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Cryptoassets in Asset Allocation:

a new asset class

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Objectives

The main goals of this work are the following:

1. Analyze the **state of the art** about the usage of cryptoassets in asset allocation in order to reduce portfolio volatility
2. Study the properties of cryptoassets as financial instruments: **correlations**, **returns** and **volatility**
3. Study the **optimal allocation** for a portfolio that contains cryptoassets and mainstream assets

Introduction

Cryptoassets are a type of digital assets that depend primarily on cryptography and distributed ledger technology as part of their perceived or inherent value. Since the launch of Bitcoin on the 3^{rd} of January 2009 a wide range of cryptoassets have been established, each one with slightly different characteristics

Introduction

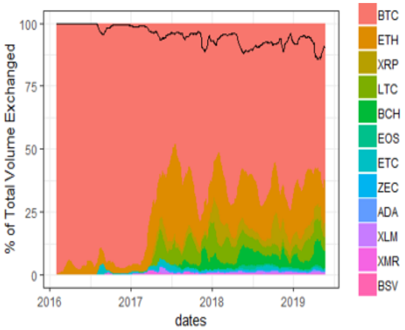
The first protocol to solve the problem of **double-spending** without the need for a centralized party and to achieve **scarcity** in the digital realm

Backed by a blockchain, the technology is aimed at a specific use case: **smart** contracts

Bitcoin's closest rival in terms of the use case. There is a **limited supply** of 84 million litecoins, compared to 21 million bitcoins

A cross-border **payments solution** for large financial institutions based on blockchain technology. A transaciont of XRP can be settled in 4 seconds

More than 90% of total volumes exchanged is covered by tha main 4 digital assets



Outline

Dataset I

The dataset contains 886 observations of the prices (expressed in USD) of 20 assets valued daily (excluding holidays and weekends) from the 1^{st} of January 2016 till the 24^{th} of May 2019 (some data provided by Bloomberg and others, the ones related to the cryptoassets, by Coinmarketcap).
The assets we included in our analysis are grouped into five classes:

1. Cryptoassets:
   - **Bitcoin** (btc): price of a single bitcoin
   - **Ethereum** (eth): price of a single ether
   - **Litecoin** (ltc): price of a single litecoin
   - **Ripple** (xrp): price of a single ripple
2. Stock indexes:
   - **S&P500** (sp500): American stock market index based on 500 large company with stock listed either on the NYSE or NASDAQ
   - **EUROSTOXX 50** (eurostoxx): equity index of eurozone stocks, covering 50 stocks from 11 eurozone countries
   - **MSCI BRIC** (bric): market cap weighted index designed to measure the equity market performance across the emerging country indexes of Brazil, Russia, India and China
   - **NASDAQ**(nasdaq): market cap weighted index including all NASDAQ tiers: Global Select, Global Market and Capital Market

Dataset II

3. Bond indexes:
   - **BBG Pan European** (bond_europe): Bloomberg Barclays Pan-European Aggregate Index that tracks fixed-rate, investment-grade securities issued in different European currencies
   - **BBG Pan US** (bond_us): BBG US Aggregate Bond Index, a benchmark that measures investment grade, US dollar-denominated, fixed-rate taxable bond market
   - **BBG Pan EurAgg** (bond_eur): similar to the Pan European but it only considers securities issued in Euros

4. Currencies:
   - **EUR/USD** (eur): spot price of one Euro
   - **GBP/USD** (gbp): spot price of one British Pound
   - **CHF/USD** (chf): spot price of one Swiss Franc
   - **JPY/USD** (jpy): spot price of one Japanese Yen

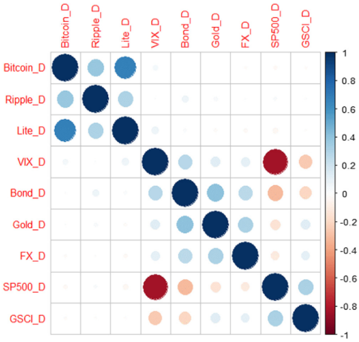
5. Commodities:
   - **Gold** (gold): price of gold measured in USD/Oz
   - **WTI** (wti): price of crude oil used as benchmark in oil pricing and as the underlying commodity in the NYMEX oil future contracts
   - **Grain** (grain): S&P GPSCI index that measures the performance of the grain commodity market
   - **Metals** (metal): S&P GSCI Industrial Metals index that measures the movements of industrial metal prices including aluminium, copper, zinc, nickel and lead

Outline

Correlations

In literature there are few studies about correlations between cryptoasstes and often the results are contradictory. They are strongly related to the time window one considers

January 2013 - July 2017



August 2015 - April 2018

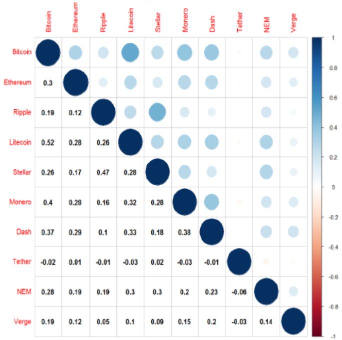


Figure: Correlation matrices presented in Corbet et al. (2018) (left matrix) and Liu (2018) (right matrix)

Markowitz Model

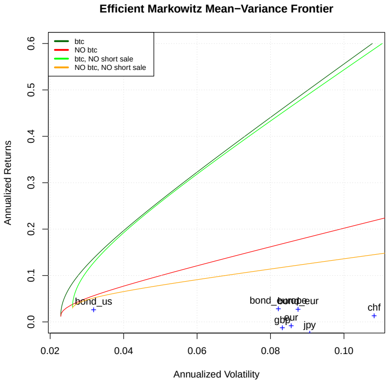
The **Efficient Frontier** is the set of portfolios which satisfy the condition that no other portfolio exists with a higher expected return but with the same standard deviation of return. One can obtain this set by solving the following quadratic problem and by taking the positively sloped portion of the resulted hyperbola:

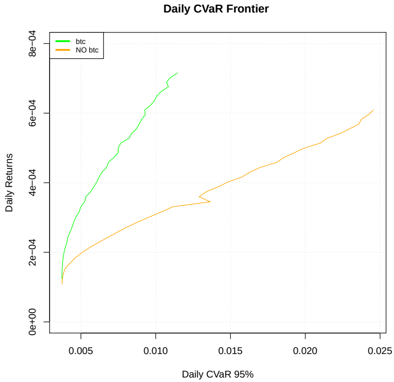
$$\begin{aligned} \min_{w \in \mathcal{W}} \quad & \frac{1}{2} w^t \Sigma w \\ \text{s.t.} \quad & \mathbb{E}\left[R_p\right] = \mu \\ & e^T w = 1 \end{aligned} \tag{1}$$

for $\mu \in (-\inf, \inf)$.

Efficient Frontiers

In Vianello (2018) the dataset goes from July 2010 to November 2018 and it contains Bitcoin and several financial instruments that rapresent the asset classes. The author computed efficient frontier with the usual objective function and with the CVaR objective function:





In both cases including bitcoin is a winning strategy.

Outline

Empirical Correlations

The empirical correlation is computed using Pearson's sample correlation formula on the daily log-returns obtained from the price dataset.

	btc	eth	ltc	xrp	bric	sp500	eurostoxx	nasdaq	bond_europe	bond_us	bond_eur	eur	gbp	chf	jpy	gold	wti	grain	metal
btc	100																		
eth	45	100																	
ltc	59	43	100																
xrp	35	29	39	100															
bric	1	3	7	8	100														
sp500	3	3	5	6	46	100													
eurostoxx	1	-3	4	4	53	54	100												
nasdaq	4	4	7	6	46	95	49	100											
bond_europe	2	2	3	2	5	3	8	6	100										
bond_us	-2	0	-4	1	-11	-28	-29	-24	46	100									
bond_eur	3	4	3	1	2	0	-1	3	87	50	100								
eur	2	5	-3	1	11	4	-8	2	-14	15	-8	100							
gbp	2	-1	-3	0	18	19	22	16	15	-5	-12	55	100						
chf	0	8	-2	1	2	-12	-22	-13	-3	28	0	78	42	100					
jpy	2	3	-1	0	-18	-34	-42	-30	15	52	21	37	5	50	100				
gold	3	5	0	1	-3	-19	-31	-17	11	43	18	44	13	47	61	100			
wti	-1	-7	-1	2	29	33	33	25	2	-18	-2	3	14	-4	-12	1	100		
grain	6	2	2	1	12	8	10	7	0	0	-1	10	6	5	3	7	11	100	
metal	1	3	5	3	35	23	24	20	0	-16	-8	16	14	7	-9	13	29	11	100

The results clearly show that:

- Cryptoassets has low correlation with every other asset
- Assets in the same class usually have a high correlation among them

P-Values

We then computed the significance of historical correlations through Pearson's t-test and Permutation test:

		bric	sp500	eurostoxx	nasdaq	bond_europe	bond_us	bond_eu
btc	Correlation	0.01	0.03	0.01	0.04	0.02	-0.02	0.03
	Pearson %	82.01	34.80	83.23	22.26	46.85	60.01	32.79
	Permutation %	81.20	35.40	81.60	25.20	42.80	63.40	33.00

		eur	gbp	chf	jpy	gold	wti	grain	metal
btc	Correlation	0.02	0.02	0.00	0.03	0.03	-0.01	0.06	0.01
	Pearson %	55.38	61.86	95.44	55.09	43.73	73.35	8.44	80.79
	Permutation %	52.60	61.40	96.80	59.40	44.80	73.80	9.00	82.40

Table 3.2: hypothesis test btc correlations

		bric	sp500	eurostoxx	nasdaq	bond_europe	bond_us	bond_eu
eth	Correlation	0.03	0.03	-0.03	0.04	0.02	0.00	0.04
	Pearson %	44.35	41.67	41.48	23.22	49.71	90.66	29.09
	Permutation %	47.40	41.60	41.20	22.20	51.00	88.80	30.80

		eur	gbp	chf	jpy	gold	wti	grain	metal
eth	Correlation	0.05	-0.01	0.08	0.03	0.05	-0.07	0.02	0.03
	Pearson %	11.04	73.73	2.06	38.20	12.31	4.41	65.20	38.74
	Permutation %	11.80	70.40	1.80	38.40	13.40	3.00	65.40	36.60

Table 3.3: hypothesis test eth correlations

		bric	sp500	eurostoxx	nasdaq	bond_europe	bond_us	bond_eu
ltc	Correlation	0.07	0.05	0.04	0.07	0.03	-0.04	0.03
	Pearson %	5.24	11.05	23.44	4.60	38.33	25.24	35.83
	Permutation %	4.40	12.20	19.60	5.40	34.00	26.40	35.00

		eur	gbp	chf	jpy	gold	wti	grain	metal
ltc	Correlation	-0.03	-0.03	-0.02	-0.01	0.00	-0.01	0.02	0.05
	Pearson %	34.41	34.69	58.46	84.82	99.16	85.25	57.12	12.70
	Permutation %	33.20	37.20	58.20	87.40	99.00	87.40	56.20	13.20

Table 3.4: hypothesis test ltc correlations

		bric	sp500	eurostoxx	nasdaq	bond_europe	bond_us	bond_eu
xrp	Correlation	0.08	0.06	0.04	0.06	0.02	0.01	0.01
	Pearson %	2.08	8.41	23.69	9.03	45.93	79.43	73.08
	Permutation %	2.80	7.40	24.40	9.00	46.40	81.40	71.40

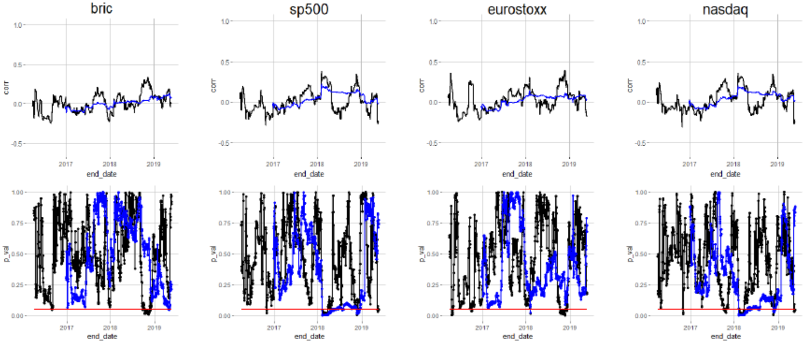
		eur	gbp	chf	jpy	gold	wti	grain	metal
xrp	Correlation	0.01	0.00	0.01	0.00	0.01	0.02	0.01	0.03
	Pearson %	84.02	90.38	83.88	95.71	70.48	64.27	75.19	31.56
	Permutation %	83.40	88.80	83.40	92.40	73.00	60.00	72.40	30.40

Table 3.5: hypothesis test xrp correlations

In almost every case there is no statistical evidence that correlations are different from zero and when this is the case, the correlations are always below 0.1 in absolute value

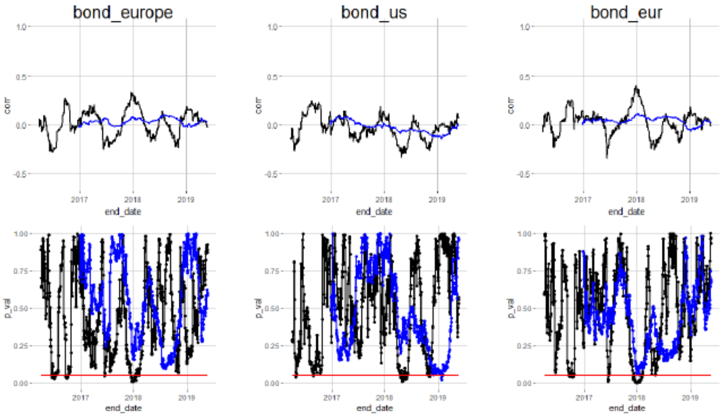
Bitcoin Rolling Correlations

Equities



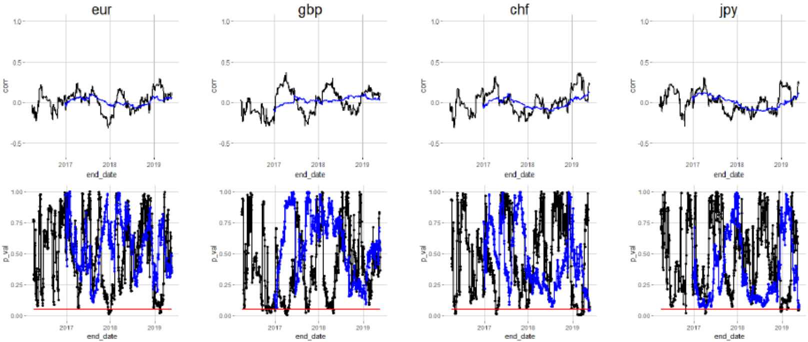
Bitcoin Rolling Correlations

Bonds



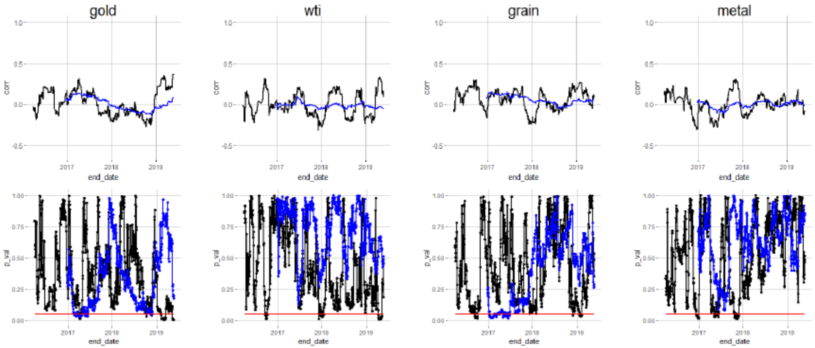
Bitcoin Rolling Correlations

Currencies

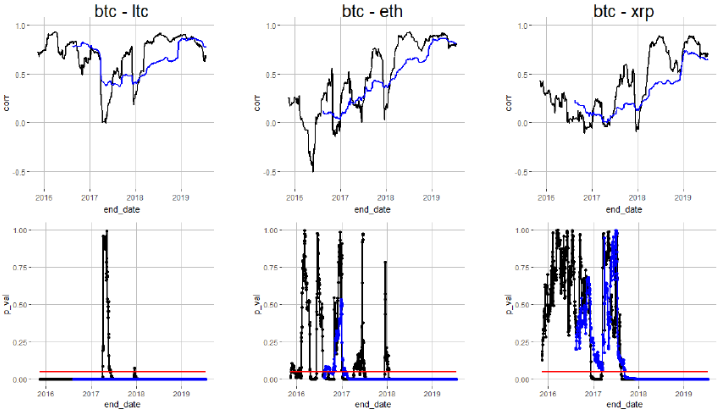


Bitcoin Rolling Correlations

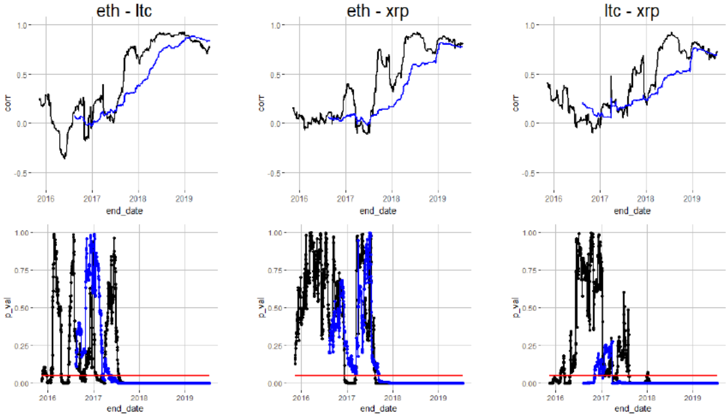
Commodities



Cryptoassets Rolling Correlations

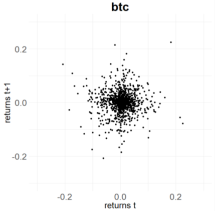


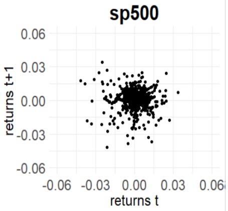
Cryptoassets Rolling Correlations

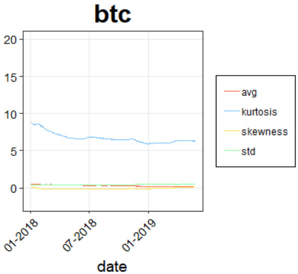


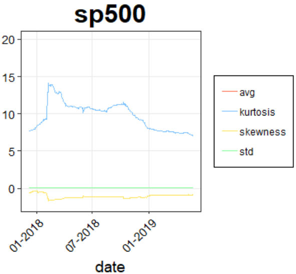
Returns Distribution

Are returns of cryptoassets **i.i.d.**?







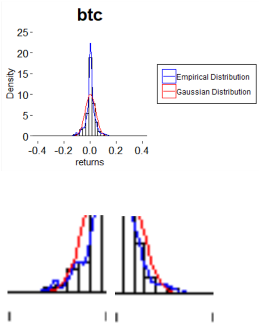


The distribution parameters are calculated on a 2-years rolling window

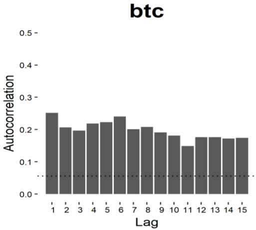
Return Distribution

But they also have the same drawbacks of standard assets' returns

Fat Tails



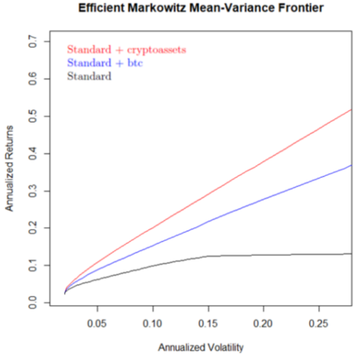
Volatility Clustering



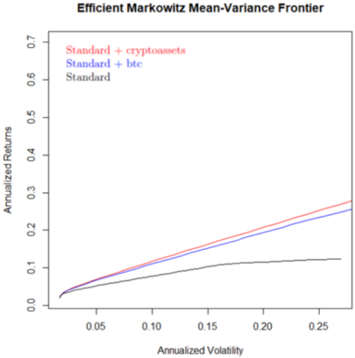
Outline

Efficient Frontiers

From the 1^{st} of January 2016 till the 24^{th} of May 2019



From the 14^{th} of July 2017 till the 24^{th} of May 2019



	Whole dataset	Second half
Standard + cryptoassets	8.87%	3.59%
Standard + btc	5.87%	3.62%
Standard	3.88%	3.05%

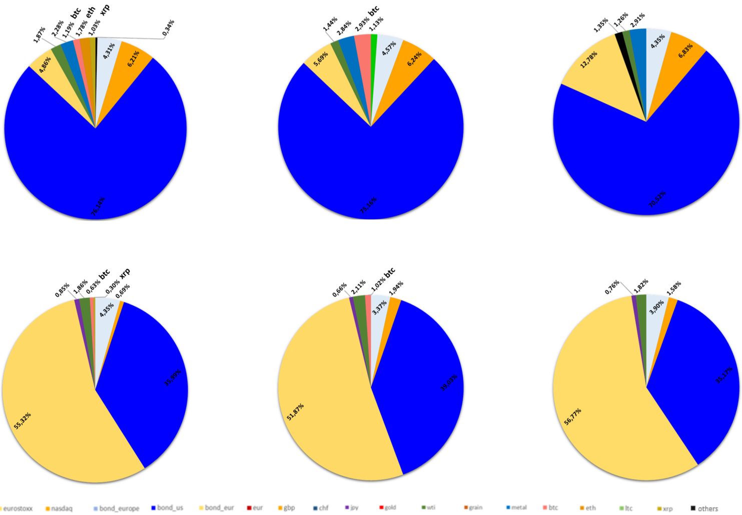
Optimal Portfolio

Best Sharpe Ratio portfolios are allocated as below:

Standard + cryptoassets | Standard + btc | Standard

Whole data set

Half data set



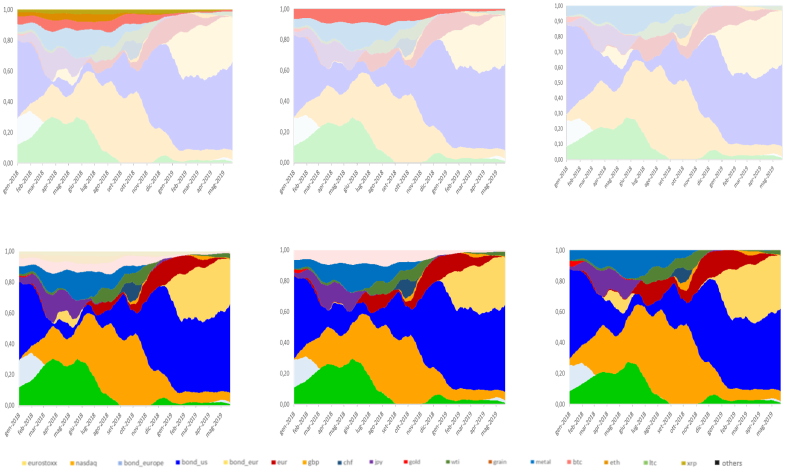
Rolling Optimal Portfolios

2-years rolling time windows for the optimal portfolio, smoothed with a monthly time window:

Standard + cryptoassets | Standard + btc | Standard

Focus on cryptoasset

Focus on Standard Asset



Outline

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Outline

Conclusions

1. Cryptoassets returns behave like standard assets returns: Fat tails and Volatility clustering
2. Cryptoassets are a new asset class
3. In an optimal allocation framework cryptoassets generate value
4. To diversify among digital assets does not contribute to the value generation, thus it is convenient to bet on a single one of these assets

Conclusions

GRAZIE

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