

## Cryptoassets in Asset Allocation:

a new asset class

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## **Objectives**

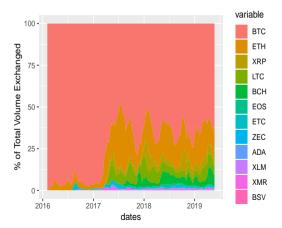
The main goals of this work are the following:

- 1. Analyze the **state of the art** about the usage of cryptoassets in asset allocation in order to reduce portfolio volatility
- Study the properties of cryptoassets as financial instruments: correlations, returns and volatility
- Study the optimal allocation for a portfolio that contains cryptoassets and mainstream assets
- 4. The **original contribution** of this work has been:
  - ► Improve/complete the available statistical analysis
  - investigate the diversification obtained by introducing other cryptoassets beyond bitcoin

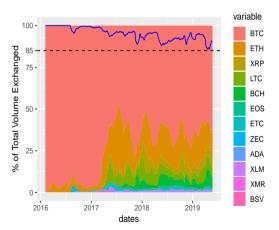
Cryptoassets are a type of digital assets that depend primarily on cryptography and distributed ledger technology as part of their perceived or inherent value. Since the launch of Bitcoin on the 3<sup>rd</sup> of January 2009 a wide range of cryptoassets have been established, each one with slightly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



Bitcoin was more than 85% of total volumes until 2017, more than 50% until the middle of 2019



More than 90% of total volumes exchanged is covered by the 4 major digital assets





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

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### Dataset I

The dataset contains 886 observations of the prices (expressed in USD) of 19 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

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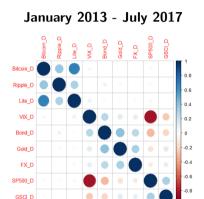
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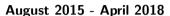
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## Correlations

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





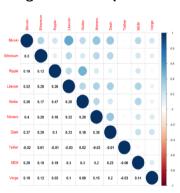


Figure: Correlation matrices presented in Corbet et al. [5] (left matrix) and Liu [12] (right matrix)

## 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:

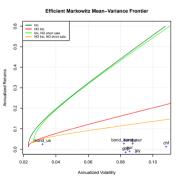
$$\min_{w \in \mathcal{W}} \frac{1}{2} w^t \Sigma w$$
s.t.  $\mathbb{E}[R_p] = \mu$ 

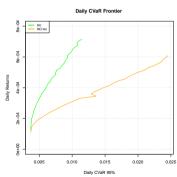
$$e^T w = 1$$
(1)

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

## Efficient Frontiers

In Ametrano-Vianello [25] 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.

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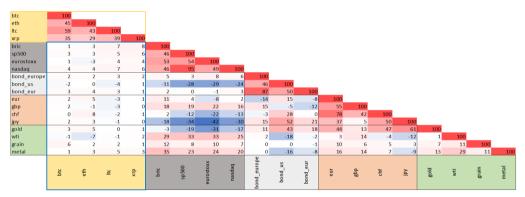
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## **Empirical Correlations**

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



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
	Correlation	0.01	0.03	0.01	0.04	0.02	-0.02	0.03
otc	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	јру	gold	wti	grain	metal
	Correlation	0.02	0.02	0.00	0.03	0.03	-0.01	0.06	0.01
otc	Pearson % Permutation %	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

		bric	sp500	eurostoxx	nasdaq	bond_europe	bond_us	bond_eu
	Correlation	0.03	0.03	-0.03	0.04	0.02	0.00	0.04
냝	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				gold			
	Correlation	0.05	-0.01	0.08	0.03	0.05	-0.07	0.02	0.03
t,	Pearson %	11.04	73.73	2.06	38.20	12.31	4.41	65.20	38.74
•	Correlation Pearson % Permutation %	11.80	70.40	1.80	38.40	13.40	3.00	65.40	36.60

		bric	sp500	eurostoxx	nasdaq	bond_europe	bond_us	bond_eu
		0.07	0.05	0.04	0.07	0.03	-0.04	0.03
tc	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

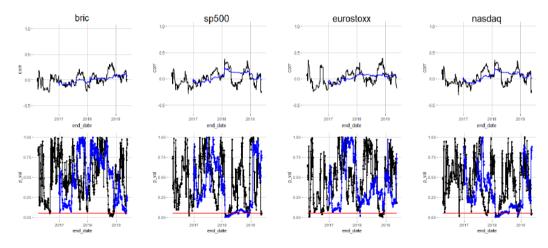
		eur		chf		gold			metal
	Correlation	-0.03	-0.03	-0.02	-0.01	0.00	-0.01	0.02	0.05
允	Pearson %	34.41	34.69	58.46	84.82	99.16	85.25	57.12	12.70
	Correlation Pearson % Permutation %	33.20	37.20	58.20	87.40	99.00	87.40	56.20	13.20

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

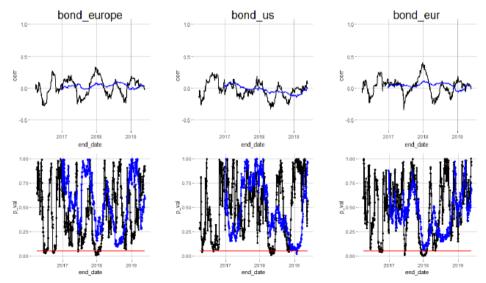
			eur		chf				grain	
		Correlation	0.01	0.00	0.01	0.00	0.01	0.02	0.01	0.03
ď	ď	Pearson %	84.02	90.38	83.88	95.71	70.48	64.27	75.19	31.56
	^	Correlation Pearson % Permutation %	83.40	88.80	83.40	92.40	73.00	60.00	72.40	30.40

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

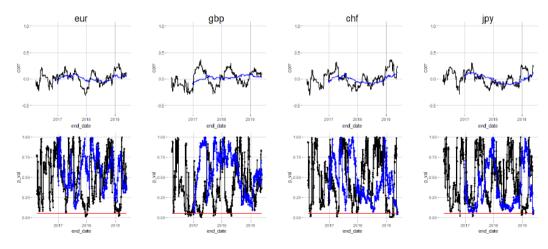
#### **Equities**



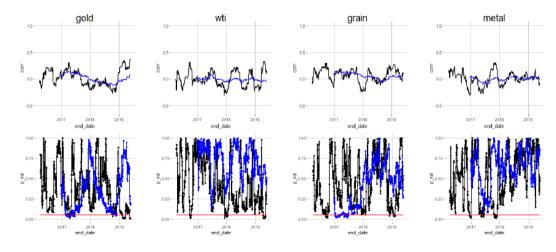
#### Bonds



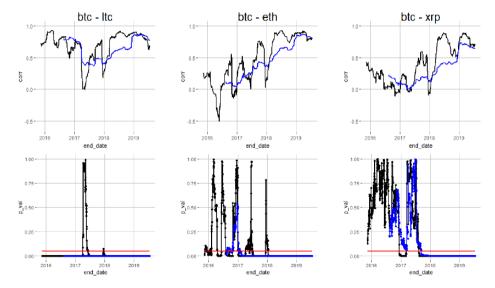
#### Currencies



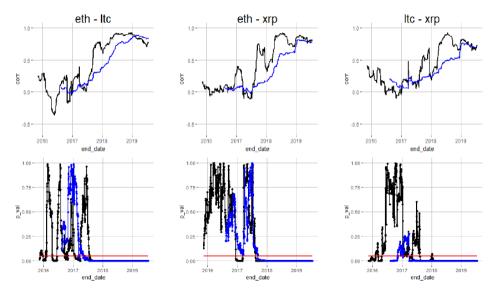
#### Commodities



# Cryptoassets Rolling Correlations

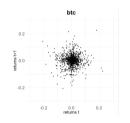


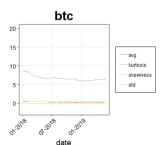
# Cryptoassets Rolling Correlations

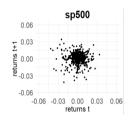


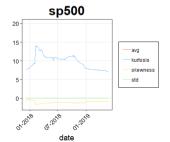
## Returns Distribution

Are returns of cryptoassets i.i.d.?



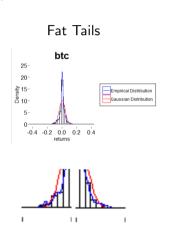


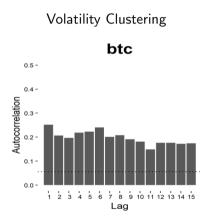




## Returns Distribution

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





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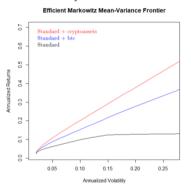
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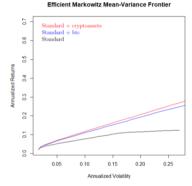
## Efficient Frontiers

From the 1<sup>st</sup> of January 2016 till the 24<sup>th</sup> of May 2019



From the 14th of July 2017 till the 24th of May 2019

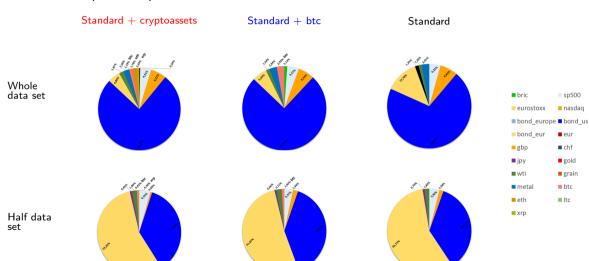




	Whole dataset	Second half
Standard + cryptoassets	8.87%	3.59%
Standard + btc	5.87%	3.62%
Standard	3.88%	3.05%

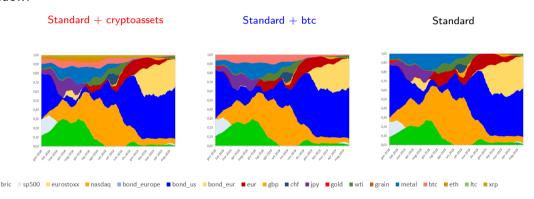
# Optimal Portfolio

Best Sharpe Ratio portfolios are allocated as below:



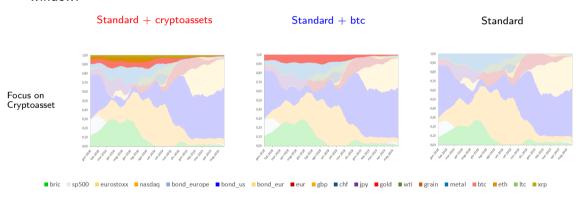
# Rolling Optimal Portfolios

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



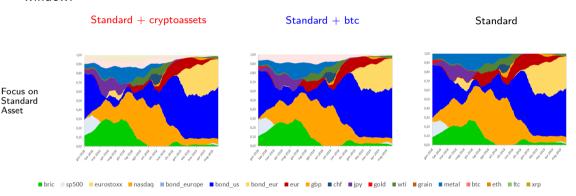
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## Rolling Optimal Portfolios

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