046	-2.1646	-0.1992	-3.1174	-2.4576	-2.1174
0.4	-4.2043***	-3.2033	-2.5683	-2.2283	-4.0864***	-3.1876	-2.5479	-2.2079
0.5	-6.0129***	-3.1733	-2.5293	-2.1893	-5.4504***	-3.1078	-2.4487	-2.1078
0.6	-5.2588***	-3.0739	-2.4175	-2.0739	-5.8054***	-3.0277	-2.3748	-2.0277
0.7	-4.6598***	-2.9527	-2.298	-1.9457	-4.9173***	-2.9362	-2.2794	-1.9261
0.8	-8.9533***	-2.7909	-2.1201	-1.7601	-7.2463***	-2.8464	-2.1785	-1.8195
0.9	-10.766***	-2.5328	-1.8568	-1.4968	-11.81***	-2.4934	-1.8167	-1.4567
	CAC40				FTSE100			
0.1	3.00552	-2.7941	-2.1234	-1.7634	3.09273	-2.6398	-1.966	-1.606
0.2	2.34672	-2.9965	-2.346	-1.9965	1.64661	-3.0525	-2.3977	-2.0525
0.3	1.25437	-3.1574	-2.5086	-2.1686	0.87728	-3.1462	-2.494	-2.154
0.4	-3.4016***	-3.2088	-2.5755	-2.2355	-0.4914	-3.1919	-2.5534	-2.2134
0.5	-5.1115***	-3.1574	-2.5087	-2.1687	-2.5928**	-3.1666	-2.5206	-2.1806
0.6	-6.1314***	-3.0412	-2.3873	-2.0412	-3.8657***	-3.1019	-2.4433	-2.1019
0.7	-6.5345***	-2.9715	-2.3192	-1.968	-8.7318***	-3.0127	-2.3609	-2.0127
0.8	-10.097***	-2.8567	-2.19	-1.8317	-9.9554***	-2.8883	-2.2255	-1.8692
0.9	-10.916***	-2.506	-1.8295	-1.4695	-14.602***	-2.6003	-1.9257	-1.5657

Equity indexes

	FTSE250				Israel TA125			
0.1	2.39564	-2.7715	-2.1003	-1.7403	0.4441	-2.6012	-1.9266	-1.5666
0.2	3.32373	-2.9814	-2.3303	-1.9798	0.43197	-2.9447	-2.2891	-1.9363
0.3	3.3693	-3.0745	-2.418	-2.0745	-1.5988	-3.1403	-2.4864	-2.1464
0.4	-0.4695	-3.1942	-2.5564	-2.2164	-3.0715**	-3.2252	-2.5983	-2.2594
0.5	-1.979	-3.1442	-2.4914	-2.1514	-5.1405***	-3.2078	-2.5741	-2.2341
0.6	-8.8482***	-3.0093	-2.3578	-2.0093	-6.7753***	-3.1147	-2.4551	-2.1147
0.7	-12.453***	-2.882	-2.2185	-1.8617	-7.6302***	-3.0362	-2.3826	-2.0362
0.8	-13.843***	-2.7482	-2.0766	-1.7166	-7.398***	-2.9186	-2.2596	-1.9052
0.9	-12.234***	-2.5949	-1.9202	-1.5602	-4.9513***	-2.6698	-1.9966	-1.6366
	IBEX35				NASDAQ100			
0.1	2.49207	-2.8616	-2.1956	-1.8376	-1.357	-2.6282	-1.9542	-1.5942
0.2	2.66585	-3.0208	-2.3685	-2.0208	-0.3471	-2.9692	-2.3166	-1.9653
0.3	2.31321	-3.1374	-2.4827	-2.1427	-0.8374	-3.2231	-2.5949	-2.2555
0.4	-1.266	-3.1816	-2.54	-2.2	-0.3607	-3.295	-2.695	-2.3721
0.5	-1.8347	-3.2018	-2.5663	-2.2263	-0.6016	-3.2575	-2.6501	-2.3176
0.6	-5.4938***	-3.0956	-2.4374	-2.0956	-0.5325	-3.2253	-2.5985	-2.2596
0.7	-7.9022***	-2.9963	-2.3458	-1.9963	-0.2694	-3.0912	-2.4334	-2.0912
0.8	-7.979***	-2.8847	-2.2216	-1.865	-0.5537	-2.9307	-2.2733	-1.9196
0.9	-11.168***	-2.506	-1.8295	-1.4695	-0.7615	-2.6543	-1.9808	-1.6208

	NIKKEI.225				PSI20			
0.1	-0.144	-2.8306	-2.1607	-1.8007	0.98415	-2.6167	-1.9424	-1.5824
0.2	0.84438	-3.0665	-2.4107	-2.0665	1.48046	-2.9791	-2.3277	-1.977
0.3	1.2168	-3.1663	-2.5202	-2.1802	-1.2285	-3.1524	-2.5022	-2.1622
0.4	-0.3227	-3.23	-2.6059	-2.2679	-2.0047	-3.2174	-2.5866	-2.2466
0.5	-0.8696	-3.2254	-2.5986	-2.2597	-1.7758	-3.2318	-2.609	-2.2713
0.6	-3.9687***	-3.1825	-2.5413	-2.2013	-2.8488**	-3.175	-2.5315	-2.1915
0.7	-2.773**	-3.1152	-2.4556	-2.1152	-6.1778***	-3.0258	-2.3731	-2.0258
0.8	-11.048***	-2.8909	-2.2286	-1.8724	-7.6672***	-2.9089	-2.2488	-1.8937
0.9	-11.309***	-2.5579	-1.8825	-1.5225	-6.4071***	-2.572	-1.8968	-1.5368
	NASDAQ COMPOSITE							
0.1	-0.6616	-2.6308	-1.9568	-1.5968				
0.2	-0.108	-2.9906	-2.3405	-1.9906				
0.3	-0.3855	-3.225	-2.598	-2.259				
0.4	-1.0566	-3.2564	-2.6483	-2.3155				
0.5	-1.0716	-3.2468	-2.6328	-2.2982				
0.6	-0.9473	-3.1937	-2.5558	-2.2158				
0.7	-1.0929	-3.0853	-2.428	-2.0853				
0.8	-1.1854	-2.9197	-2.2609	-1.9065				
0.9	-1.2201	-2.6121	-1.9378	-1.5778				

This seems to suggest that stock markets in general seem to bounce back to long-run normal values even after significant shocks to their return series. This makes this class of assets more predictable and comparatively less risky in general. This is in sharp contrast to our findings for the cryptocurrency group in this paper which exhibits very strong persistence or long-term memory.

Bonds

Quantiles	YZt_{ks}	asymptotic critical values 1%	5%	10%	YZt_{ks}	asymptotic critical values 1%	5%	10%
	BD BENCHMARK 10 YEAR DS GOVT. INDEX				US BENCHMARK 10 YEAR DS GOVT. INDEX			
0.1	-0.993	-2.8454	-2.1774	-1.8183	-6.1375***	-2.7044	-2.0318	-1.6718
0.2	-2.6336**	-3.0258	-2.3731	-2.0258	-4.2651***	-2.9976	-2.347	-1.9976
0.3	-2.0937	-3.2382	-2.6191	-2.2827	-2.2105*	-3.1568	-2.5078	-2.1678
0.4	-1.375	-3.2797	-2.6797	-2.3525	-0.3316	-3.244	-2.6284	-2.2932
0.5	-2.306	-3.2545	-2.6452	-2.3121	1.23159	-3.2498	-2.6377	-2.3037
0.6	-0.2082	-3.2192	-2.589	-2.249	2.99	-3.2412	-2.6239	-2.2881
0.7	-0.0471	-3.156	-2.5068	-2.1668	3.77628	-3.1678	-2.5221	-2.1821
0.8	-0.6427	-3.1011	-2.4425	-2.1011	5.5928	-2.9725	-2.3204	-1.9693
0.9	-0.5348	-2.8274	-2.1573	-1.7973	8.12153	-2.5562	-1.8807	-1.5207
Quantiles	FR BENCHMARK 10 YEAR DS GOVT. INDEX				UK BENCHMARK 10 YEAR DS GOVT. INDEX			
0.1	-1.2014	-2.8234	-2.1532	-1.7932	-1.8076	-2.8768	-2.2126	-1.8555
0.2	-2.6893**	-2.9836	-2.3328	-1.9824	-2.1333	-3.1569	-2.508	-2.168
0.3	-1.0142	-3.2074	-2.5736	-2.2336	-2.0624	-3.2435	-2.6275	-2.2922
0.4	-0.7969	-3.2787	-2.6787	-2.3512	-1.0876	-3.2806	-2.6806	-2.3537
0.5	-0.2948	-3.2601	-2.6541	-2.3222	0.24229	-3.2914	-2.6914	-2.3675
0.6	-0.6324	-3.2253	-2.5985	-2.2595	0.83366	-3.2066	-2.5725	-2.2325
0.7	-0.2697	-3.1419	-2.4884	-2.1484	0.06726	-3.1097	-2.4505	-2.1097
0.8	-0.5536	-2.9246	-2.2664	-1.9123	-0.0432	-3.0064	-2.3551	-2.0064
0.9	-0.5864	-2.9131	-2.2535	-1.8987	0.07656	-2.7163	-2.044	-1.684

Thus, as a group, 10-year Government bonds display high persistence and the possibility for mean reversion only in very low quantiles with UK bonds being the most persistent of the 4 studied. While the German, US and French bonds show some tendency to mean revert, the possibility remains limited to very low quantiles of the shock only.

Cryptocurrency

Quantiles	YZt_{ks}	asymptotic critical values			YZt_{ks}	asymptotic critical values		
		1%	5%	10%		1%	5%	10%
	BTC				ETH			
0.1	-1.3409	-2.7802	-2.1092	-1.7492	-1.4848	-2.7847	-2.1138	-1.7538
0.2	-1.7354	-3.0776	-2.4208	-2.0776	-0.7578	-3.1304	-2.4735	-2.1335
0.3	-1.7654	-3.1871	-2.5472	-2.2072	-1.3095	-3.2102	-2.5773	-2.2373
0.4	-1.2465	-3.2439	-2.6282	-2.293	-0.8798	-3.2398	-2.6216	-2.2856
0.5	-0.9484	-3.1971	-2.5602	-2.2202	-0.301	-3.2569	-2.649	-2.3163
0.6	0.0812	-3.2414	-2.6242	-2.2885	-0.3847	-3.2657	-2.6631	-2.3323
0.7	0.47548	-3.232	-2.6091	-2.2715	0.26781	-3.1807	-2.5388	-2.1988
0.8	0.70528	-3.0418	-2.3878	-2.0418	-0.1911	-3.0495	-2.3949	-2.0495
0.9	0.1053	-2.7799	-2.1089	-1.7489	-0.3628	-2.6988	-2.0262	-1.6662
	LTC							
0.1	0.09126	-2.663	-1.9896	-1.6296				
0.2	-0.4707	-2.9997	-2.349	-1.9997				
0.3	-1.7816	-3.0664	-2.4106	-2.0664				
0.4	-2.5592**	-3.1784	-2.536	-2.196				
0.5	-2.2245	-3.2133	-2.5813	-2.2413				
0.6	-1.8386	-3.2011	-2.5655	-2.2255				
0.7	-1.3955	-3.1632	-2.5161	-2.1761				
0.8	-1.4033	-3.0142	-2.3623	-2.0142				
0.9	-1.0647	-2.5954	-1.9207	-1.5607				

- We fail to reject the null of unit root for all quantiles studied. This implies a very high degree of persistence, no matter the size of the shock.
- This makes this asset class highly risky in the long run in terms of unpredictability of returns

Quick summary

- Cryptocurrencies have a very high degree of persistence, no matter the size of the shock that makes this asset class highly risky in the long run in terms of unpredictability of returns.

BUBBLING DURING COVID19

Jalan, A., Matkovskyy, R., and Poti, V. (2022). Shall the winning last? A study of recent bubbles and persistence. Finance Research Letters 45, 102162, https://doi.org/10.1016/j.frl.2021.102162

Bubbling during COVID19

- we chose to focus on companies with stocks from the six sectors that exhibited the most significant price rises as a consequence of the COVID pandemic i.e., Work-from-home product/service companies, Stay-at-home product/service, cryptocurrency related companies, and Coronavirus Vaccine and therapeutics companies.
- We hand-select the 43 companies that are most representative of the 6 industries that benefitted the most from the unprecedented COVID-19 crisis owing to the nature of their product/service offered

Bubbling during COVID19, methodology

- The literature provides several approaches to detect bubbles, such as the Residual Augmented Least Square Dickey-Fuller test of Taylor & Peel (1998), or the Log-Periodic Power Law method (Sornette, 2003; Jiang et al. 2010).
- Gürkaynak (2008) shows that econometric detection of asset price bubbles should be taken with some degree of caution.
- Phillips et al. (2011) propose a SADF test method based on the supremum of a set of forward recursive right-tailed ADF tests.
- Zhang et al. (2018) document that, in identifying multiple bubbles, the SADF method is less effective than extant alternatives.
- Phillips, Shi & Yu (2015; 2017) extend the SADF to enhance test performance in identification of multiple bubbles.

Bubbling during COVID19, sample.

	Group 1		Group 2		Group 3		Group 4		Group 5		Group 6	
	Work-from-home product/service companies (companies that provide products and technological services related to continuity of business in the new COVID-19 conditions)		Stay-at-home product/service companies		Cryptocurrency companies (companies that provide products/services related to cryptocurrency market)		Bitcoin companies (companies that provide products/services linked bitcoin market or invested into bitcoin)		Coronavirus Vaccine companies		Coronavirus therapeutics companies	
1	LOGI	Logitech	ROKU	Roku, Inc.	NVDA	Nvidia Corporation	MSTR	Microstrategy Incorporated	PFE	Pfizer Inc	REGN	Regeneron, Inc
2	BOX	Box, Inc.	NFLX	Netflix	AMD	Advanced micro Devices	OSTK	Overstock.com Inc	MRNA	Moderna, Inc	GILD	Gelead Sciences, Inc.
3	ZM	Zoom video communication.	DOCU	DocuSign, Inc.	SQ	Square, Inc	HVBTF	HIVE Blockchain Technologies Ltd	BNTX	BioNTech SE	SRNE	Sorrento Therapeutics, Inc.
4	TWLO	Twillio	PTON	Pelaton Interactive, Inc.	IBKR	Interactive Brokers Group, Inc. (IBG, Inc.)	RIOT	Riot blockchain Inc.	JNJ	Johnson and Johnson	AMGN	Amgen Inc.
5	ESTC	Elastic	PINS	Pinterest	CME	CME group	MARA	Marathon Patent Group Inc	AZN	AstraZaneca PLC	ABBV	AbbVie Inc.
6	VNW	Vmware	CHWY	Chewy, Inc.	V	Visa Inc.	CAN	Canaan Inc	NVAX	Novavax, Inc	GSK	GlaxoSmithKline PLC
7	UPLD	Upland software			PYPL	PayPal holdings, Inc.	GBTC	Grayscale Bitcoin Trust	INO	Inovio Pharmaceuticals, Inc.	LLY	Eli Lilly and Company
8	MSFT	Microsoft										
9	GOOGL	Alphabet										

We collect daily close-price observations for the selected 43 companies over the period 21/11/2019 – 20/1/2021 (Thomson-EIKON). The length of our time series is defined by data availability.

Bubbling during COVID19, results

- We **document the presence of price bubbles in almost all markets analyzed**.
- In terms of persistence, **24 of our 43 companies demonstrate complete absence of mean reversion, implying higher risk in the long run**.
- Some firms in the work-from-home, cryptocurrency and coronavirus-vaccine groups show reversion in **higher quantiles**.
- **The presence of mean reversion contradicts the Efficient Market Hypothesis and may imply pricing irregularities that are inconsistent with equilibrium asset pricing models** (Forbes, 1996).
- Another implication of our results is their applicability to trading strategies**. Bubbles can be exploited by arbitrageurs to outperform other traders** (Westphal & Sornette, 2020).
- In terms of persistence, several studies (e.g., Balvers et al. 2000; Gropp, 2004) document **that excess returns can be generated by exploiting mean reversion of prices**.
  – During periods of bubbles, valuation is temporarily mean averting, implying that expected returns from valuation change are positive.

HERDING IN COVID

Yarovaya, L., Matkovskyy, R., Jalan, A. (2021). The effects of a “black swan” event (COVID-19) on herding behavior in cryptocurrency markets. Journal of International Financial Markets, Institutions and Money, 75, 101321 (https://doi.org/10.1016/j.intfin.2021.101321)

Herding in COVID

- In the aftermath of several crises, “herd” has again become a popular term.
- Herding is met in very different settings from neurology and zoology, to sociology, psychology, economics, and finance.
- Generally speaking, in economics and finance with the term **herding or herd behavior** we mean ***the process where economic agents are imitating each other actions and/or base their decisions upon the actions of others***.
- “Investors and fund managers are portrayed as herds that charge into risky ventures without adequate information and appreciation of the risk-reward trade-offs and, at the first sign of trouble, flee to safer havens.”
- **Herding by market participants exacerbates volatility, destabilizes markets**.

What is herding?

- For an investor to imitate others, she must be aware of and be influenced by others' actions.
- Intuitively, **an individual can be said to herd if she would have made an investment without knowing other investors' decisions, but does not make that investment when she finds that others have decided not to do so.**
- Alternatively, **she herds when knowledge that others are investing changes her decision from not investing to making the investmen*t***.

The main reasons to herd

- Others may know something about the return on the investment and their actions reveal this information.
- market participants may infer information from the actions of previous participants
- investors may react to the arrival of fundamental information
- analysts may herd in order to protect reputation
- institutional investors may herd for reasons related to remuneration
- investors may simply be irrational and herd behavior can arise as the consequence of psychological and/or social conventions.

Why is it not good?

- When investors are influenced by others' decisions, they may herd on an investment decision that is wrong for all of them.
- Suppose that **100 investors each have their own assessments, possibly different, about the profitability of investing in an emerging market**.
- For concreteness, **suppose that 20 of the investors believe that this investment is worthwhile** and the remaining **80 believe that it is not**.
- **Every investor knows only her own estimate of the profitability of this investment**; she does not know the assessments of others' or which way a majority of them are leaning.
- **If these investors pooled their knowledge and assessments, they would collectively decide that investing in the emerging market is not a good idea.**
- But they **do not share their information and assessments with each other**.
- Moreover, these 100 investors **do not take their investment decisions at the same time**.
- Suppose that **the first few investors** who decide **are among the 20 optimistic investors** and they make a decision **to enter the emerging market**.
- Then several of **the 80 pessimistic investors may revise their beliefs and also decide to invest**.
- This, in turn, could have **a snowballing effect**, and lead to most of the 100 individuals investing in the emerging market.
- Later, when the unprofitability of the decision becomes clear, these investors exit the market.

Theories of herding

- Some authors argue that under certain circumstances **herding is a rational choice**. For instance,
  - money managers may *mimic the actions of other* money managers
  - in order to *preserve reputation* and/or compensation
  - *younger analysts know that if they make bold forecasts and deviate from the consensus they are more likely to be fired*
  - during a bank crisis depositors contribute to runs on banks because they see long lines of other depositors outside banks and know that if they do not join the line early there may be no funds left for them

Theories of herding: Information cascades

- The above example shows several aspects of information cascades or herd behavior arising from informational differences.
- First, **the actions** (and the assessments) of investors who decide early **may be crucial in determining which way the majority will decide**.
- Second, **the decision** that investors herd on **may well be incorrect**.
- Third, **if** investors take **a wrong decision**, **then with experience and/or the arrival of new information, they are likely to eventually reverse their decision starting a herd in the opposite direction**.
- **This, in turn, increases volatility in the market**.

Theories of herding: Information cascades, cont.

- **An informational cascade takes place when it is optimal for individuals to follow the observable actions of individuals before them, disregarding their own information** (Bikhchandani, Hirshleifer, and Welch, 1992).
- For example, for investors that enter the market at a later stage it may be an optimal decision to ignore their own private information and mimic the trading behavior of previous investors since they may infer that previous investors possess private information.
- Informational cascades may have an influence over perfectly rational individuals and lead to the creation of bubbles.
- A decision model where it is rational for decision makers to look at the decisions made by previous decision makers since previous decision makers may possess related information that is important is analyzed by Banerjee (1992).

Theories of herding: Information cascades, cont.

- A general sequential choice model where a decision maker will act only on the information obtained from previous decisions ignoring private information (as will later decision makers) is discussed by Bikhchandani, Hirshleifer, and Welch (1992)
- They argue that, **irrespective of the social desirability of the outcome, the reasoning may be entirely rational** (see also, Welch, 1992).
- Note that informational cascades may be linked with partial or complete information aggregation blockages, increased fragility to even small informational shocks, fads and stampedes (Hirshleifer and Teoh, 2003; among others).

Theories of herding: Information cascades, cont.

- Avery and Zemsky (1998) find that herding in the form of an informational cascade is not possible, if simple information structures and a price mechanism are assumed.
- **In case of complicated information structures, however, herding is possible and it may affect asset prices only when the market is uncertain for both the asset value and the information of the average trader.**
- In a laboratory experiment, Cipriani and Guarino (2005) study herding in financial markets and their results are in line with the results of Avery and Zemsky, i.e. **when the subjects are trading for informational reasons in a frictionless market herding occurs rarely**, although in some cases they observe that subjects follow a contrarian strategy or choose to ignore private information.

Theories of herding: Spurious herding

- Herding results from an obvious intent by investors to copy the behavior of other investors.
- This should be distinguished from "**spurious herding**" where groups facing similar decision problems and information sets take similar decisions.
  - Thus, "spurious" herding where investors face a similar fundamental-driven information set and thus make similar decisions
- "**intentional**" herding where investors have an intention to copy the behavior of others.
- The "**spurious herding**" may lead to an efficient outcome while the "**intentional**" may not
- Empirically distinguishing "spurious herding" from "intentional" herding is easier said than done and may even be impossible, since typically, a multitude of factors have the potential to affect an investment decision.
- Fundamentals-driven spurious herding out of equities could arise if, for example, interest rates suddenly rise and stocks become less attractive investments.
  - Investors under the changed circumstances may want to hold a smaller percentage of stocks in their portfolio. This is not herding according to the definition above because investors are not reversing their decision after observing others. Instead, they are reacting to commonly known public information, which is the rise in interest rates.

Theories of herding: a need to share the blame

- Scharfstein and Stein (1990) argue that reputation concerns in labor markets with no perfect information and **a need to share the blame** when things go bad may lead managers to follow each other's actions.
- They present a learning model where the labor market is able to update its understanding of the manager's ability from the investment decisions a manager is making.
- **Thus, manager concern for labor market reputation may lead to rational (but socially inefficient) herd behavior, i.e. managers may ignore significant private information and follow the decisions of other managers.**
- In other words, **herding may be viewed as insurance against manager underperformance** (Rajan, 2006).

Theories of herding: the perception of analyst abilities affects analyst compensation

- In Trueman (1994) **the perception of analyst abilities affects analyst compensation**.
- **Trueman's theoretical model indicates** that the earnings forecasts of analysts do not necessarily reflect in an unbiased manner their private information, but rather **there is a tendency to release forecasts closer to prior earnings expectations.**
- Furthermore, **analysts also tend to forecast earnings similar to those previously announced by other analysts in an effort to copy higher ability and obtain higher compensation, even when private analyst information does not justify this behavior**.

Theories of herding: high reputation or low ability

- Graham (1999) develops a model where analysts are more likely to herd:
  - when they **are characterised by high reputation or low ability** (e.g. **high reputation analysts have greater incentives to hide in the consensus in order to protect their reputation**),
  - **when there is strong public information inconsistent with analyst private information**, and
  - when private information signals across analysts exhibit positive correlation.

Theories of herding: short horizons

- Froot, Scharfstein, and Stein (1992) show that **if speculators have short horizons they may herd on the same information trying to learn what other informed investors know**.
- Their model allows for some speculators to have short trading horizons, which implies that they may allocate research resources in a non-optimal way.
  - *This may violate informational efficiency* (although at the pricing stage the market may be efficient) *in the sense that investors may have the tendency to concentrate on one information source* (that may be of poor quality or have no relation to fundamentals) *rather than employ a diverse set of information sources.*
  - As a growing number of speculators acquire this information it will be disseminated in the market and thus it is profitable to acquire this information at an early stage (positive informational spillovers); in their model there may be multiple herding equilibria.

Theories of herding: irrationality

- **Other authors suggest that investors (or a subset of) are irrational and that the existence of such irrational investors may give rise to bubble-like phenomena and herd behavior.**
- Furthermore, non-rational herd behavior can arise as the consequence of psychological stimuli and restraints, such as pressure from social circles and/or social conventions.
  - For instance, Keynes (1936) argues that investors are affected by sociological factors (e.g. social conventions) that may drive market participants to imitate the actions of others during periods of uncertainty.
- Baddeley, Curtis and Wood (2004) demonstrate that even experts may resort to herd behavior, given information scarcity, asymmetry and the employment of common heuristic rules.

Theories of herding: arbitragers

- Shleifer and Summers (1990), **distinguish between arbitrageurs who are fully rational and noise traders** (Black, 1986), i.e. **irrational investors who act on noise and whose trading behavior suffers from systematic biases**.
- They suggest that **some shifts in investor demand for assets and changes in investor sentiment appear to be irrational and not justified by fundamentals**, e.g. investors' reaction to pseudo-signals such as advice by "financial gurus".
- Consider the case where a fraction of investors follows trends.
  - Arbitrageurs, instead of opposing this bandwagon, rationally decide to jump on it.
  - The new higher demand will lead prices even higher and further away from fundamentals, attract more irrational investors, and the rational arbitragers will exit when prices are near the top in order to collect their profits.
  - *In other words, the behavior of rational arbitragers, in the short run, will nourish the irrational price bubble*.

Measuring herding in financial markets

- How is herd behavior measured in empirical studies?
- Generally speaking, we can classify empirical methodologies into two main categories:
  - studies that rely on micro-data or proprietary data and investigate whether specific investor types herd,
  - and studies that rely on aggregate price and market activity data and investigate herding towards the market consensus.

Measuring herding in financial markets, cont.

- We estimate herding behavior by means of the Chang et al. (2000) approach.
- Despite the availability of alternative models (Bohl et al. 2013; Lee, 2017; Clements et al., 2017), we choose this approach given its wide use in literature to be able to ensure comparability of our results with those of prior studies.
- Chang et al. (2000) argue that **if investors tend to follow aggregate market behavior during periods of large average price movements, then the linear and increasing relation between dispersion and market return will no longer hold and it can become non-linearly increasing or even decreasing**.
- Thus, they utilize a non-linear regression specification to estimate the relation **between the cross-sectional absolute deviation of returns and the market return**.
- **If investors trust market expectations and follow them, investors' return will not deviate from market return, whereas dispersion level or variance between individuals' return and market return, in light of adopting herd behavior by investors, will be zero**.
- **When stock return differs from market return, dispersion increases, and in case investors follow market's expectations, dispersion will become significantly less than the mean.**

Measuring herding in financial markets, cont.

- They propose a test of herding behavior that also requires a parameter to capture any possible non-linearity in the relation between asset return dispersions and the market return.
- We use the **cross-sectional absolute deviation** at time t (CSADt)
- **CSAD is estimated as the average AVD (Absolute Value of Deviation) of each stock relative to the return of the equally-weighted market portfolio**.
- **The notion behind this approach is that if herding is present during periods of extreme market conditions then there should be a less than proportional increase (or even decrease) in the CSAD measure.**
- Note here that CSAD is not used as a metric for herding: **herding is identified through the relationship between CSAD and the market return.**

Measuring herding in financial markets, cont.

- The following specification for estimates is used:

$$CSAD_{m,t} = \beta_0 + \beta_1 \left| R_{m,t} \right| + \beta_2 R_{m,t}^2 + e_t$$

where $\left| R_{m,t} \right|$ is the average absolute market return of all actively traded selected equities in a market, at time t, $CSAD_{m,t}$ is the Cross Sectional Absolute Deviation of returns and is calculated as follows:

$$CSAD_{m,t} = \frac{\sum_{i=1}^{n} \left| R_{i,t} - R_{m,t} \right|}{n}$$

where $R_{i,t}$ is the first logarithmic difference of closing prices for an equity *i* at time *t*

$$R_{i,t} = InP_t - InP_{t-1}$$

Measuring herding in financial markets, cont.

- **If herding is not present in a market, the relationship between the cross-sectional return dispersion, $CSAD_{m,t}$, and absolute market returns, $|R_{m,t}|$, would be expected to be positive and linear, implying that β_1 would be expected to be significantly positive, while β_2 insignificant.**
- On the contrary, **in the presence of herding, when values of $|R_{m,t}|$ are high and thus substantial market movements are observed, the relationship between $CSAD_{m,t}$ and $|R_{m,t}|$ would be non-linear, implying that β_2 would be negative and significant.**
- Thus, **herding lowers cross-sectional dispersion of returns compared to the case of rational pricing.**
- Bernales et al. (2019) postulate that herding can be considered to be stronger when β_1 is negative, implying a negative relationship between the cross-sectional deviation of the cryptocurrency's return and the magnitude of respective market returns.

Measuring herding in financial markets, cont.

- To assess herding on up/down market days $CSAD_{m,t} = \beta_0 + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + e_t$ is extended:

$$\boldsymbol{CSAD_{m,t} = \beta_0 + \beta_1 D^{up}|R_{m,t}| + \beta_2(1 - D^{up})|R_{m,t}| + \beta_3 D^{up} R_{m,t}^2 + \beta_4(1 - D^{up}) R_{m,t}^2 + e_t}$$

- where D^{up} is equal to one (zero) on days with positive (negative) values of $R_{m,t}$.
- Significantly negative values of β_3 (β_4) would indicate the presence of herding on days of positive (negative) average market performance.

Parameters estimation

- It is a regression!
  - Thus you can apply any regression method that satisfies the data you have in your hands.
- First, non-linear OLS then estimate the classic Newey-West (Newey & West, 1987) Heteroscedasticity and Autocorrelation consistent (HAC) estimators to linear regressions using Bartlett kernel weights as described in Newey & West (1987, 1994). (because of time-series regressions).
- Then Bayesian regression, Markov-regime switching, quanile regression etc.

Herding in cryptocurrency during COVID19

	USD cryptocurrency market	Euro cryptocurrency market	JPY cryptocurrency market	KRW cryptocurrency market
Exchanges	Binance, Bitbay, BitFinex, Bitstamp, Bittrex, Cexio, CoinBase, Gemini, Kraken, Poloniex	Bitbay, Bitstamp, Exmo, Kraken, CoinBase	OKOIN, Zaif, Bitflyer, Kraken	Bithumb
Cryptocurrencies	BTC, LTC, ETH	BTC, LTC, ETH	BTC, BCH, LTC, ETH, MONA, XEM, ZAIF	BTC , BTG, ETH, LTC, XMR , XRP

Herding in cryptocurrency during COVID19

- These parameters are estimated using several methods.
- First, we apply the classic Newey-West (Newey & West, 1987) Heteroscedasticity and Autocorrelation consistent (HAC) estimators to linear regressions using Bartlett kernel weights as described in Newey & West (1987, 1994).
- To corroborate the received estimates, we estimate robust linear Bayesian model with the priors estimated as in Lewandowski, Kurowicka, and Joe (2009) and Markov-Switching regressions using the EM algorithm as in Hamilton (1989), Hamilton (1994), Goldfeld and Quantd (2005) to check for the presence of herding given different regimes.
- Quantile regression (Sim and Zhou 2015) is applied to test the behaviour of the coefficients across quantiles.
- Then, Time-Varying Regressions, TVR (Bollerslev, Patton and Quaedvlieg, 2016; Casas, Mao, and Veiga, 2018) are estimated to assess evolution of herding over time.
- Time-varying correlation among the selected markets in terms of herding is estimated by means of the time-varying parameter copula models, i.e., GAS models with conditional multivariate Student–t distribution and time–varying correlations (Creal et al. 2011, 2013; Harvey 2013). These type of models allow for time-varying parameters in copulas and thus help exploit the complete density structure of the data, rather than merely means and higher moments.

Herding in cryptocurrency during COVID19

	(Intercept)	β1	β2
Cryptocurrency USD market (std.error, t-stat)	0.001*** (0.0005, 25.5881)	0.2527*** (0.011, 22.0579)	**-0.891***** (0.130, -6.8484)
Cryptocurrency JPY market (std.error, t-stat)	0.0033*** (0.0001, 32.7129)	0.502*** (0.025, 19.82)	**-1.703***** (0.389, -4.3784)
Cryptocurrency Euro market (std.error, t-stat)	0.0014 *** (0.000044, 32.495)	0.23*** (0.01, 19.383)	**-0.35***** (0.155, -2.272)
Cryptocurrency KRW market (std.error, t-stat)	0.002*** (0.000, 23.519)	0.287*** (0.038, 7.620)	*2.223(.)* (1.279, 1.738)

Herding behavior estimates (Yarovaya, Matkovskyy, Jalan, 2021)

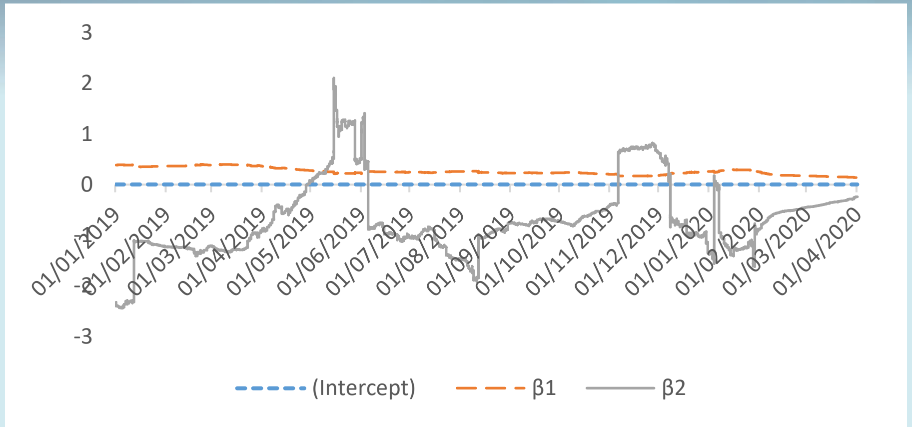
Note: 1. The Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) estimators are provided for linear regressions; Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

2. We also estimated using aggregated daily data, but the results are statistically insignificant.

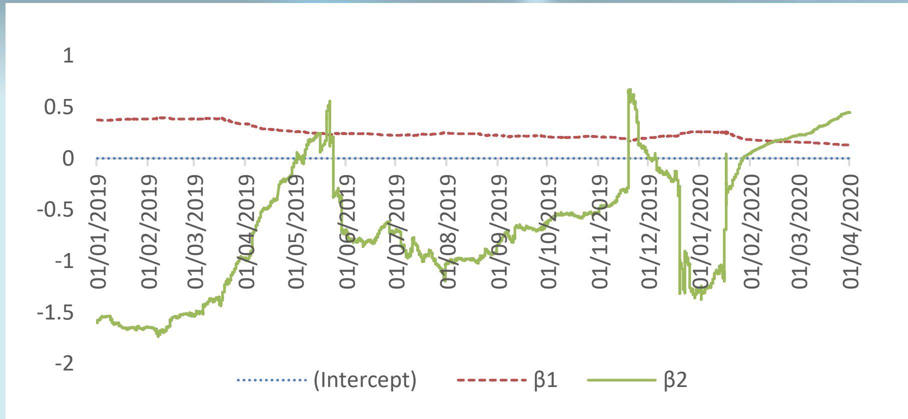
3. The models were also estimated by means of the robust linear Bayesian model with the priors estimated as in Lewandowski, Kurowicka, and Joe (2009). The coefficients have the same sign and magnitude as those reported above.

- Here one observes positive and significant (at 1%) coefficients for β1 across all markets.
- These are not directly interpreted to assess herding behavior.
- However, negative and significant β2 values indicate strong herding behavior.
- **Coefficients on β2 are negative and significant at 1% for all markets except for KRW, which is positive with a significance level of 95%.**
- **This seems to indicate the presence of unconditional herding for all markets except the KRW**

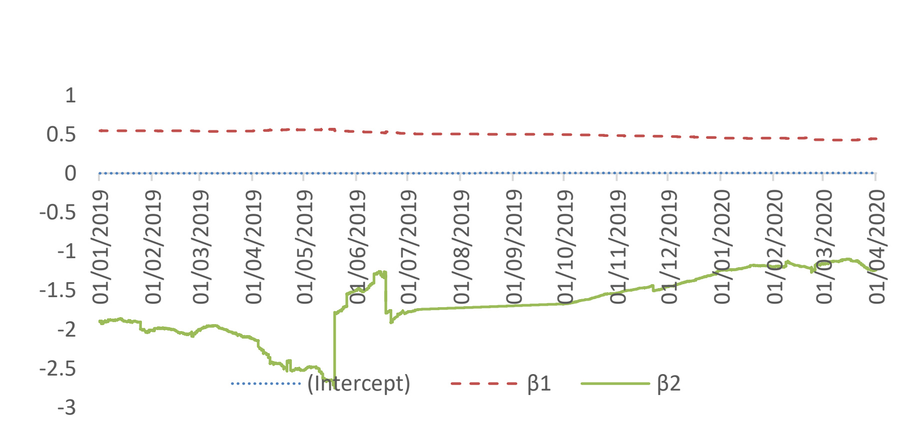
Herding in cryptocurrency during COVID19, cont.



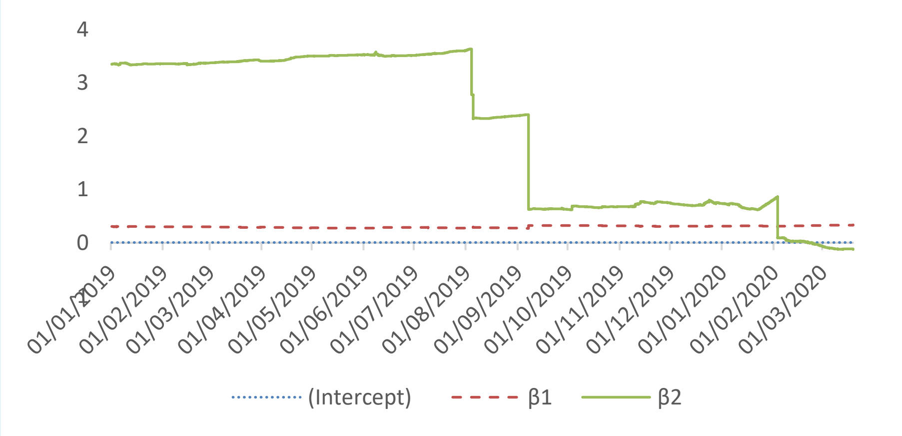
Cryptocurrency USD market



Cryptocurrency Euro market



Cryptocurrency JPY market



Cryptocurrency KRW market

(Yarovaya, Matkovskyy, Jalan, 2021)

Herding in cryptocurrency during COVID19, cont.

(Yarovaya, Matkovskyy, Jalan, 2021)

Conditional on up/down market days Herding behavior estimates

- **Significantly negative value of β3 (β4) can suggest the presence of herding on days of positive (negative) average performance for the cryptocurrency market.**
- **In the case of Bitcoin USD market both β3 and β4 are negative and statistically significant, meaning herding on positive and negative average market performance**, though herding on positive average market performance is stronger (absolute value of β3 > absolute value of β4).

	(Intercept)	β1	β2	β3	β4
Cryptocurrency USD (std.error, t-stat)	0.001*** (0.000, 25.058)	0.300*** (0.014, 21.5)	0.215*** (0.011, 18.837)	-1.56*** (0.106,-14.658)	-0.499*** (0.079,-6.306)
Cryptocurrency JPY (std.error, t-stat)	0.003*** (0.000, 33.614)	0.549*** (0.031, 17.978)	0.452*** (0.022, 20.430)	-1.774(.) (1.044,-1.699)	-1.388*** (0.375,-3.701)
Cryptocurrency Euro (std.error, t-stat)	0.001*** (0.000, 33.055)	0.271*** (0.014, 19.433)	0.193*** (0.012, 16.666)	-0.916*** (0.161,-5.678)	0.101 (0.198, 0.510)
Cryptocurrency KRW (std.error, t-stat)	0.002*** (0.000, 22.757)	0.352*** (0.060, 5.896)	0.217*** (0.039, 5.539)	2.095 (2.935, 0.714)	2.683* (1.264, 2.123)

1. The Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) estimators are provided for linear regressions; Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

2. We also estimated the parameters by using aggregated daily data, but the results are statistical insignificant.

3. The models were also estimated by means of the robust linear Bayesian model with the priors estimated as in Lewandowski, Kurowicka, and Joe (2009). The coefficients have the same sign and magnitude.

SPORT (FOOTBALL) VS CRYPTO

Matkovskyy, R. and Jalan, A. (2022) Football vs Cryptos: Which Scores the Goal During COVID-19?
https://ssrn.com/abstract=4017746

Sport (football) vs crypto

- The COVID-19 has significantly impacted economic and social life, including professional football clubs (PFCs).
- Professional football “continues to be a social business; economic in basis, but social in nature” (Morrow,2013).
- State-imposed restrictions to avoid person-to-person contact have resulted in postponement of championships like the UEFA Champions and cancellation of matches, impacting club profitability and the global football ecosystem.
- In this light, Tovar (2020) likens the COVID pandemic to war times.
- FCs illiquid financial structure makes them highly susceptible to crises (Szymanski & Weimar, 2019).

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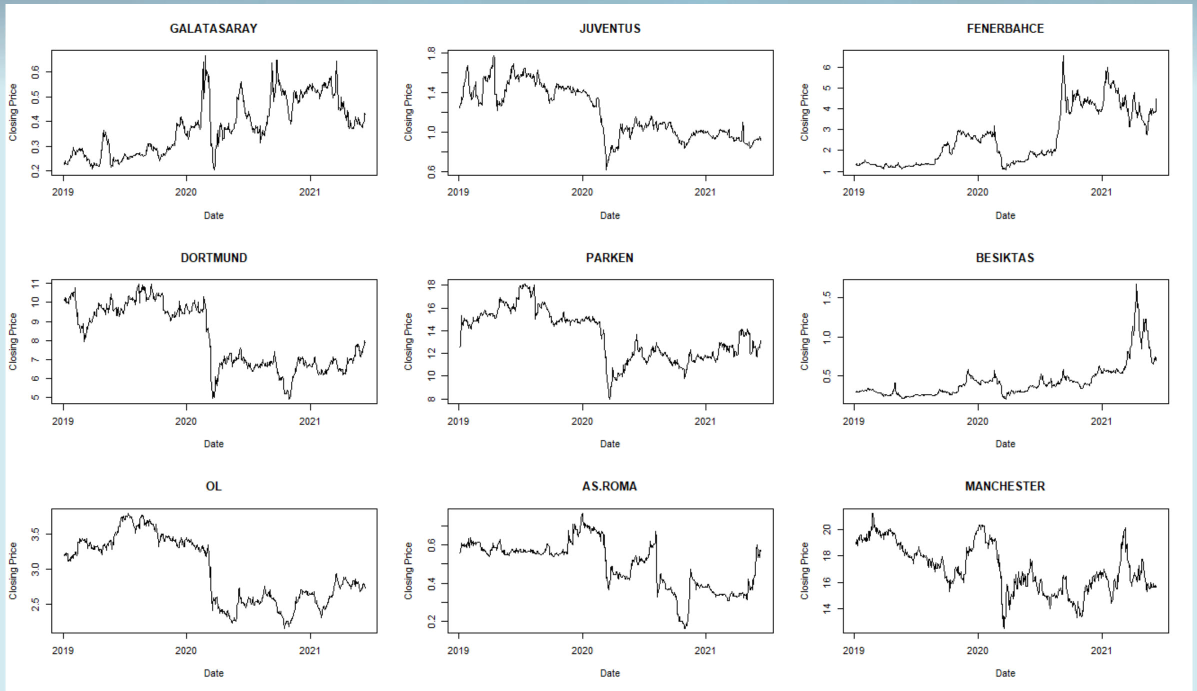
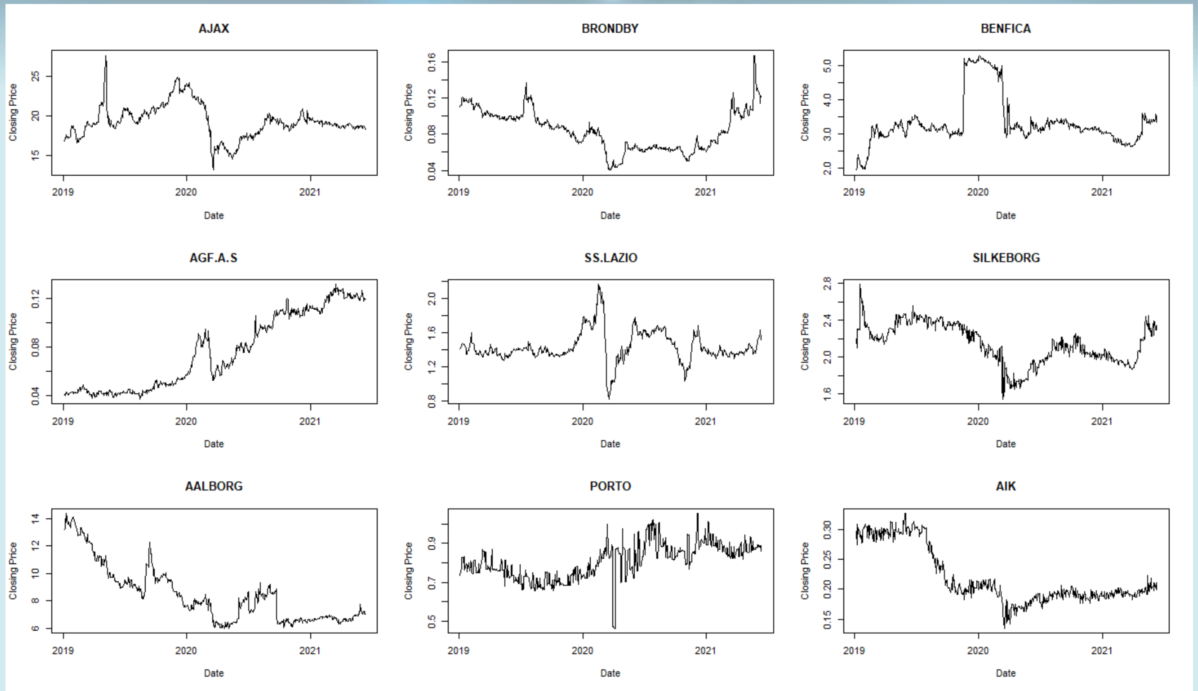
- In this light, Tovar (2020) likens the COVID pandemic to war times.
- FCs illiquid financial structure makes them highly susceptible to crises (Szymanski & Weimar, 2019).
- The COVID-19 pandemic has brought the hedging/diversifier role of cryptos in the spotlight. While Jiang et al.(2021) document that most cryptocurrencies can be used as a hedge during the pandemic, Yarovaya et al.(2021) question their safe haven characteristics during the crisis.

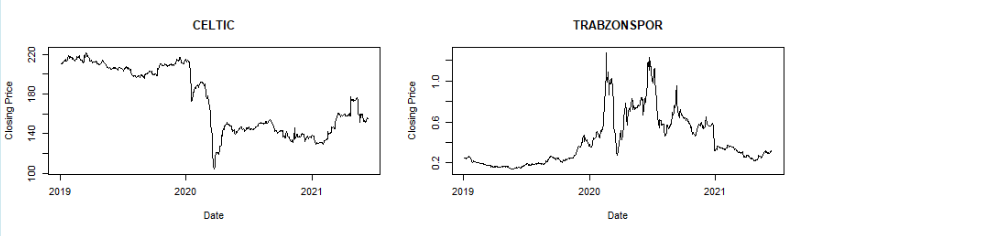
Sport (football) vs crypto

- Our dataset covers daily closing prices of 20 actively traded football clubs' equities and top 10 cryptocurrencies by capitalization, from 4/01/2019 to 12/06/2021. The dataset is split into pre and during pandemic periods (4/01/2019-19/02/2020 and 20/02/2020-6/12/2021, respectively).
- Selected football clubs include Galatasaray(Turkey), Juventus(Italia), Fenerbahce(Turkey), Dortmund(Germany), Parken(Denmark), Besiktas(Turkish), OL(France), Roma(Italia), Manchester United (U.K), Trabzonspor(Turkey), Celtic(U.K), Ajax(Netherlands), Brondby (Denmark), Benfica(Portugal), AGF A/S(Denmark), Lazio(Portugal), Silkeborg(Denmark), Aalborg(Denmark), Porto(Portugal), and Aik(Sweden) . Price dynamics are depicted in Fig.1.
- The 10 cryptocurrencies include Bitcoin, Ethereum, Binance, Coin, Cardano, Dogecoin, Xrp, Bitcoin, Cash, Litecoin, Chainlink, and Theta , based on market cap on 12/06/2021. Following Matkovskyy et al.(2021), we exclude stable coins (Tether, USD-coin) and non-existent coins on 4/01/2019, our dataset start date (Fig.1). Data comes from Coinmarket.com. It has been transformed into a 5 day-week pattern with equity prices converted to US dollars using daily exchange rates.

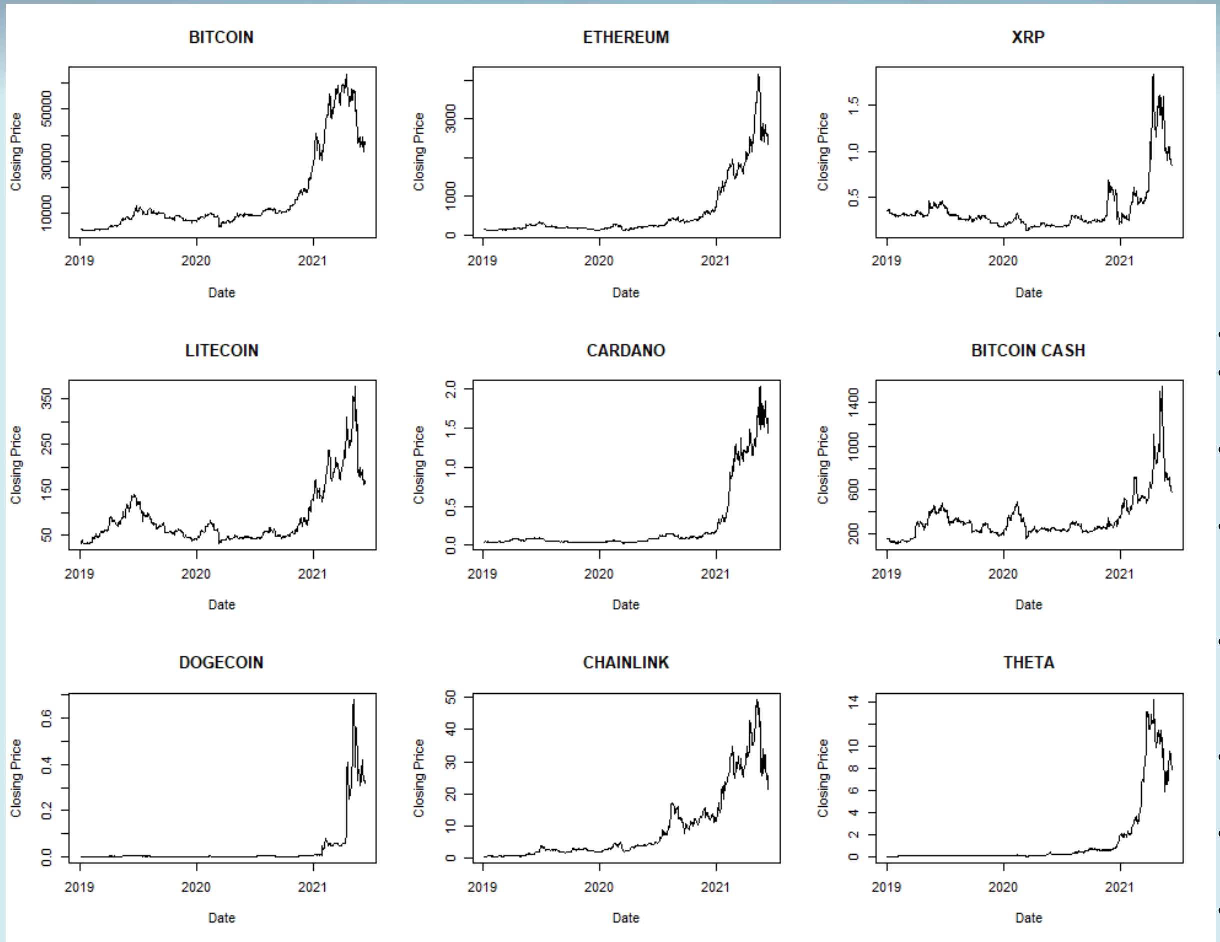
Sport (football) vs crypto

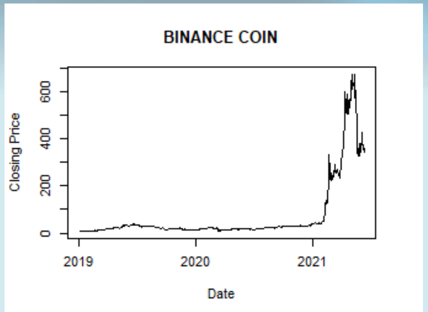






Sport (football) vs crypto





- The stock prices of selected football clubs **are relatively low**.
- **huge price differences are observed for the cryptocurrency group**, with Bitcoin peaking at USD 63,503.46 in May 2021 and Cardano never surpassing USD 0.68.
- **The kurtosis of the football clubs' equity prices is generally negative, while that for cryptocurrencies is positive, indicating more extreme values**.
- In terms of performance, **crypto-asset returns are generally positive, while those for most sports clubs are negative**. In the former group, Theta is the best performer, closely followed by Dogecoin.
- During the pre-COVID period, Turkish football clubs had higher mean returns than most cryptocurrencies. While cryptocurrencies outperformed football clubs on average, they also exhibited higher standard deviation.
- From the beginning of the pandemic, **cryptocurrency returns boomeranged**, particularly Dogecoin and Theta.
- Dogecoin achieved a maximum return of 138.87%, 20 times higher than the best-yielding football clubs.
- **Football clubs' equities performed poorly**, with many generating negative mean returns over the COVID-19 period, like Juventus (-0.10%).

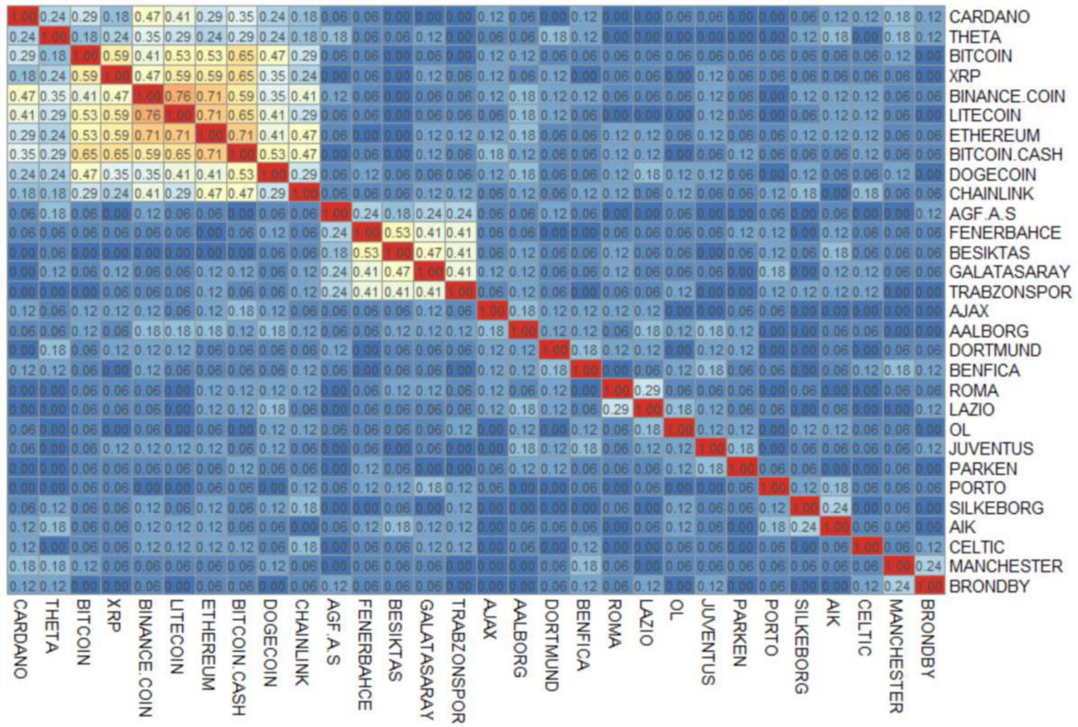
Sport (football) vs crypto

Correlation

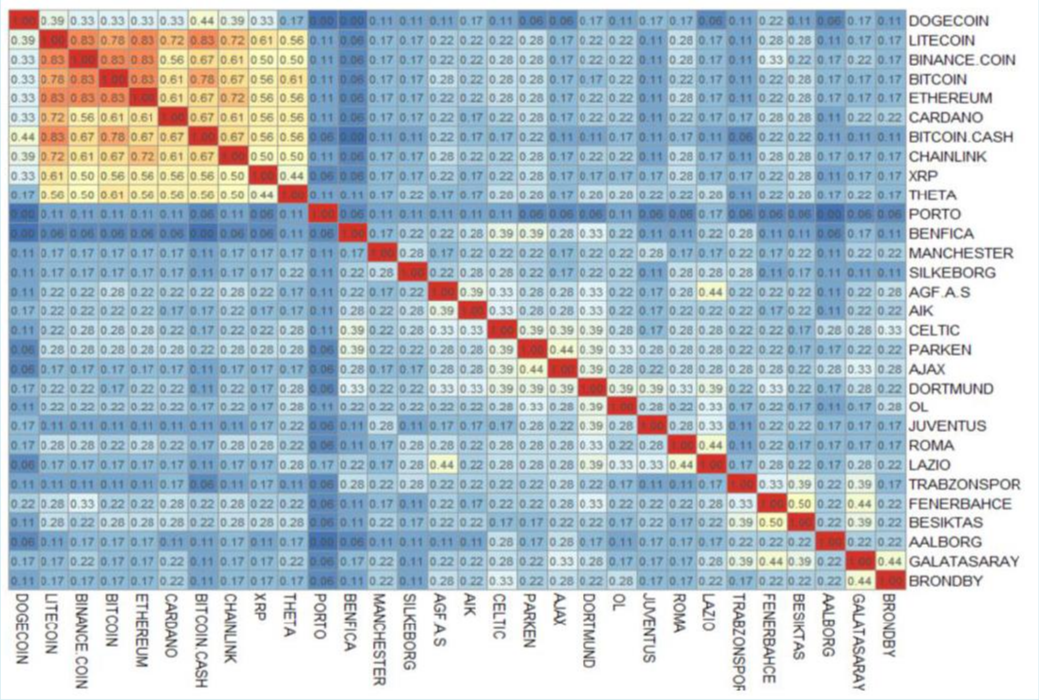
- We start with well-established non-parametrical measures of asymptotical dependence in tails, as in Schmidt & Stadtmüller(2006). It detects how extreme values in one series are likely to be accompanied by equally large(low) extreme values in the other.
- We also estimate time-varying correlation of football-clubs' and crypto-asset returns using a corrected dynamic conditional correlation GARCH model, cDDC-GARCH, proposed by Engle et al.(2017) and Nakagawa et. al.(2018).
  - Estimates are derived using the Composite likelihood method of Pakel et al.(2014).

Sport (football) vs crypto

Correlation



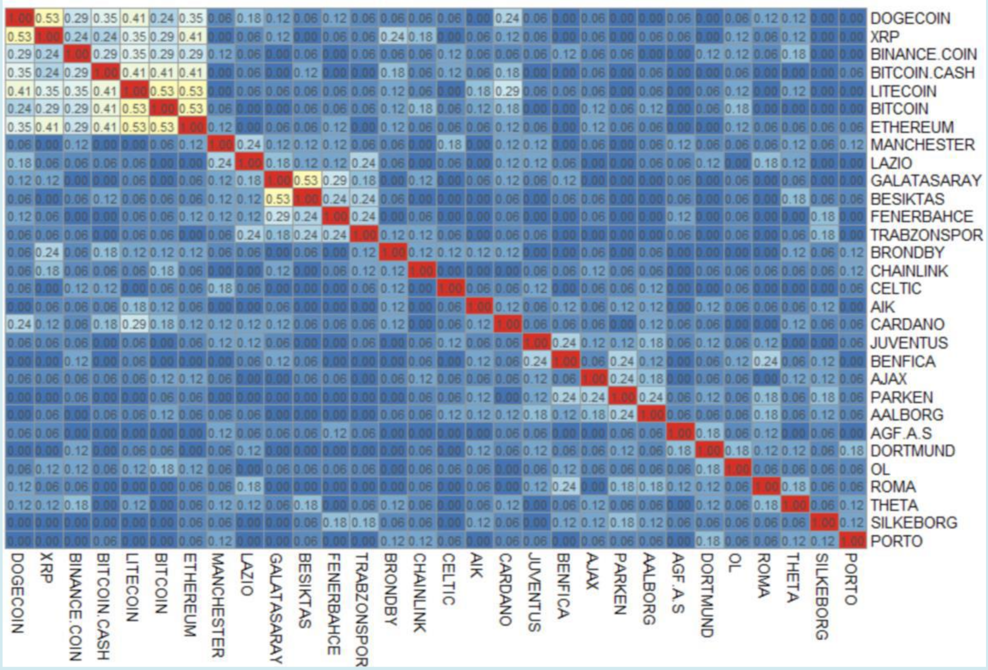
Pre-COVID: Lower tail return correlation



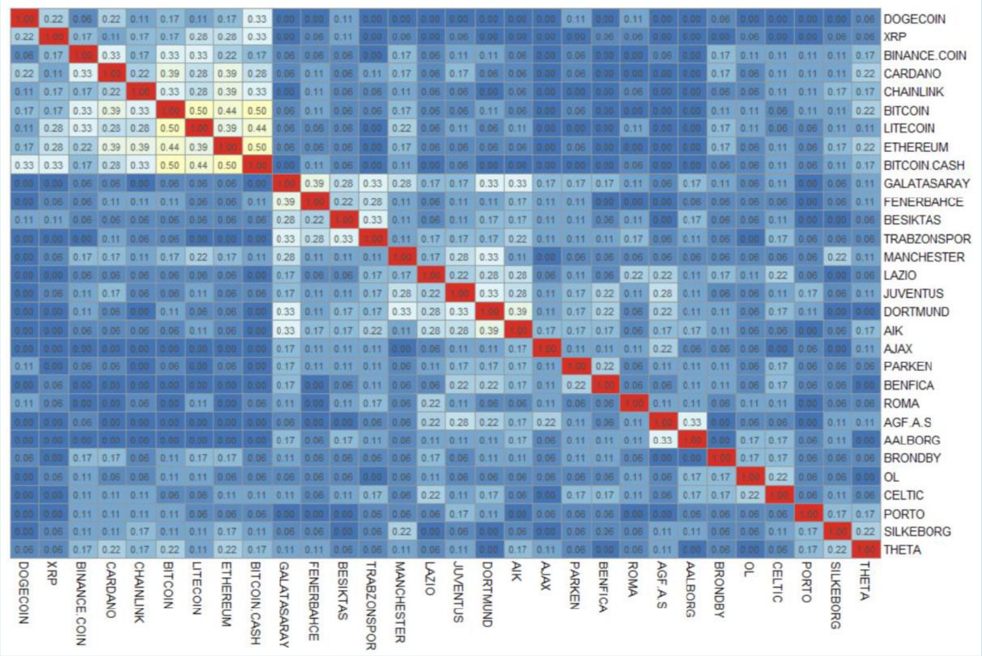
COVID period: Lower tail return correlation

Sport (football) vs crypto

Correlation



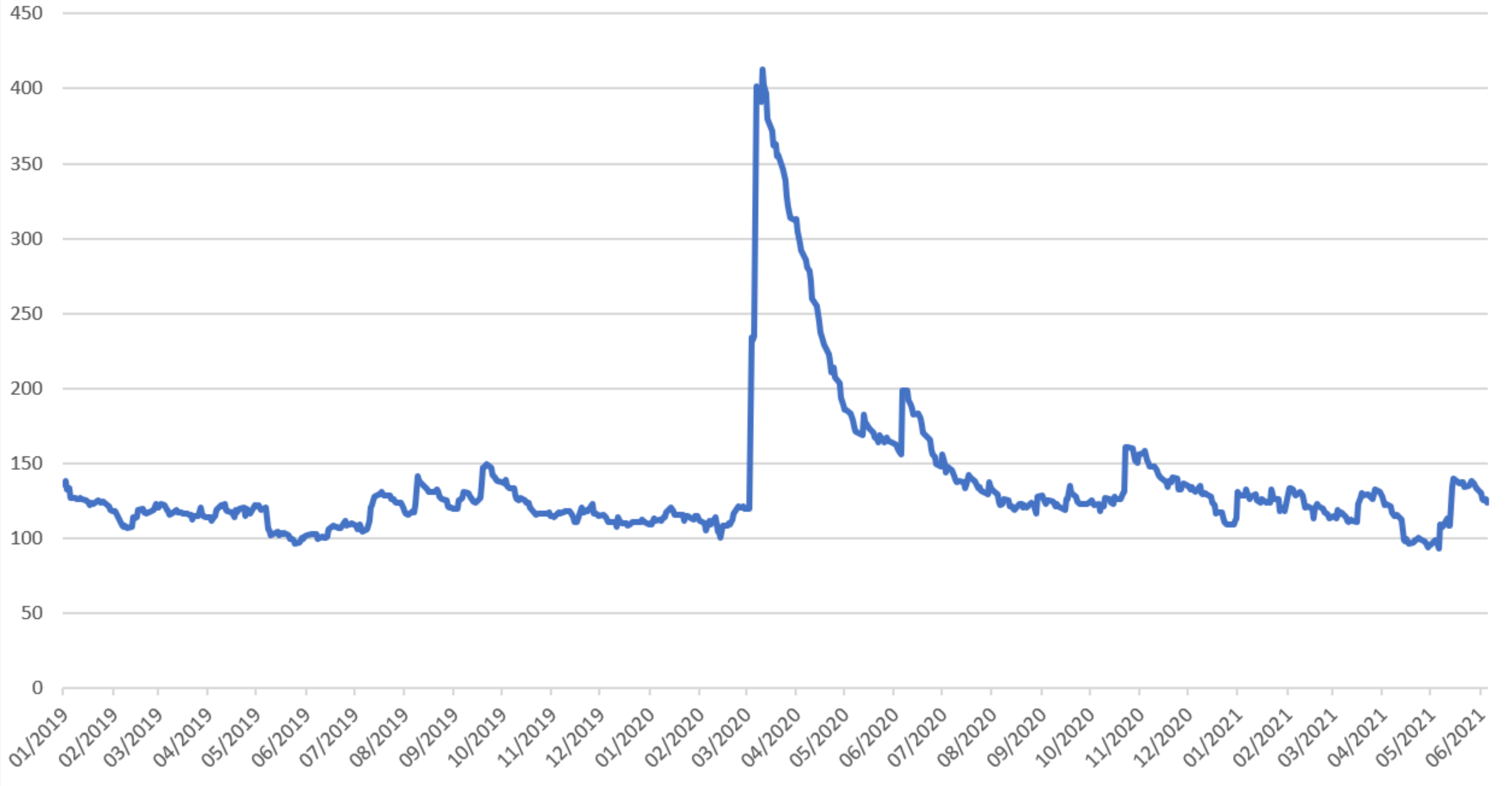
Pre-COVID: Upper tail return correlation



COVID period: Upper tail return correlation

Sport (football) vs crypto

Correlation



Sport (football) vs crypto

Liquidity

- We calculate four indices - the high-low ratio spread estimator (Corwin &Schultz,2012), the adjusted quoted close spread (Chung &Zhang,2014), Amihud illiquidity (Amihud,2002), and volatility-over-volume (Fong et al.,2017), referred to as CS, HLR, ILLIQ, and VoV, respectively. ILLIQ and VoV reflect illiquidity, meaning that lower ratios imply higher liquidity.
- $HLR_t = \frac{H_t - L_t}{0.5\,(H_t + L_t)}, VoV_t = \frac{\ln\left({}^{H_t}/_{L_t}\right)}{\sqrt{volume}},$
- $CSt = \frac{2(e^{\propto t}-1)}{1+e^{\alpha t}}\;\alpha_t = \frac{\sqrt{2\beta_t} - \sqrt{\beta_t}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma_t}{3-2\sqrt{2}}},\; \beta_t = \left[ln\left(\frac{H_t}{L_t}\right)\right]^2 + \left[ln\left(\frac{H_{t+1}}{L_t+1}\right)\right]^2$ where H_t is the high price on day t, L_t is the low price on day t, and γ_t is $\ln\left((\max\{H_t|H_{t+1}\})\right) / (\min\{L_t|L_{t+1}\}))$.

Sport (football) vs crypto

Liquidity

- Results are presented in Table.
- All four estimators indicate higher liquidity for the crypto-asset group. Silkeborg, Aalborg, Porto, and AIK clubs are particularly illiquid.
- Except for Porto, all these clubs play in the Danish league and are relatively unknown.
- ILLIQ and VoV ratios suggest that four football clubs - Galatasaray, Juventus, Fenerbahce, and Dortmund are more liquid than Theta, one of the smallest cryptocurrencies and the most illiquid in the sample.

Asset	CS	HLR	ILLIQ	VoV
GALATASARAY	1.E-02	5.E-02	4.E-09	2.E-05
JUVENTUS	8.E-03	3.E-02	3.E-09	1.E-05
FENERBAHCE	9.E-03	5.E-02	6.E-09	2.E-05
DORTMUND	8.E-03	3.E-02	7.E-09	2.E-05
PARKEN	8.E-03	3.E-02	3.E-07	1.E-04
BESIKTAS	1.E-02	6.E-02	1.E-08	2.E-05
OL	6.E-03	2.E-02	3.E-07	1.E-04
ROMA	1.E-02	4.E-02	5.E-08	6.E-05
MANCHESTER	7.E-03	3.E-02	1.E-08	2.E-05
TRABZONSPOR	1.E-02	6.E-02	1.E-08	3.E-05
CELTIC	2.E-02	3.E-02	3.E-08	7.E-05
AJAX	8.E-03	3.E-02	3.E-07	1.E-04
BRONDBY	2.E-02	5.E-02	1.E-06	3.E-04
BENFICA	9.E-03	3.E-02	8.E-06	4.E-04
AGF	2.E-02	5.E-02	4.E-06	4.E-04
LAZIO	9.E-03	4.E-02	9.E-08	7.E-05
SILKEBORG	9.E-03	3.E-02	2.E-04	6.E-04
AALBORG	7.E-03	3.E-02	5.E-05	6.E-04
PORTO	2.E-03	8.E-03	2.E-03	5.E-04
AIK	0.E+00	0.E+00	5.E-03	0.E+00
All selected football clubs	**9.E-03**	**3.E-02**	**3.E-04**	**2.E-04**
BITCOIN	1.E-02	5.E-02	1.E-12	3.E-07
ETHEREUM	1.E-02	6.E-02	3.E-12	5.E-07
BINANCE COIN	2.E-02	8.E-02	1.E-10	4.E-06
CARDANO	3.E-02	8.E-02	3.E-10	5.E-06
DOGECOIN	2.E-02	8.E-02	4.E-10	6.E-06
XRP	2.E-02	7.E-02	2.E-11	1.E-06
BITCOIN CASH	2.E-02	8.E-02	2.E-11	2.E-06
LITECOIN	2.E-02	7.E-02	1.E-11	1.E-06
CHAINLINK	2.E-02	1.E-01	1.E-09	9.E-06
THETA	4.E-02	1.E-01	9.E-09	3.E-05
All selected crypto-assets	**2.E-02**	**8.E-02**	**1.E-09**	**6.E-06**

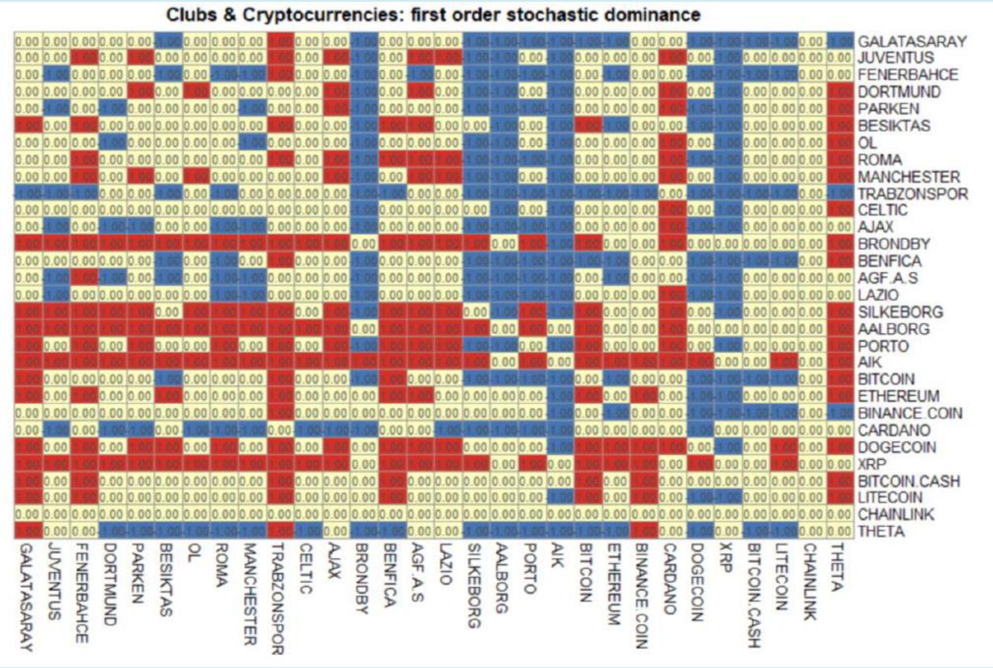
Sport (football) vs crypto

Stochastic dominance

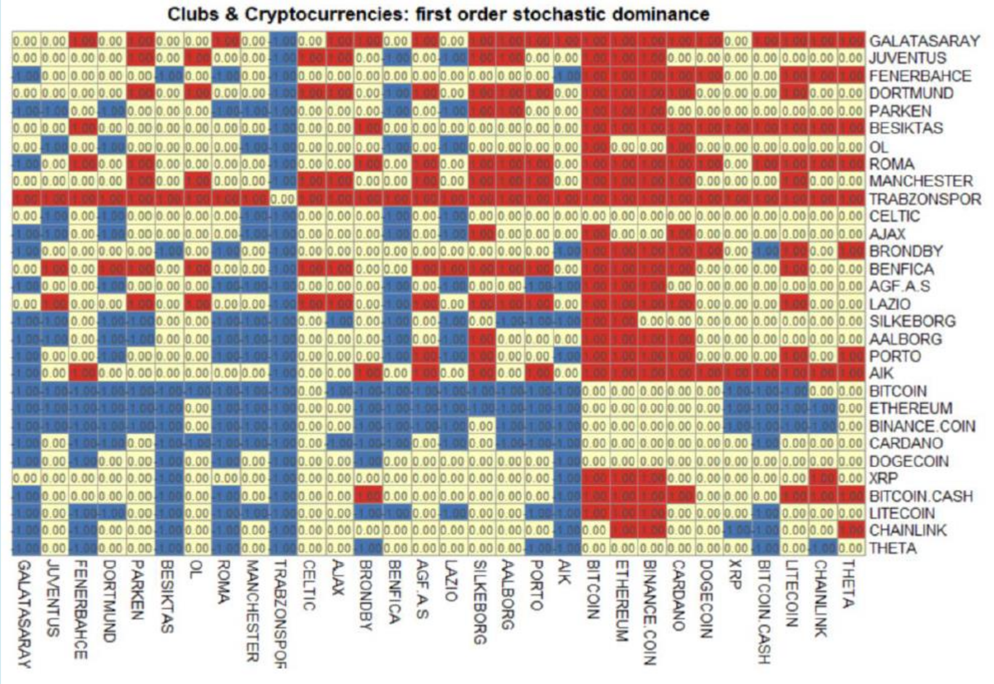
- We use Vinod (2004) and Linton et al.(2010) to estimate stochastic dominance, SD, which requires no underlying assumption about underlying return distribution. We consider dominance significant only if pair-wise results for assets are symmetrical, i.e., if A dominates B and B is dominated by A.
- If A dominates B at first order, the returns of A are always higher than those of B. Second order stochastic dominance refers to non-satiated and risk averse investor preferences. Thus, second order SD highlights assets that offer better return per unit of risk.
- Third order SD extends non-satiation and risk aversion with a preference for positive skewness. If A and B have the same mean and variance but A has more positively skewed distribution, a third order SD investor prefers A to B.

Sport (football) vs crypto

Stochastic dominance



Pre-COVID: First order stochastic dominance

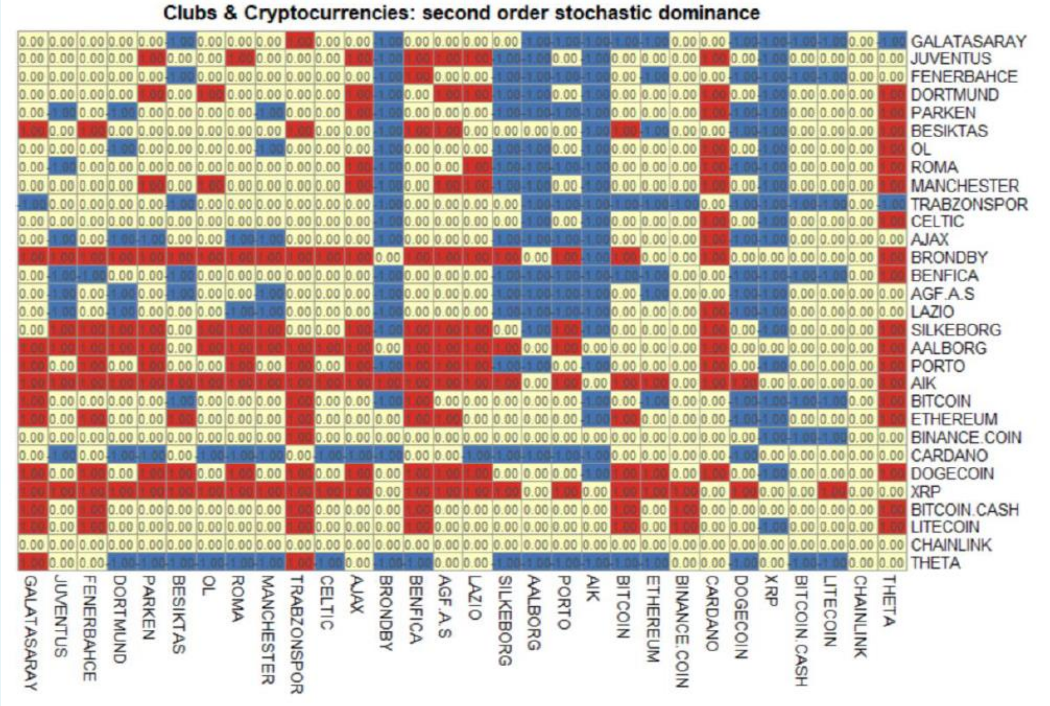


COVID period: First order stochastic dominance

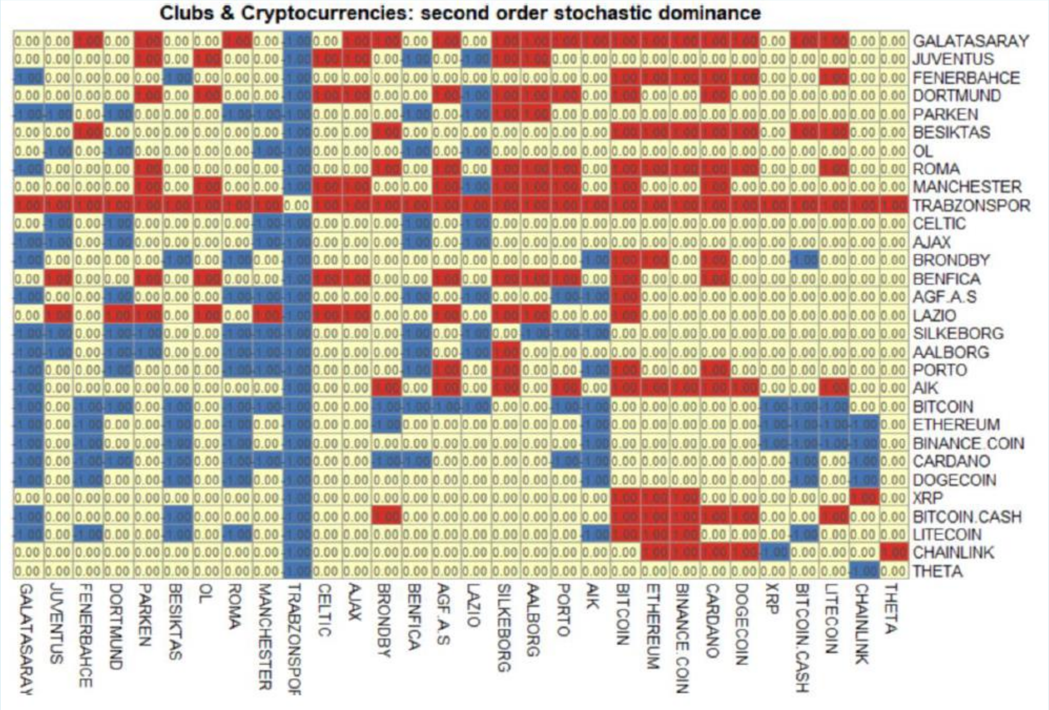
- In the pre-COVID period, Turkish clubs Galatasaray, Fenerbahce, Trabzonspor and Benfica dominate Dogecoin, XRP, Bitcoin Cash, and Litecoin.
- On average, football clubs' equities dominate the crypto-asset group during pre covid period.
- During the COVID period, most football clubs demonstrate plummeting returns, while crypto-assets demonstrate first-order stochastic dominance over football clubs. Bitcoin dominates all but one football club (Celtic).

Sport (football) vs crypto

Stochastic dominance



Pre-COVID: Second order stochastic dominance

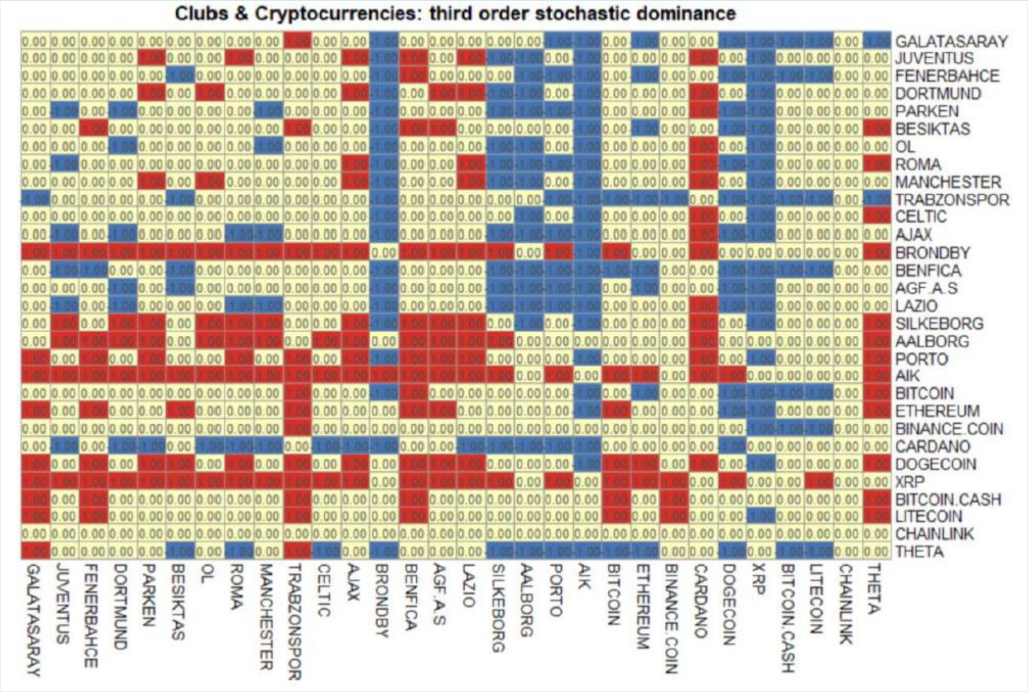


COVID period: Second order stochastic dominance

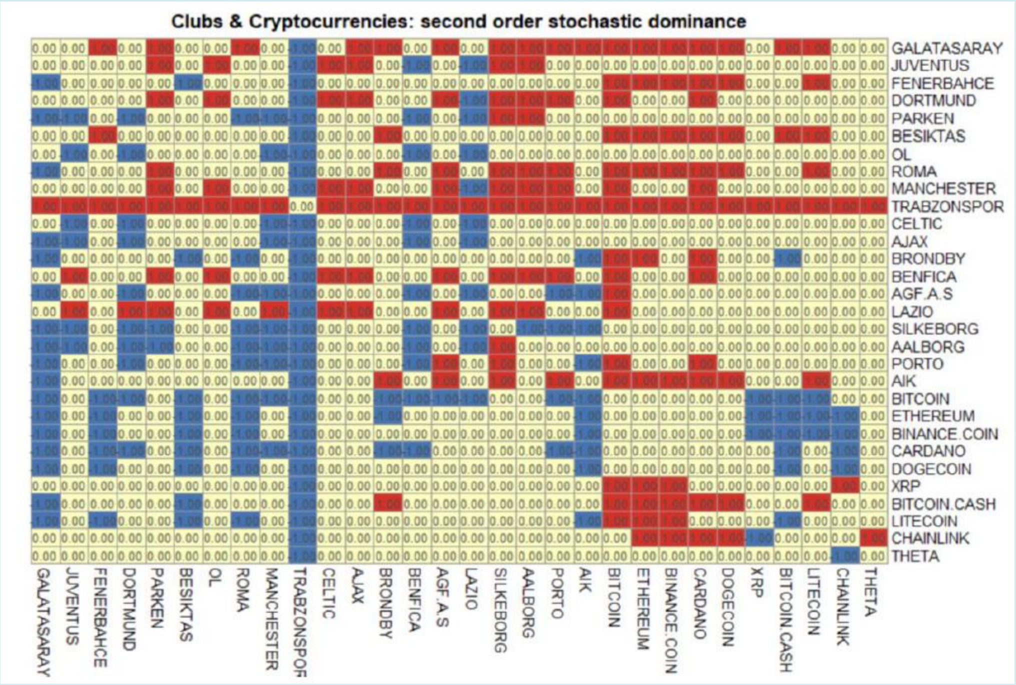
- For the pre-COVID period, the second order stochastic dominance is similar to the first order SD.
- However, during COVID, the second order SD results indicate a reduction in crypto dominance, stemming from higher risk levels compared to football clubs’ equities

Sport (football) vs crypto

Stochastic dominance



Pre-COVID: Third order stochastic dominance



COVID period: Third order stochastic dominance

- For the pre-COVID period, third order SD results are consistent.
- For the COVID period, third order SD indicates lower prominence of crypto domination.

Sport (football) vs crypto

Portfolio optimization

- We optimize portfolios using Probabilistic Utility (Matkovskyy, R., Jalan, A., Dowling, M., Bouraoui, T.(2021). From bottom ten to top ten: The role of cryptocurrencies in enhancing portfolio return of poorly performing stocks. Finance Res.Letters 38, 101405.).
- This approach is less sensitive to sample size and yields less concentrated portfolios.
- We apply variations of the Metropolis-Hastings methods (Tierney,1994; Vihola,2012).
- The proportion of wealth allocated between risky and less risky assets is set at ‘moderate’ with investment horizons spanning 5 to 293 days.

Sport (football) vs crypto

Portfolio optimization

Asset	Sample-5	Sample-10	Sample-20	Sample-60	Sample-126	Sample-252	Sample-293
Galatasaray	2.90%	2.89%	2.87%	3.13%	3.31%	3.71%	3.51%
Juventus	1.83%	1.85%	1.69%	1.53%	1.31%	1.17%	1.15%
Fenerbahce	2.63%	2.20%	2.10%	2.26%	1.90%	2.24%	2.00%
Dortmund	1.64%	2.04%	1.84%	1.37%	1.23%	1.02%	1.00%
Parken	1.97%	1.63%	1.77%	1.51%	1.39%	1.17%	1.09%
Besiktas	2.85%	2.93%	2.46%	2.95%	3.04%	2.73%	3.11%
Ol	1.84%	1.82%	1.58%	1.30%	1.22%	0.94%	0.85%
Roma	1.85%	1.84%	1.97%	1.79%	1.24%	1.23%	1.18%
Manchester United	2.02%	1.90%	1.69%	1.69%	1.18%	0.96%	0.91%
Trabzonspor	2.79%	3.03%	3.07%	3.18%	3.63%	3.32%	3.52%
Celtic	1.95%	1.91%	1.68%	1.38%	1.09%	1.06%	0.87%
Ajax	2.27%	1.78%	1.99%	1.53%	1.20%	1.13%	1.04%
Brondby	2.18%	1.75%	1.50%	1.31%	1.03%	1.03%	0.93%
Benfica	11.16%	10.57%	12.14%	8.97%	4.24%	2.99%	2.64%
Agf.a.s	2.19%	1.86%	1.95%	1.99%	1.76%	1.38%	1.62%
Lazio	2.03%	1.94%	1.85%	1.67%	1.40%	1.02%	1.07%
Silkeborg	2.01%	1.80%	1.82%	1.49%	1.35%	1.04%	1.02%
Aalborg	1.81%	1.91%	1.70%	1.59%	1.17%	1.15%	1.06%
Porto	2.38%	2.65%	2.56%	3.12%	2.51%	2.71%	2.60%
Aik	2.24%	2.03%	2.12%	2.04%	1.45%	1.12%	1.61%
All football clubs	**52.52%**	**50.34%**	**50.38%**	**45.77%**	**36.65%**	**33.12%**	**32.79%**
Bitcoin	2.16%	2.19%	2.19%	2.34%	1.76%	1.77%	2.10%
Ethereum	2.25%	2.42%	2.69%	2.31%	2.52%	2.09%	1.93%
Binance Coin	2.50%	2.74%	2.76%	3.36%	3.47%	3.78%	4.62%
Cardano	7.08%	9.63%	7.96%	10.88%	15.34%	18.05%	17.51%
Dogecoin	2.28%	2.37%	2.13%	2.21%	1.95%	1.52%	1.68%
Xrp	2.53%	2.47%	2.13%	2.39%	1.92%	1.57%	1.77%
Bitcoin Cash	6.93%	7.58%	8.73%	8.18%	9.20%	9.15%	9.43%
Litecoin	3.70%	3.40%	3.49%	3.79%	4.79%	5.24%	4.74%
Chainlink	13.64%	9.27%	9.46%	6.50%	6.84%	5.62%	5.57%
Theta	4.42%	7.58%	8.08%	12.26%	15.56%	18.11%	17.86%
All cryptocurrencies	**47.48%**	**49.66%**	**49.62%**	**54.23%**	**63.35%**	**66.88%**	**67.21%**
Sum	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
Concentration ratio	**0.09**	**0.09**	**0.09**	**0.10**	**0.13**	**0.15**	**0.15**

Asset	Sample-5	Sample-10	Sample-20	Sample-60	Sample-126	Sample-252	Sample-293
Galatasaray	2.94%	3.17%	2.83%	2.90%	2.93%	3.68%	3.72%
Juventus	2.94%	2.81%	2.92%	3.25%	2.91%	3.60%	3.46%
Fenerbahce	3.09%	2.97%	3.09%	3.27%	3.03%	2.97%	3.22%
Dortmund	2.62%	2.83%	3.02%	3.06%	3.13%	3.60%	3.83%
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Ol	2.78%	2.94%	3.42%	3.02%	2.95%	3.23%	3.32%
Roma	2.76%	3.02%	3.30%	2.80%	3.78%	3.18%	3.49%
Manchester United	3.24%	2.95%	3.15%	3.15%	3.33%	3.26%	3.50%
Trabzonspor	3.22%	2.78%	3.23%	3.11%	3.20%	3.61%	2.98%
Celtic	2.70%	2.66%	2.86%	3.07%	3.38%	3.37%	3.41%
Ajax	2.53%	3.02%	2.66%	2.97%	2.98%	3.71%	3.26%
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All football clubs	**57.90%**	**58.39%**	**60.07%**	**62.14%**	**64.72%**	**67.99%**	**68.54%**
Bitcoin	2.54%	2.77%	3.24%	3.14%	3.14%	3.87%	3.51%
Ethereum	2.87%	3.07%	2.61%	2.95%	3.41%	3.58%	3.65%
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Cardano	2.68%	2.75%	3.04%	3.17%	3.20%	3.20%	3.48%
Dogecoin	15.66%	15.67%	14.18%	9.66%	6.00%	0.95%	0.67%
Xrp	2.65%	2.98%	2.71%	3.31%	3.53%	3.80%	3.42%
Bitcoin Cash	3.31%	2.47%	2.98%	2.89%	3.04%	3.02%	3.43%
Litecoin	2.92%	3.00%	2.58%	3.04%	2.79%	3.42%	3.30%
Chainlink	3.41%	3.07%	2.82%	3.42%	3.30%	3.34%	3.36%
Theta	2.89%	3.00%	3.04%	3.11%	3.29%	3.23%	3.28%
All cryptocurrencies	**42.10%**	**41.61%**	**39.93%**	**37.86%**	**35.28%**	**32.01%**	**31.46%**
Sum	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
Concentration ratio	**0.12**	**0.13**	**0.11**	**0.07**	**0.05**	**0.04**	**0.04**

STABLECOINS

Jalan, A., Matkovskyy, R., and Yarovaya, L. (2021). Shiny crypto assets: A systemic look at gold-backed cryptocurrencies during the COVID-19 pandemic. International Review of Financial Analysis 78, 101958

Stablecoins

- Griffin and Shamst (2020) analysed whether Tether influenced Bitcoin and other cryptocurrency prices during the 2017 boom.
  - Their findings show an evidence that **Bitcoin price increased with increase of purchases with Tether**, i.e. stablecoin that backed by the USD.
- Ante et al. (2020) analysed seven fiat-backed stablecoins and found that **stablecoin issuances contribute to price discovery and market efficiency of cryptocurrencies**.
- Wang et al. (2020) analysed three USD-pegged and three gold-pegged stablecoin (DGD, HGT, and XAUR) during the period up to March 2019, and show that even **though gold-backed cryptocurrencies are not as effective save haven as gold, they still can be used as an effective tool to in reducing extreme losses.**
- Aloui et al. (2020) analysed the differences between Islamic gold-backed cryptocurrencies and non-Islamic gold-backed cryptocurrencies, showing that **Islamic gold-backed cryptocurrencies are less susceptible to the geopolitical risk than non-Islamic tokens**.
- Wasiuzzaman et al. (2021) further investigated the performance of PAX Gold during the COVID-19 pandemic, **reporting time-varying safe haven properties of this stablecoin**. However, existing empirical evidence is available only for very few gold-backed tokens from very narrow methodological approaches.

Digix Gold Token (DGX)

- Digix Gold Token (DGX) is an asset-backed token and backed by the weight of gold (1DGX=1 gram of gold).
- It uses the Proof of Provenance (PoP) protocol based on Ethereum and the Inter Planetary Files System (IPFS).

Perth Mint Gold Token (PMGT)

- Perth Mint Gold Token (PMGT) is a gold-backed stablecoin based on a public blockchain backed by government.
- It is backed by a GoldPass digital gold certificate issued by The Perth Mint and guaranteed by the Government of Western Australia.
- 1 PMGT equals 1 fine troy ounce of physical gold.
- It is an ERC20 compliant token on Ethereum network.

Tether Gold (XAUT)

- Tether Gold is a digital asset offered by TG Commodities Limited, which represents 1 troy fine ounce of gold on a London Good Delivery gold bar, and currently trading at FTX, Bitfinex, Delta Exchange and Goku Markets.
- XAUT uses Ethereum blockchain

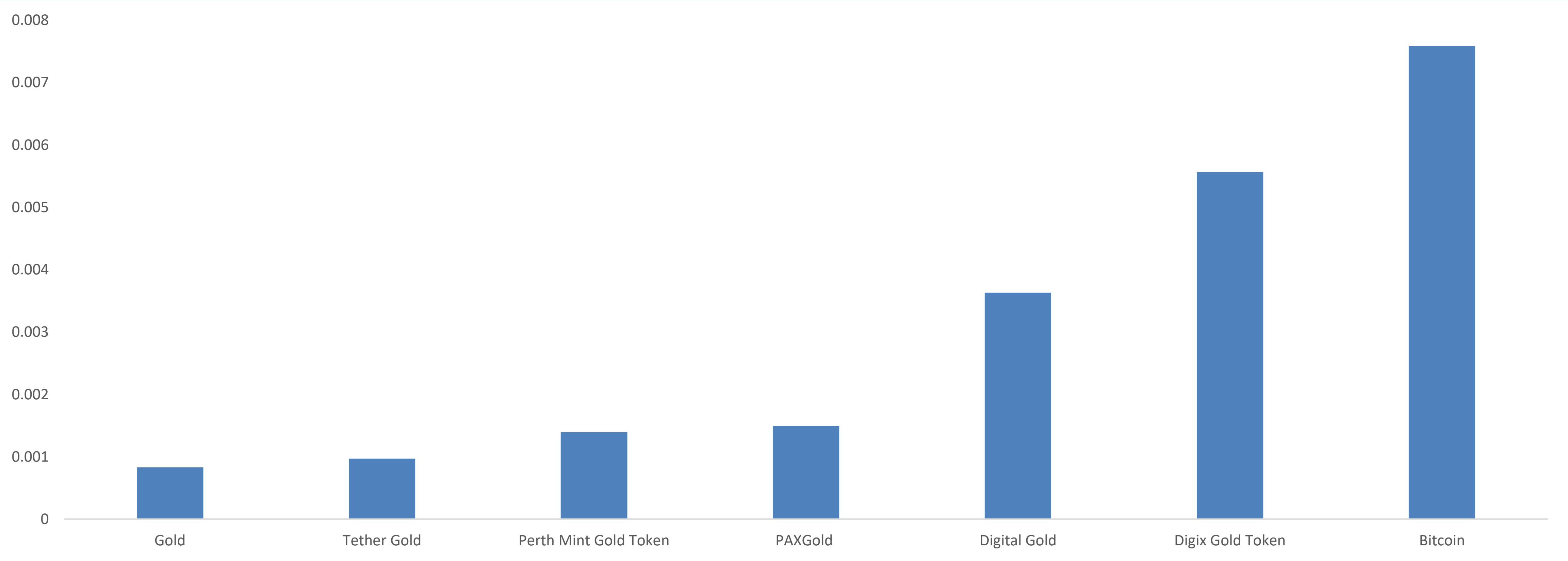
PAX Gold (PAXG)

- PAX Gold also an ERC-20 token on Ethereum Blockchain, and it is backed by one fine troy ounce (t oz) of a 400 oz London Good Delivery gold bar, that is stored in Brink's gold vaults.
- Created in September 2019, PAXG does not have government guarantee as PMGT, and the underlying physical gold is stored by Paxos Trust Company, that regulated by New York State Department of Financial Services.

Digital Gold (GOLD)

- Digital gold enables users to purchase coverage in physical gold, via the ERC-20 Ethereum-based GOLD token.
- One GOLD token equals 1 gram of physical gold 99.99 purity, and claim to have no transfer fees, however, they do charge a small percent of GOLD’s holding daily.

Average realized variance of the selected assets



Liquidity

- Liquidity is a traditionally important component that affects returns, transaction costs, market efficiency, and investment decisions in general (Bekaert, Harvey, & Lundblad, 2007; Chordia, Roll, & Subrahmanyam, 2008; Lee, 2011 etc.).
- The high-low range (HLR) following Chung and Zhang (2014)

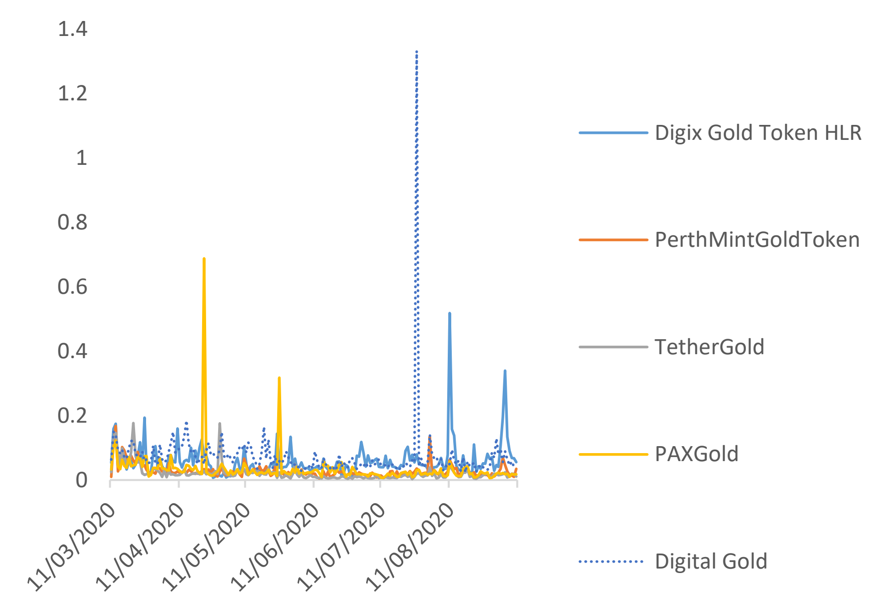
$$HLR_t = \frac{H_t - L_t}{0.5\,(H_t + L_t)}$$

- volatility over volume (VoV) using the index developed by Fong et al. (2017):

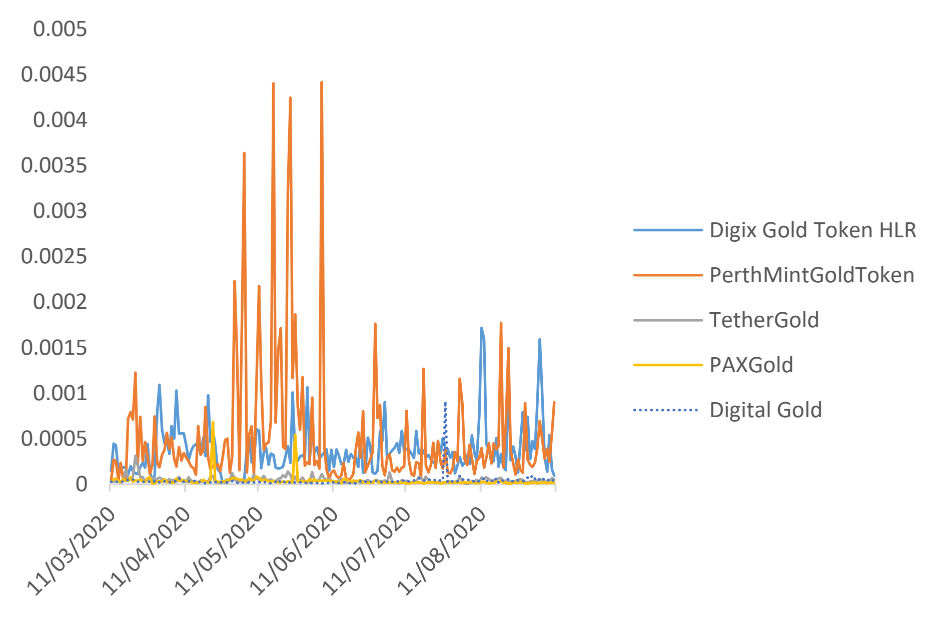
$$VoV_t = \frac{\ln\left({}^{H_t}/_{L_t}\right)}{\sqrt{volume}}$$

Liquidity Dynamics

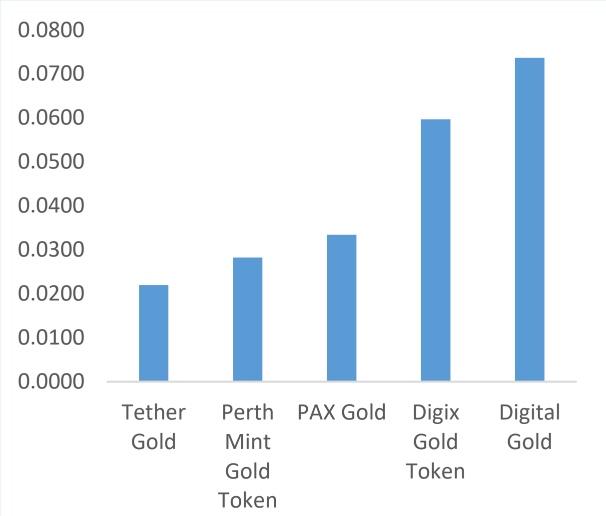
HLR liquidity of the selected stable coins.



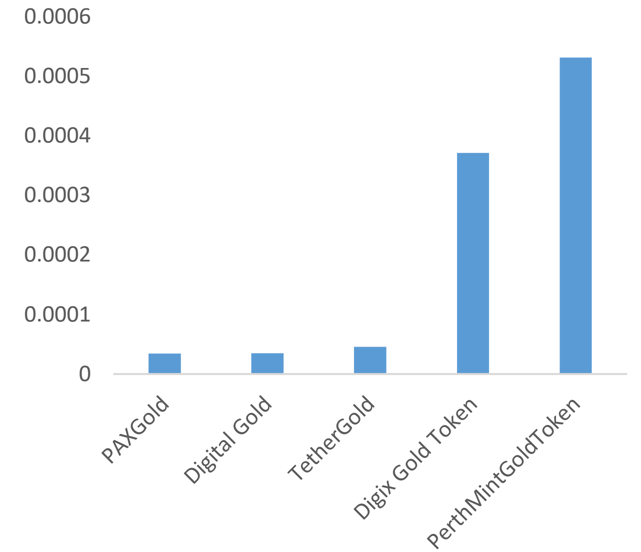
VoV liquidity of the selected stable coins.



Average Liquidity



Average HLR liquidity



Average VoV liquidity

Volumes anomalies

The Mantissa Arc Test and Pearson's Chi-squared test results

Tests	Digix Gold Token	Perth Mint Gold Token	Tether Gold	PAX Gold	Digital Gold
Pearson's Chi-squared test	χ2 =169.83, p=0.000	χ2 =92.432, p=0.3806	χ2 =0.010482, p=0.1453	χ2 =0.0938, p=0.000	χ2 = 133.41, p= 0.000
The Mantissa Arc Test p-value	0.000	0.4151	0.1453	0.000	0.000

Basewd on Table, testing the null hypothesis that volume data follows Benford's Law, we can reject it for DGX, PAXG and GOLD token, since those p-values are essentially zero.
It potentially identifies suspicious patterns in the volume data.

TRUST AND ADOPTION

Jalan, A., Matkovskyy, R., Urquhart, A. and Yarovaya, L. (2022) The role of interpersonal trust in cryptocurrency adoption,JIFMIM (https://doi.org/10.1016/j.intfin.2022.101715)

Is any effect of interpersonal trust in cryptocurrency adoption?

- On the one hand, cryptocurrencies are based on the principle of decentralized control, with participants anonymous except for their e-wallet addresses.
- On the other hand, the sophistication and fool-proof complexity of the blockchain technology that most cryptocurrencies are built on provides a high level of certainty and transparency, which may itself mitigate the need for high levels of trust in crypto adoption

Is any effect of interpersonal trust in cryptocurrency adoption?, cont

- Trust data has been collected from the WVS wave 7, covering the period 2017-2020.
  - In this survey, the main trust-related question useful for our paper is "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?". There are 5 possible answers: 1: Most people can be trusted, 2: Need to be very careful, -1: Don´t know, -2: No answer, -4: Not asked. Our sample comprises 70,867 observations.
- For our dependent/ continuous variables – the number of tweets and google trends, the number of active, sending, receiving, new and total addresses, and market capitalization of Bitcoin, Ethereum, and Litecoin, the three dominant players by market capitalization
- Empirical framework: used a Point-Biserial Correlation (a Population Product-Moment Correlation) and GLM
- For generalized linear modeling, we control for standard personal characteristics of responders, namely, "Sex", "Age", "Marital status", "Education level" , "Employment status", and "Scale of incomes", Uncertainty Avoidance Index (UAI) and long term versus short term normative orientation, LTO.
  - UAI captures the attitude of a society towards risk and uncertainty: A high score indicates general discomfort with uncertain and ambiguous situations, while a low score shows flexibility in attitude and higher likelihood of engaging in risky behavior (Hofstede, 2001). Consequently, it can be used as a proxy to measure people's trust in the future and to what extent they can deal with the fact that the future is uncertain.
  - LTO on the other hand, refers to the degree to which a society demonstrates pragmatism and a future-oriented perspective with emphasis on the future, thrift and persistence: higher scores indicate a pragmatic, future-oriented approach.
- $Y = a_0 + a_1 Trust + a_2 Sex + a_3 Age + a_4 Marital_{Status} + a_5\ Education_{level} + a_6 Employment_{status} + a_7 Scale_{of_{incomes}} + a_8 Cultural\_differences + \varepsilon$

Is any effect of interpersonal trust in cryptocurrency adoption?, cont

- **Our results indicate a positive and statistically significant effect of trust on interest in and adoption of cryptocurrencies, confirming the importance of trust in the growth of financial markets**
- **In terms of cultural dimensions:**
  - **uncertainty avoidance has a positive and statistically significant effect on interest in cryptocurrency and its adoption**, indicating that contrary to popular belief about investor rationality and risk aversion, **uncertainty and ambiguity increase the interest in cryptocurrencies and their adoption**.
  - **the Long/short term orientation index estimates remain negative and statistically significant across all models, indicating the role of 'impulse' and myopic vision in cryptocurrency investing** (higher scores on this index indicate a thoughtful, pragmatic approach, while low scores show normative, short-term vision)

CRYPTOCURRENCY DURING THE WAR

Cryptocurrency during the war

- So far, **Bitcoin had outperformed gold and most other traditional assets including U.S. Treasuries and safe-haven currencies**, which are generally perceived as a geopolitical hedge

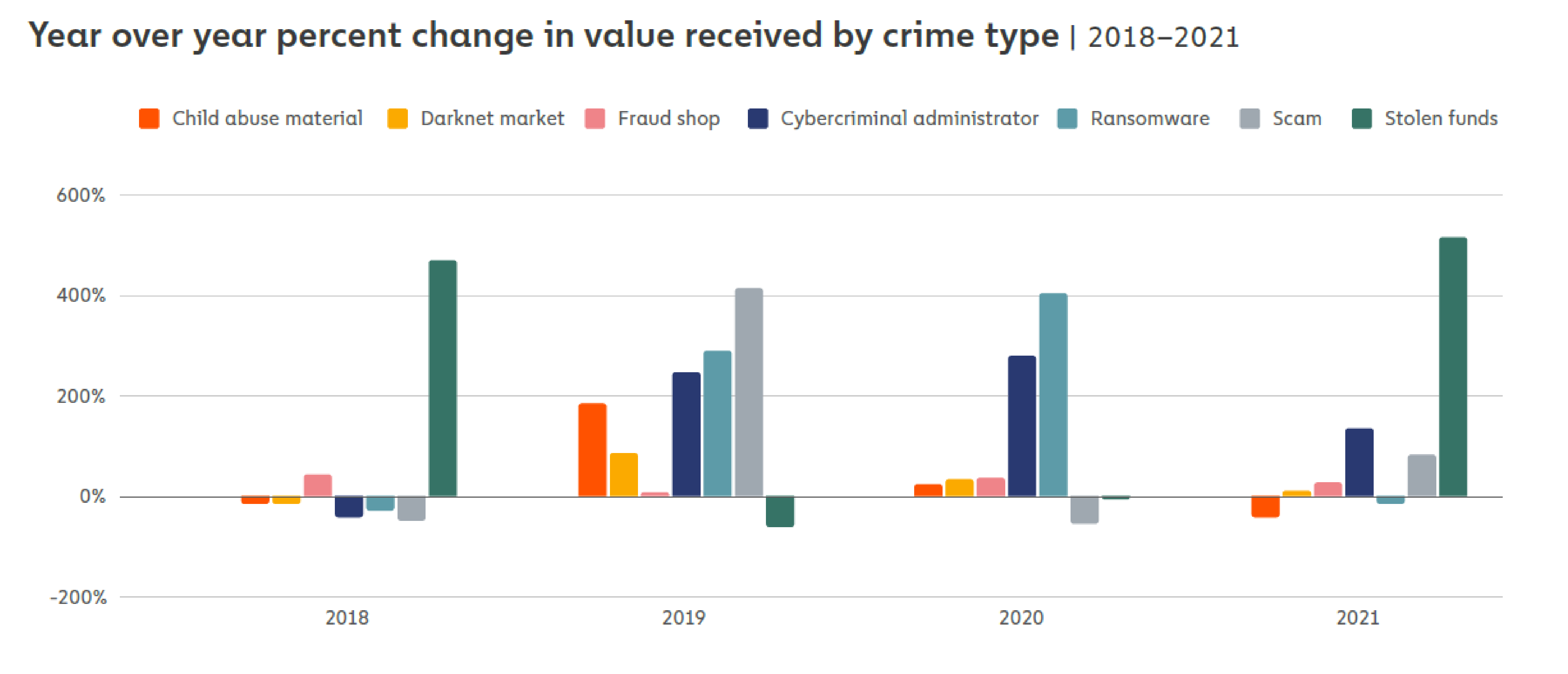
But what is happening with the cryptocurrency during the last four weeks?

- After Russian invasion on 24.02.2022, **the trading volumes in rubles jumped on the exchanges**.
  - **USDT-RUB trade volumes spiked to all time highs** and accounted for higher volumes than BTC-RUB markets.
  - Starting from 27.02.22 the **volumes were several billions of rubles a day**.
  - **The trade volumes of gold backed cryptocurrencies increased on the invasion day** e.g. PAX gold, Tether Gold (as well as gold)

- In Ukrainian hryvnias – it increased on the 26-28 of February.
  - **UAH crypto volumes soared to 5 month highs** (due to donations in cryptos).
  - Immediately following Russia's invasion, **Bitcoin traded at a 6% premium** on Binance’s Ukrainian Hryvnia (UAH) market as demand for cryptocurrencies soared.
  - **Price slippage**, defined as the difference between the expected price of a trade and the price at which the trade is fully executed, also **underwent a sharp spike and ongoing volatility on the Russian invasion**.
  - Now it is back to pre-invasion time.
  - Herding was not detected

CRYPTO CRIME

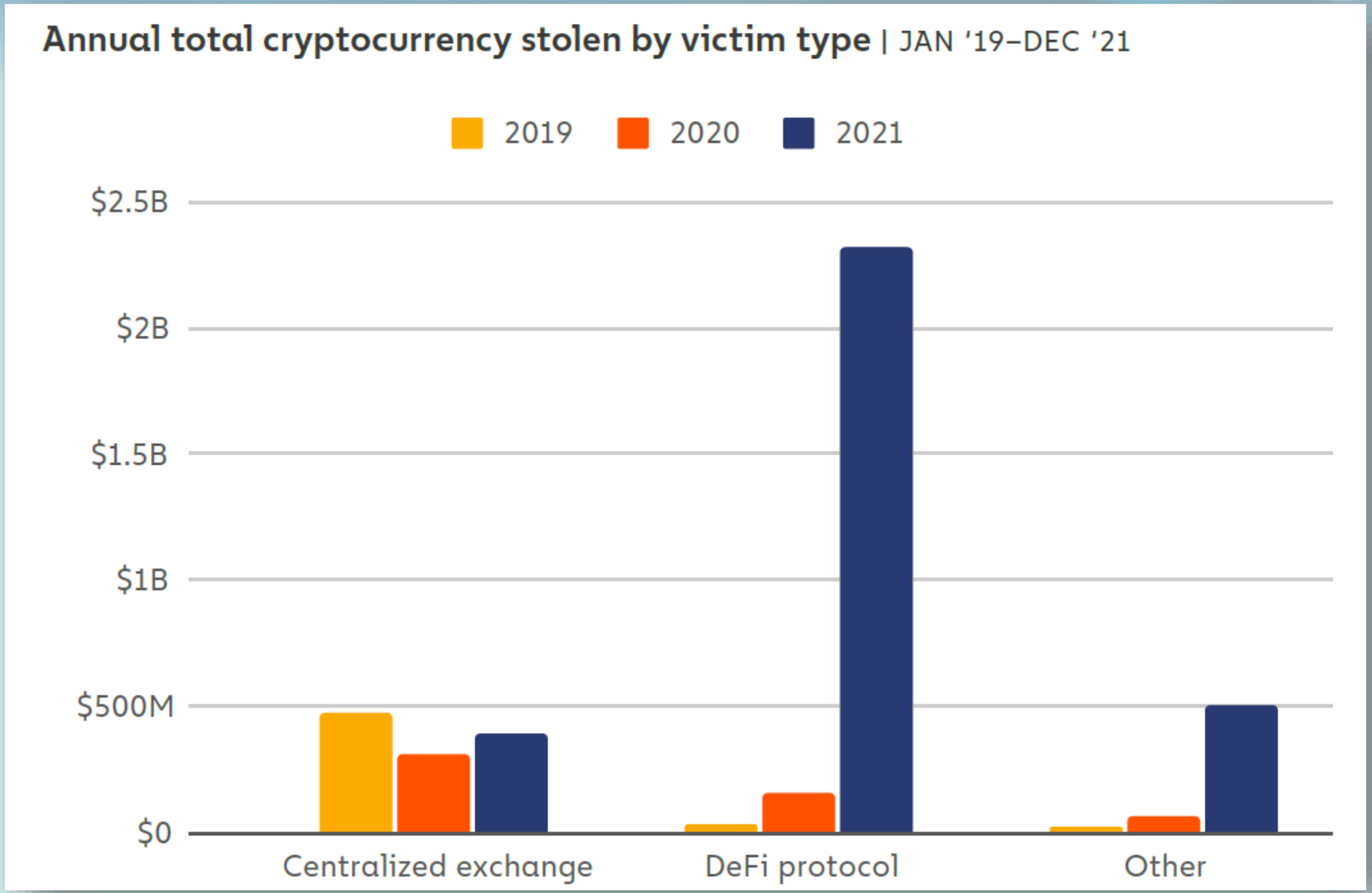
Crypto crime



THE 2022 CRYPTO CRIME REPORT

Two categories stand out for their growth: stolen funds and, to a lesser degree, scams. DeFi is a big part of the story for both.

Crypto crime



THE 2022 CRYPTO CRIME REPORT

THANK YOU!