

THE ROLE OF CRYPTOCURRENCIES IN PORTFOLIO MANAGEMENT

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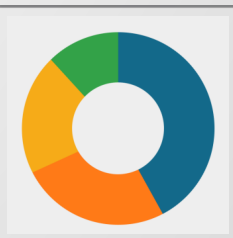
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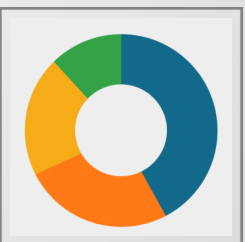
Portfolio Management



Why CCs in Portfolio Management?

□ Have potential to:

- ▶ Improve the risk-return ratio of a traditional portfolio (Härdle et al. 2019; Henriques et al. 2018)
- ▶ Act as an efficient diversifier (Feng et al. 2018)
- ▶ Provide consistent daily return of 40 bps (Härdle et al. 2019)



Why CCs in Portfolio Management?

- Not widely used in Portfolio Management yet

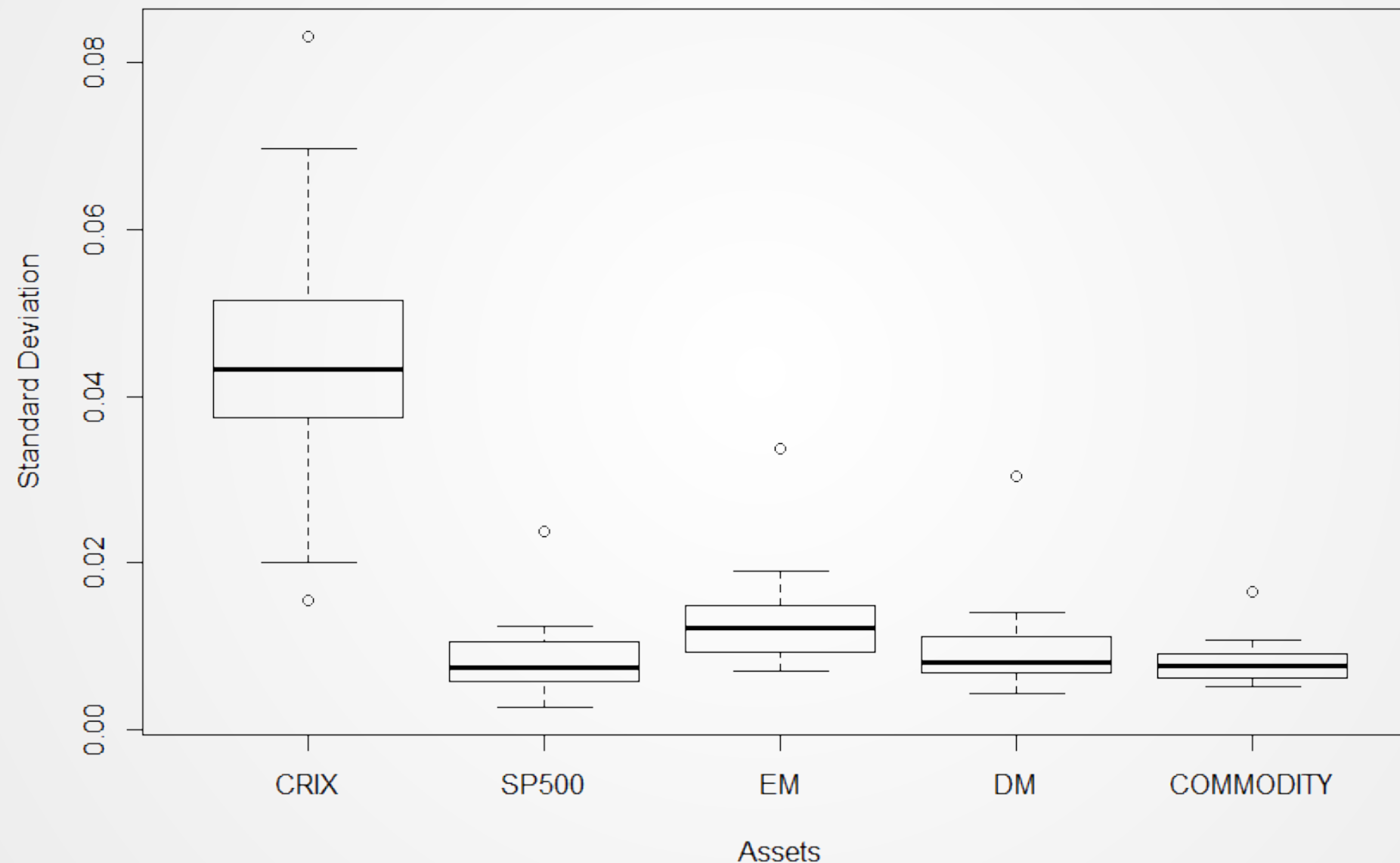
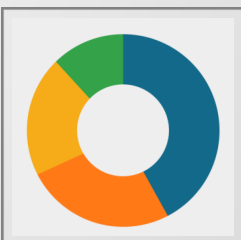


Figure 1: Boxplot of standard deviation of asset returns



Diversification abilities

▣ Levels of Diversification

- ▶ Global - Among all assets (Petukhina et al. 2018)
- ▶ Local - Cross-Sectional Portfolio (Härdle et al. 2019)

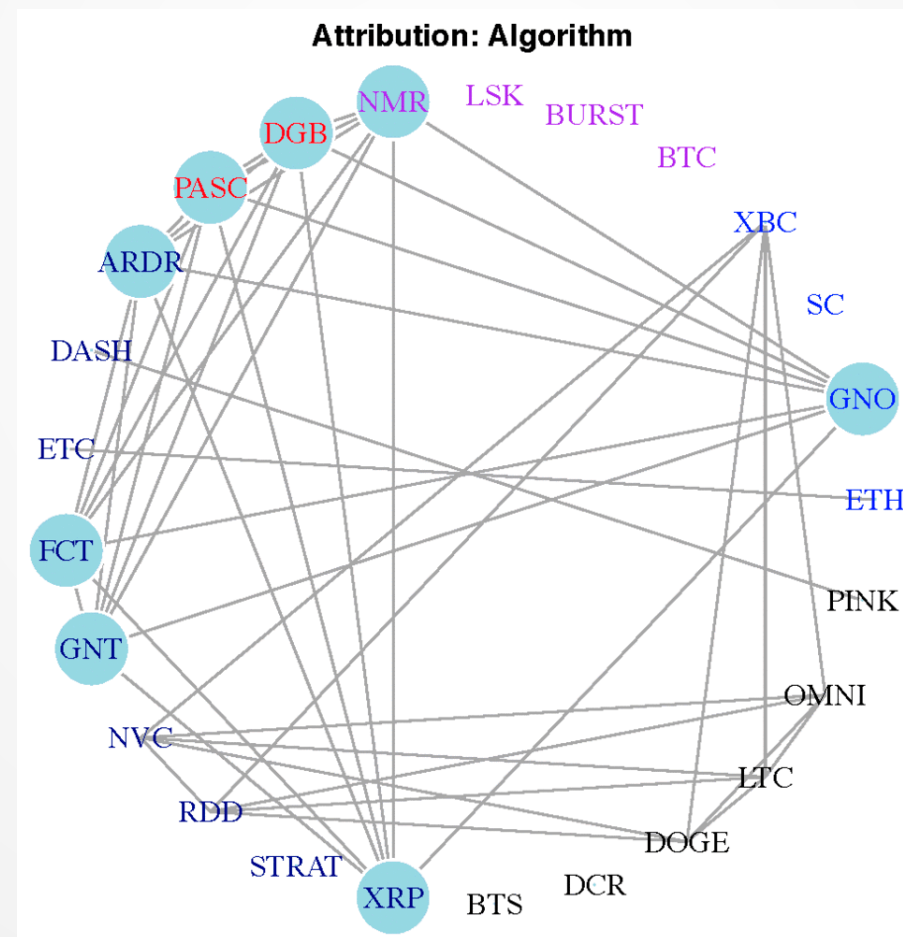
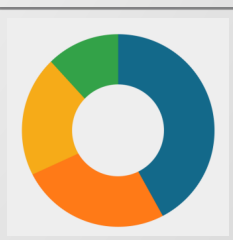


Figure 2: Algorithm-based network structure. Härdle et al, (2020)



CCs in Traditional Portfolios

- Traditional risk-return strategies do not improve with CCs
- Maximum return and maximum diversification strategies prompt higher expected returns through CC exposure
- Twice as low correlation with traditional portfolio as Gold (Henriques et. al., 2018)

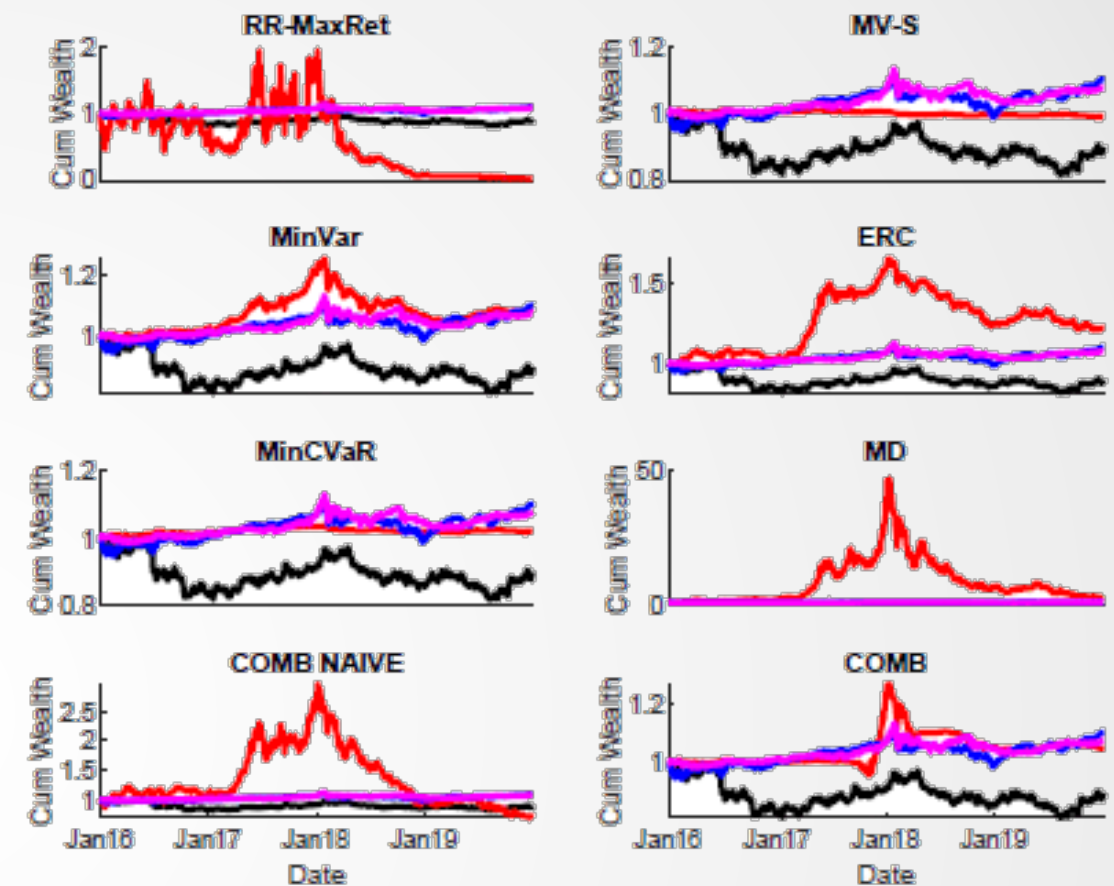
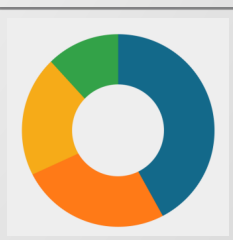
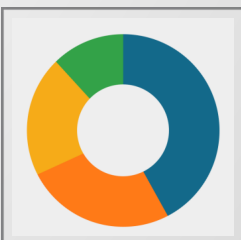


Figure 3: Performance in terms of cumulative wealth of portfolio strategies without liquidity constraints with monthly rebalancing ($l = 21$) over the period from 2016-01-01 to 2019-12-31 with the following colour code: S&P100, EW-TrA, RR-MaxRet-TrA and the corresponding allocation strategy from Table 1. “TrA” denotes only traditional, i.e., non-CC assets are included. Note that the date axes are aligned, but the wealth axes are not, due to large dispersion in scales. (Petukhina et al. 2020)



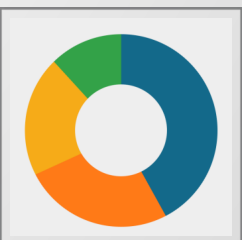
Objectives

- ▣ Study the statistical characteristics of CRIX in comparison to traditional assets
- ▣ Model the optimal portfolio with CRIX and compare it to benchmark
- ▣ Draw conclusions about the introduction of CRIX into traditional PM



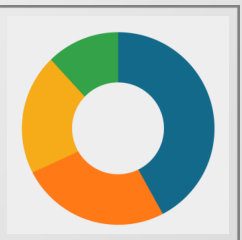
Literature Review

- ▣ Guo, L., Tao, Y., Hardle, W. K., (2019): Cryptocurrencies can be clustered based on return characteristics;
- ▣ Klein, T., H. P. Thu, and T. Walther (2018): Bitcoin is different from Gold based on the comparison of volatility, correlation, and portfolio performance;
- ▣ Petukhina, A., Trimborn S., Härdle, W. K., Elendner H. (2020): Approaches with high target returns prompt higher expected returns in contrast to traditional risk-based strategies;
- ▣ Henriques, I., Sadorsky, P., (2018): Bitcoin can replace Gold in an Investment Portfolio;
- ▣ Feng, W., Wang, Y., Zhang, Z., (2018): Tail risk characteristics allow cryptocurrencies to be an efficient diversifier, but not a hedge.



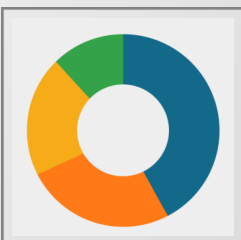
Outline

- ▣ Motivation
- ▣ Data and Statistical Description
- ▣ Methodology
- ▣ Quantitative Portfolio Analysis
- ▣ Conclusion



Data

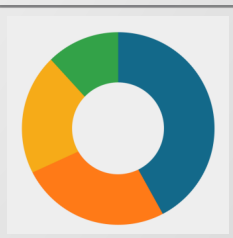
- ▣ Sample: $n = 13$ assets
- ▣ New asset class
 - ▶ CRIX : the Index for CCs
- ▣ Traditional asset class
 - ▶ Stocks (S&P 500): $n = 4$
 - ▶ Fixed Income (TLT): $n = 1$
 - ▶ Commodities (Bloomberg Commodity Index): $n = 1$
 - ▶ Exchange rates: $n = 6$
- ▣ 5 years of daily data from 2015-05-29 to 2020-05-30
 - ▶ Observations aligned on 5 trading days/week



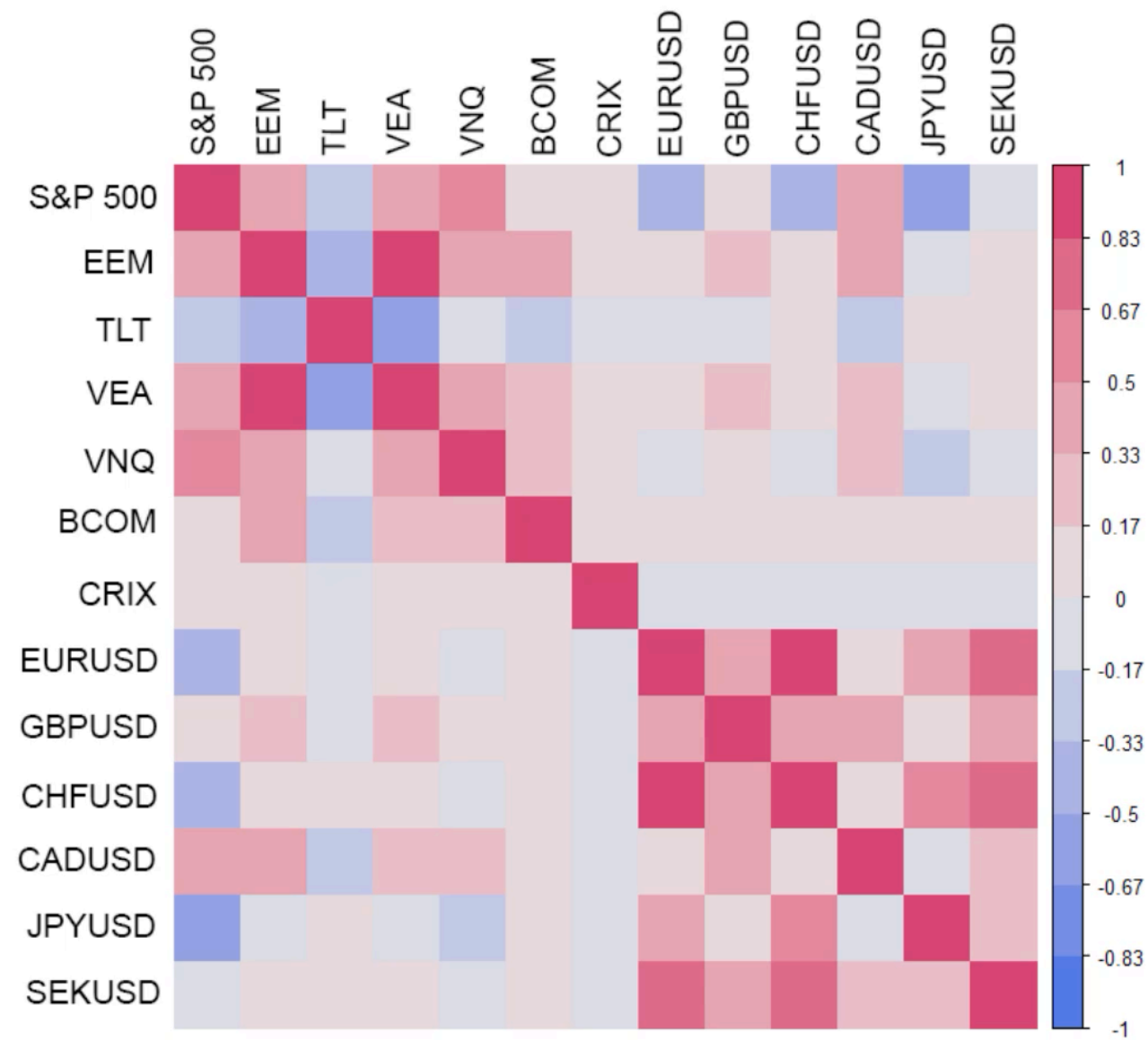
Statistical Summary of the Data

Assets	$\hat{\mu}$	$\hat{\sigma}$	\hat{S}	\hat{K}	\hat{CV}	JB
S&P500	0.00033	0.009	-0.721	7.86	29.08	3363.7
TLT	0.00026	0.008	0.087	11.53	33.17	6998.3
VEA	-0.00001	0.011	-1.988	20.84	-763.61	23650.0
EEM	0.00005	0.014	-0.967	11.30	838.04	6907.7
VNQ	0.00002	0.011	-0.970	11.79	247.88	7511.3
BCOM	-0.00033	0.008	-0.259	2.44	-25.40	328.9
CADUSD	-0.00007	0.004	0.119	1.23	-67.49	84.2
CHFUSD	-0.00001	0.004	0.325	1.70	-668.59	175.9
EURUSD	0.00002	0.005	0.091	3.26	235.76	563.2
GBPUSD	-0.00015	0.006	-1.400	19.42	-41.19	20230.0
JPYUSD	0.00013	0.005	0.253	3.03	43.75	499.9
SEKUSD	-0.00008	0.006	-0.267	2.49	-79.47	343.5
CRIX	0.00436	0.046	-0.335	6.50	10.74	2249.0

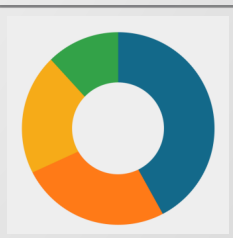
Table 1: Summary statistics for returns of traditional assets: daily arithmetic return, standard deviation, skewness, kurtosis, coefficient of variation and Jarque–Bera test for the data from June 2015 to June 2020



Correlation of Returns



June 2015 _ June 2016



Correlation of Returns

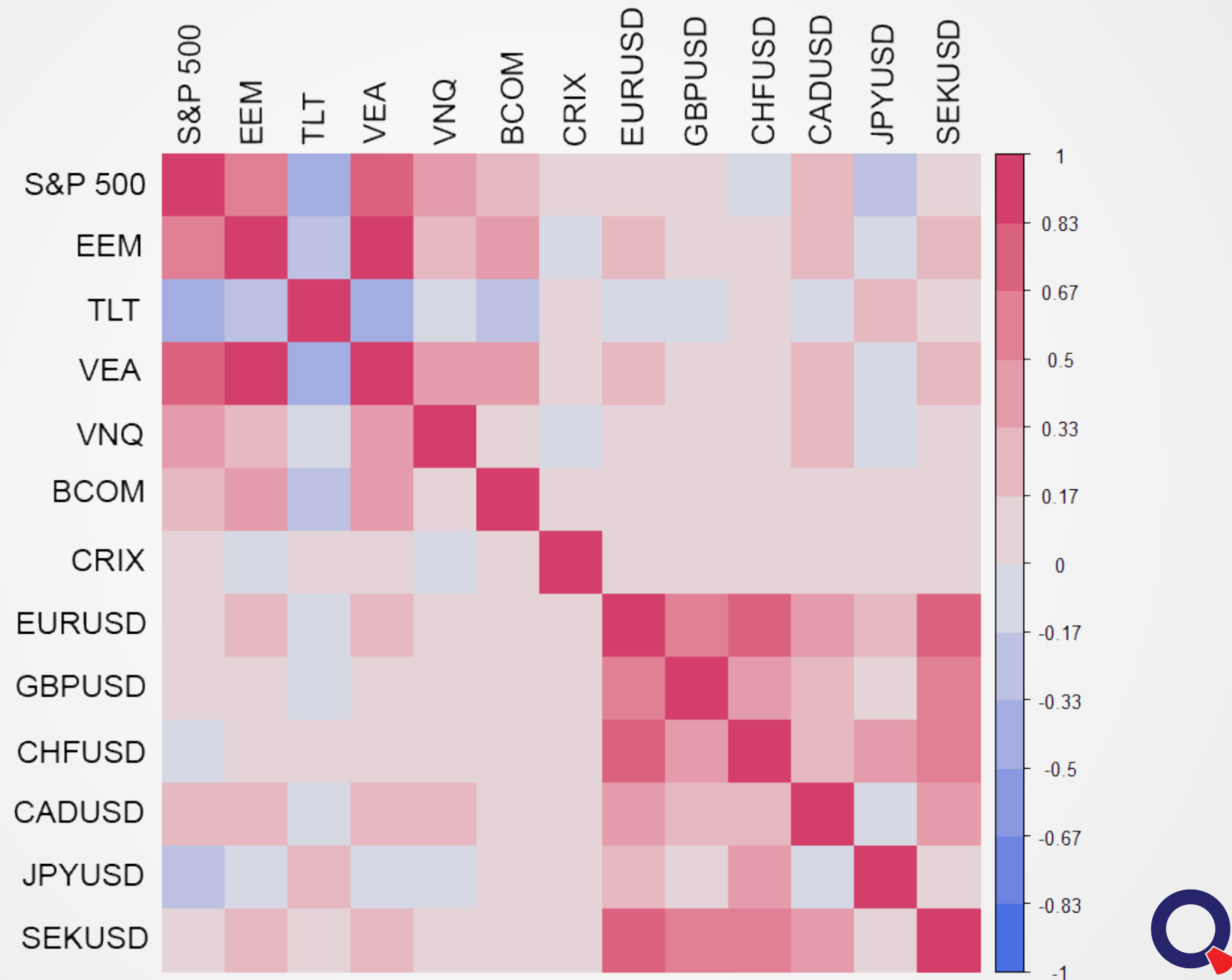
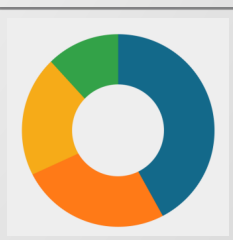
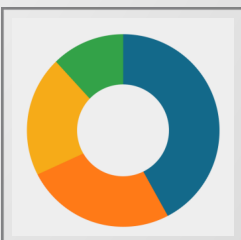
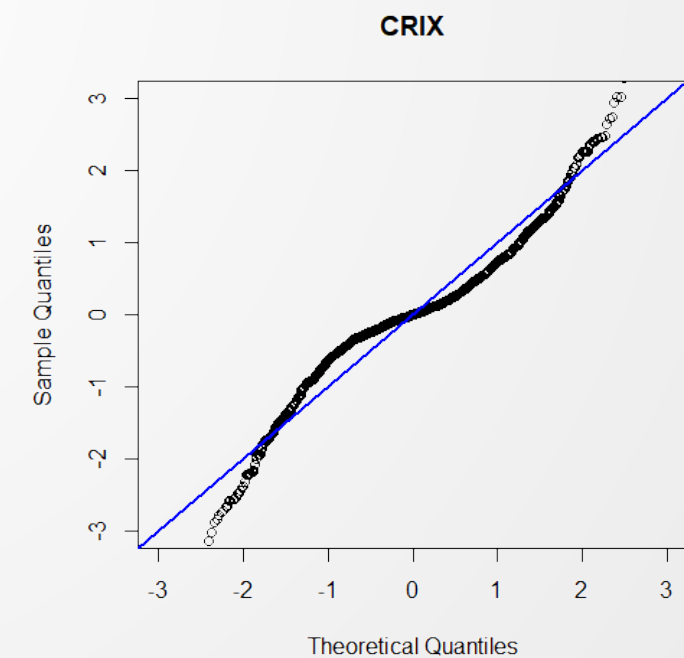
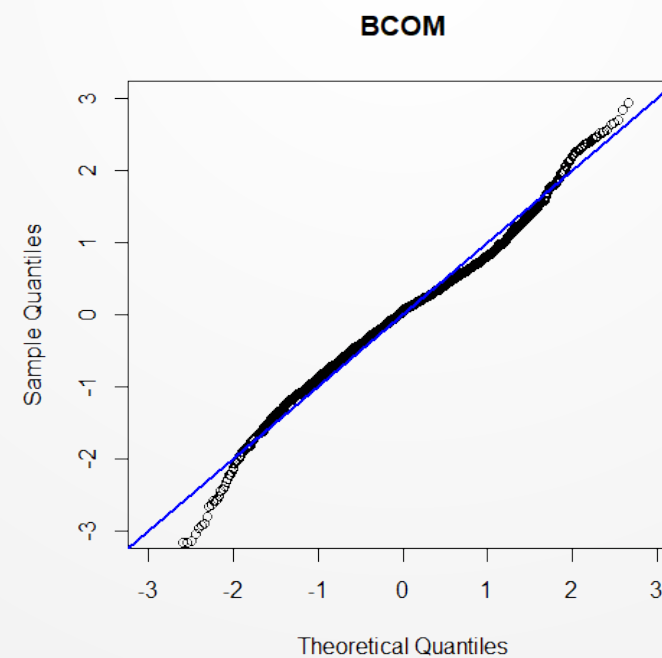
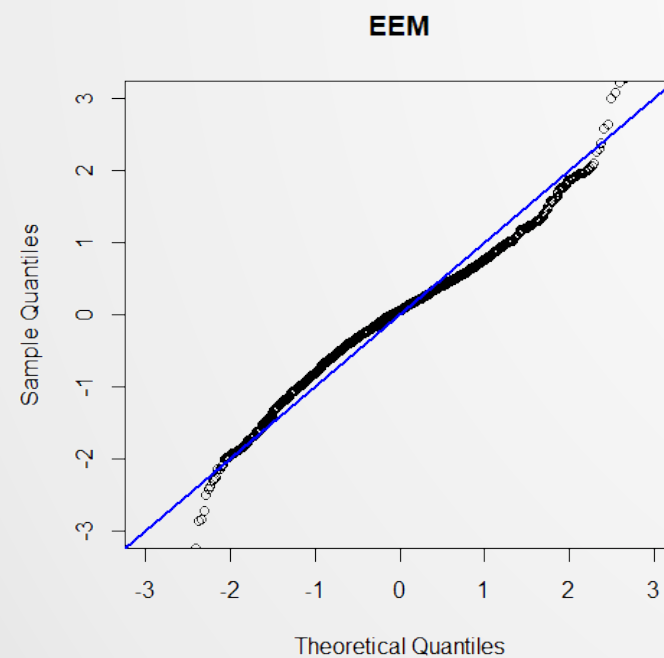
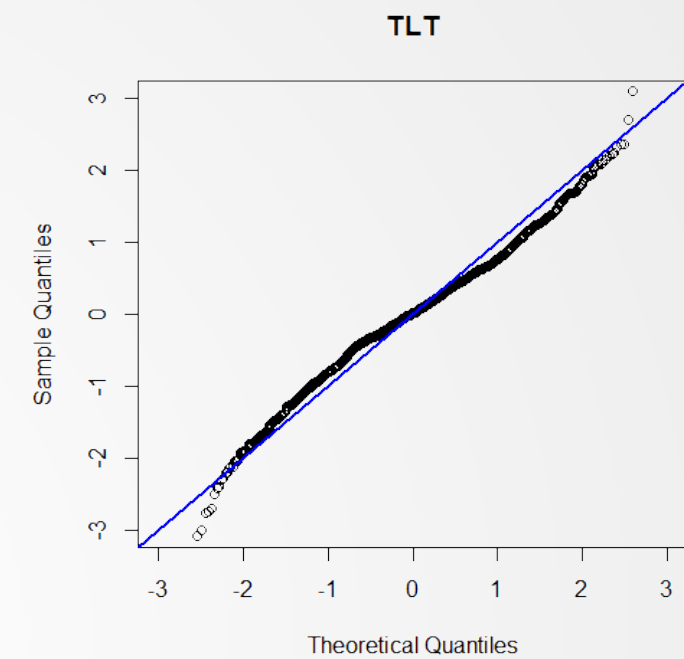
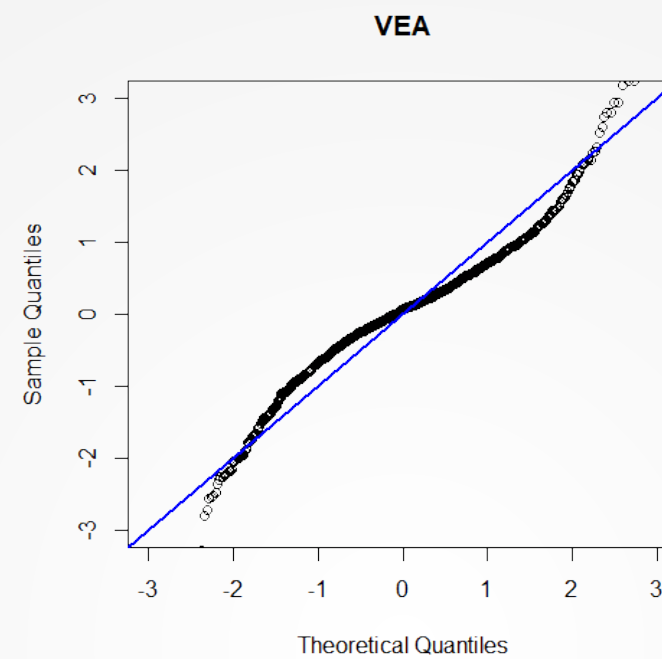
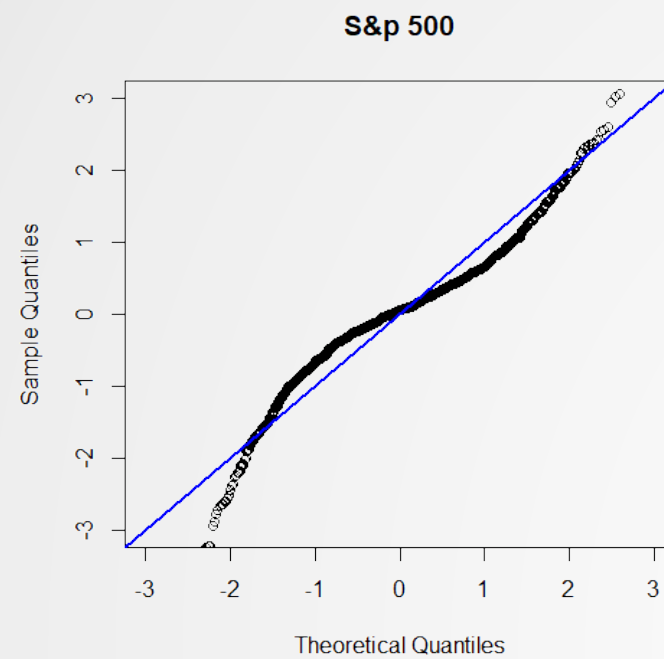


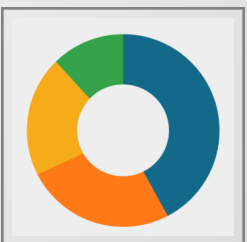
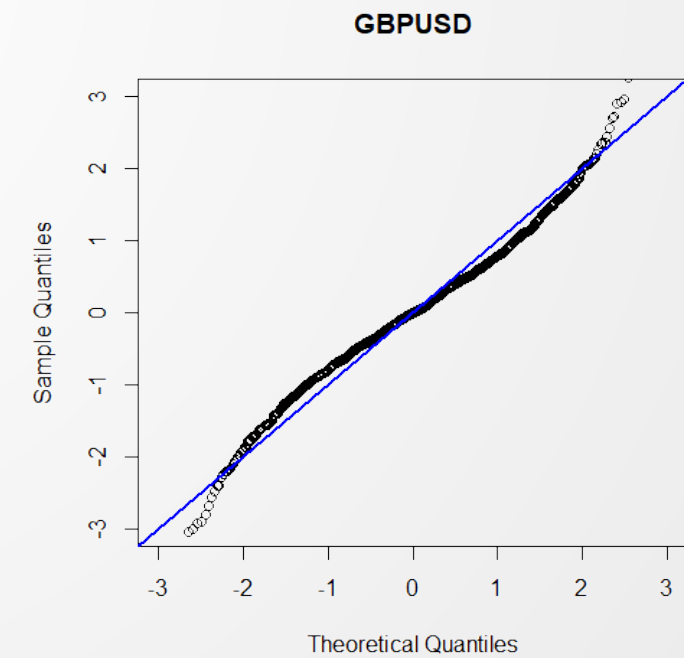
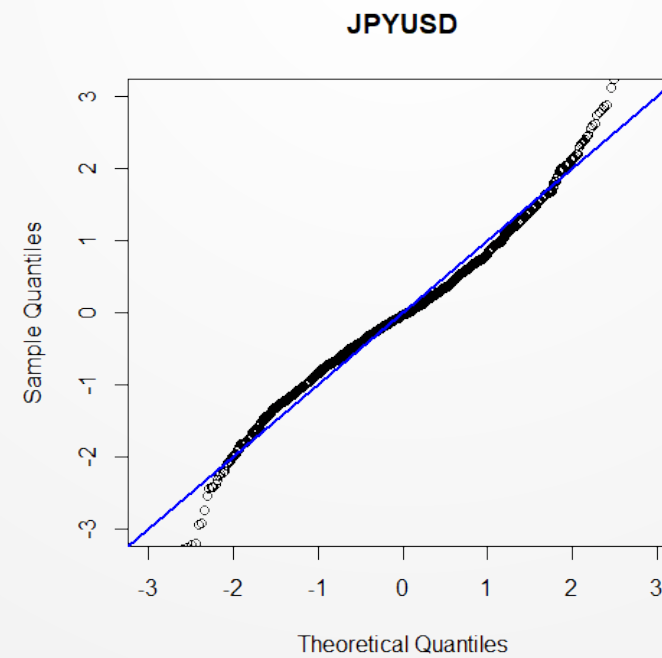
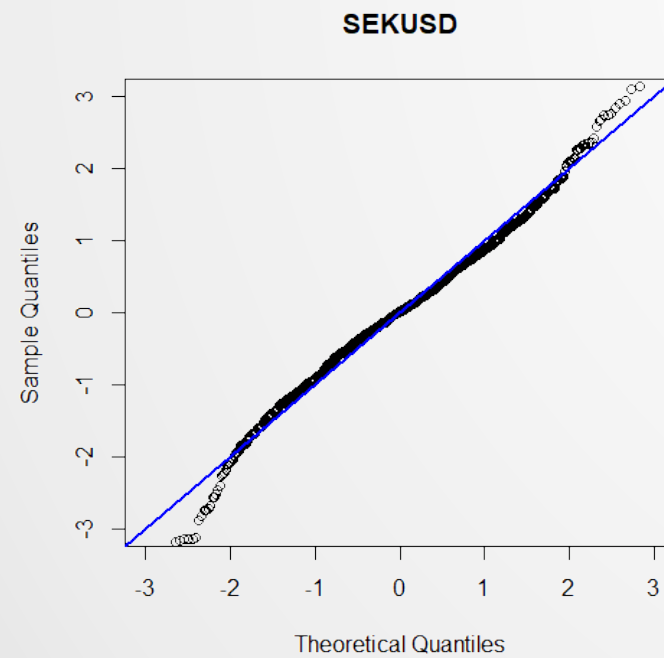
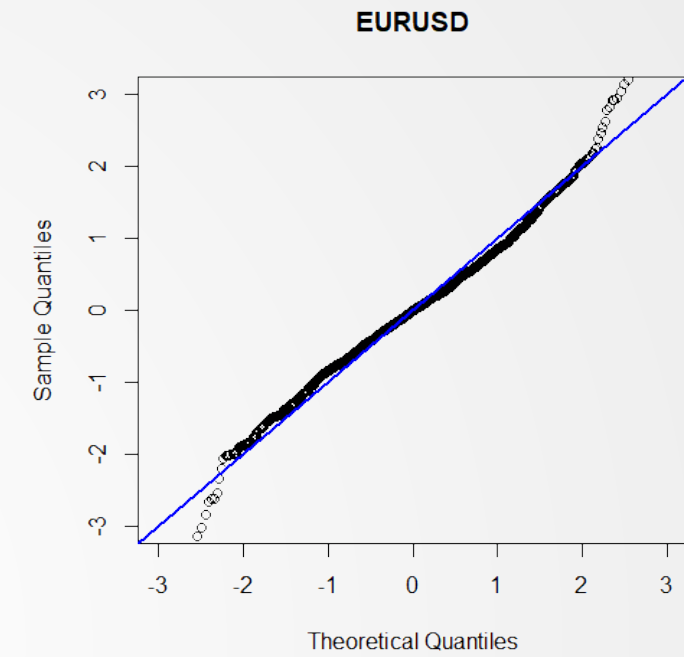
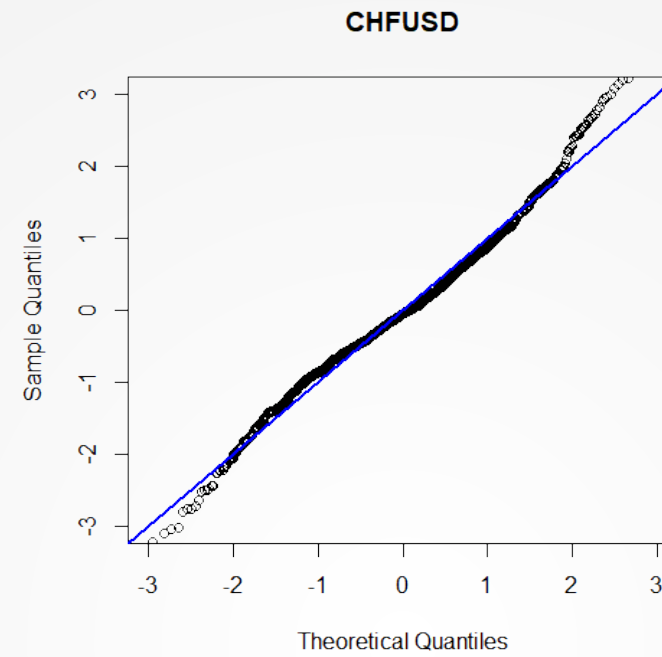
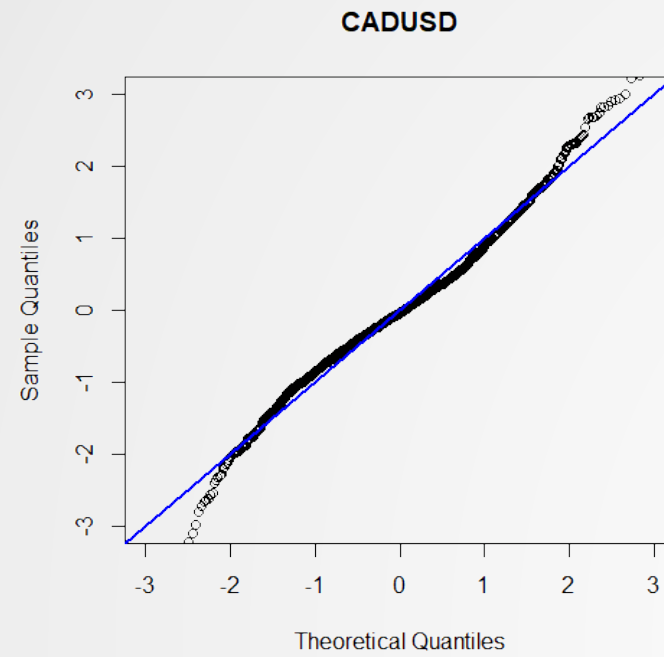
Figure 4 : correlation of arithmetic returns from June 2015 to June 2020



QQ Plots



QQ Plots

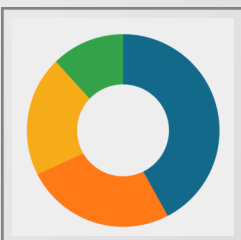


Maximum Diversification

$$\max_{w \in \mathbf{W}} DR(w) \quad (1)$$

$$DR(w_t) = \frac{w_t^\top \sigma_t}{\sqrt{w_t^\top \Sigma_t w_t}} = \frac{w_t^\top \sigma_t}{\sigma_{P,t}(w_t)} \quad (2)$$

- ▣ Where Σ is covariance matrix of returns
- ▣ σ is the vector of asset volatilities
- ▣ w is long-only asset shares vector



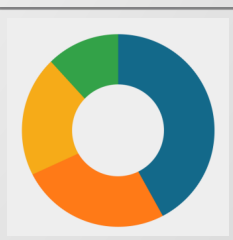
Dynamic Conditional Correlation GARCH (DCC-GARCH)

$$\mathbf{r}_t = \boldsymbol{\mu}_t + \mathbf{a}_t$$

$$\mathbf{a}_t = \mathbf{H}_t^{1/2} \mathbf{z}_t$$

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t$$

- ▣ \mathbf{r} : $n \times 1$ vector of log returns of n assets at time t
- ▣ \mathbf{a} : $n \times 1$ vector of mean-corrected returns of n assets at time t
- ▣ $\boldsymbol{\mu}$: $n \times 1$ vector of the expected value of the conditional \mathbf{r}
- ▣ \mathbf{H} : $n \times n$ matrix of conditional variances of \mathbf{a} at time t
- ▣ \mathbf{D} : $n \times n$, diagonal matrix of conditional sd of \mathbf{a} at time t
- ▣ \mathbf{R} : $n \times n$ conditional correlation matrix of \mathbf{a} at time t
- ▣ \mathbf{z} : $n \times 1$ vector of i.i.d errors
- ▣ **ADCC** - DCC with asymmetries in nonstat. conditional corr.



Weight Estimation

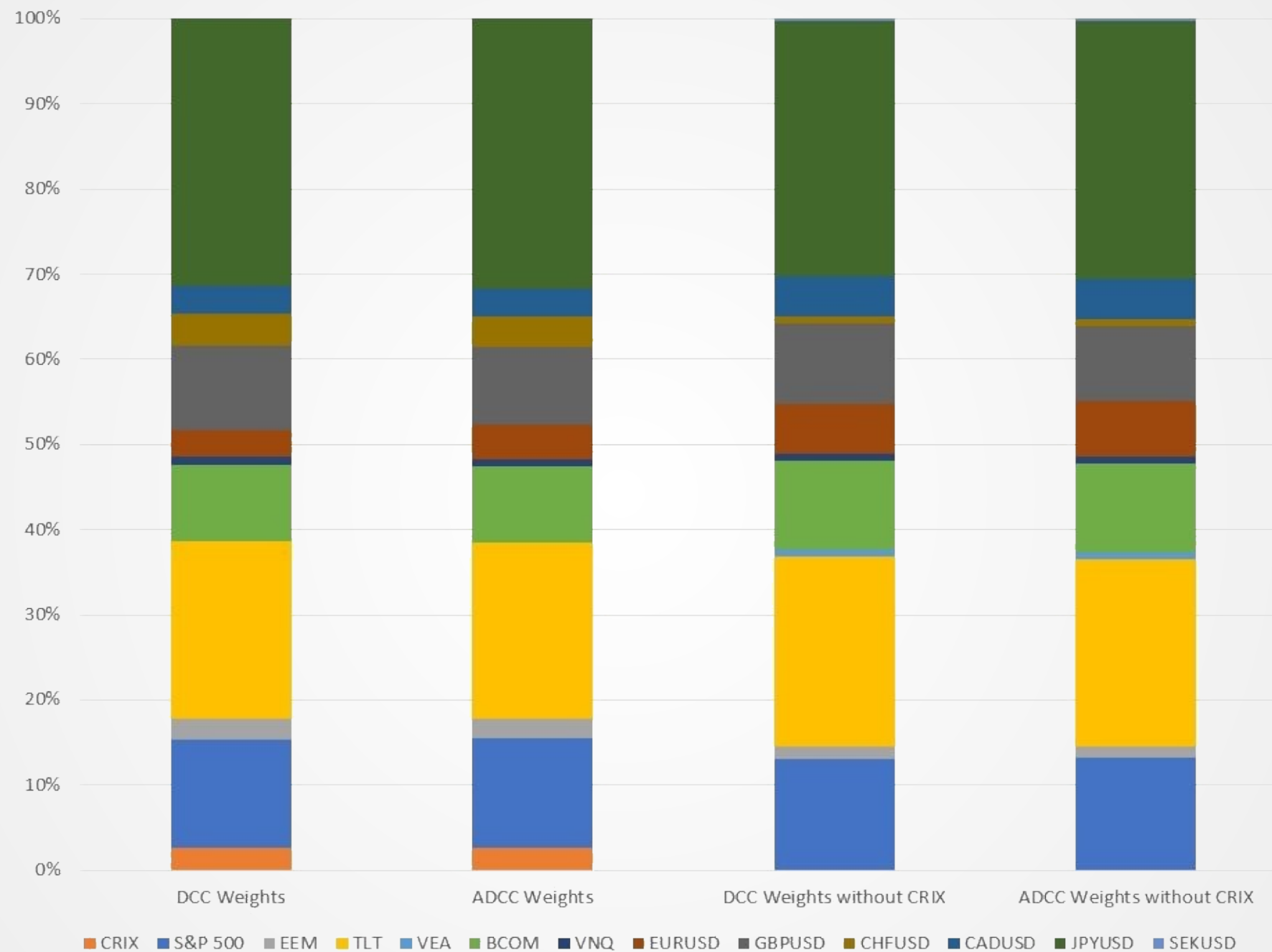
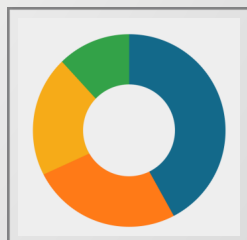


Figure 5: Adjustment of different estimated weight for the portfolios



Visualization of Results

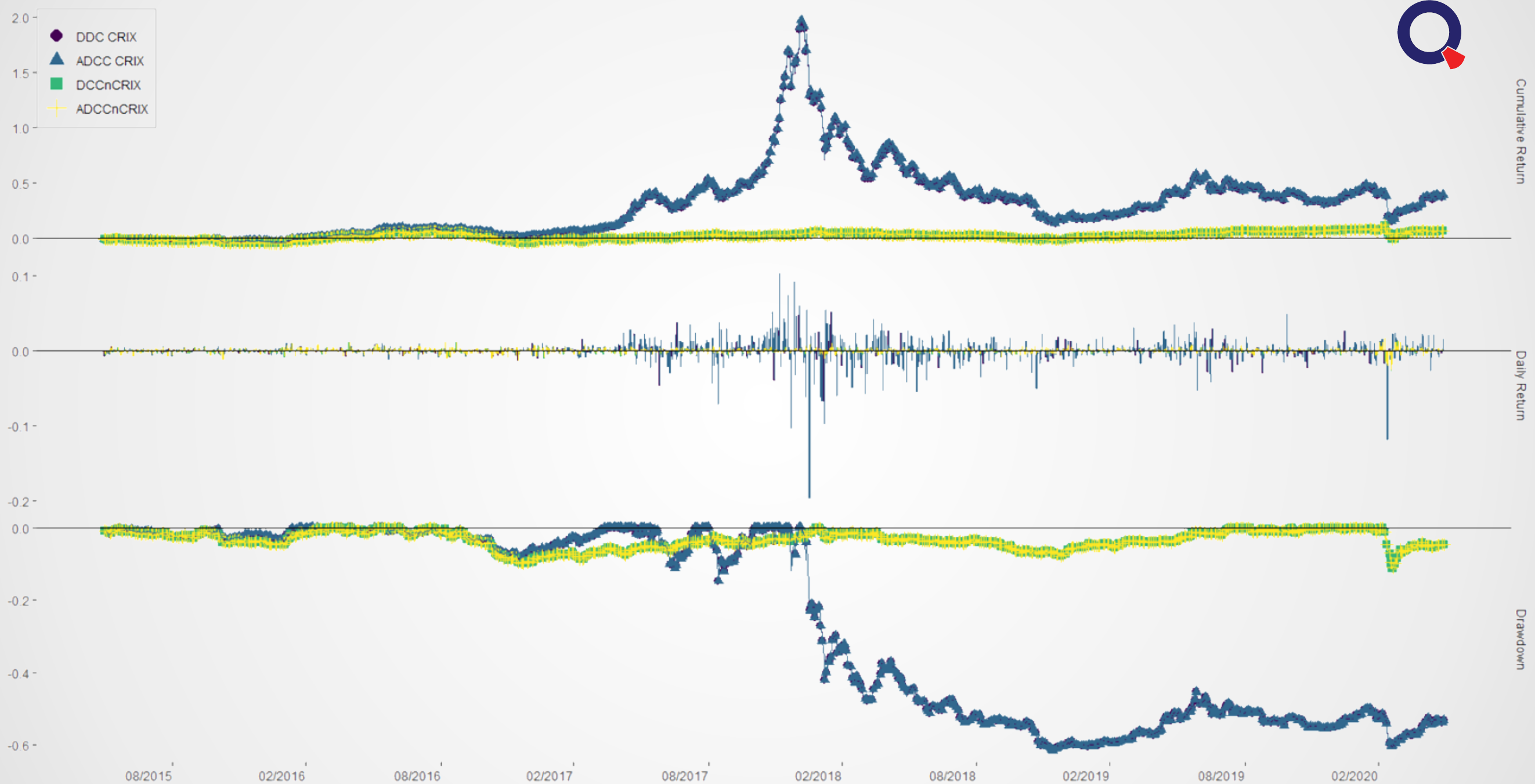
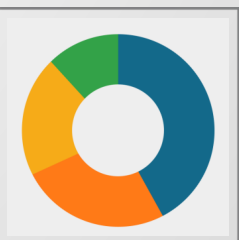


Figure 6: Returns of 4 different portfolios based on Maximum diversification method



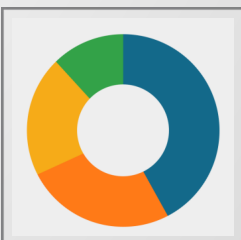
Portfolio Comparison

	Mean	Sd	CV	Sharpe	Sortino	MaxDrawdown
DCC with CRIX	0.0678	0.2435	3.59	0.2348	0.0290	0.6168
ADCC with CRIX	0.0686	0.2442	3.56	0.2373	0.0293	0.6177
DCC without CRIX	0.0130	0.0532	4.09	0.0553	0.0070	0.1147
ADCC without CRIX	0.0135	0.0531	3.95	0.0635	0.0077	0.1135

Table 2: Portfolio comparison. Long positions only.

□ Potential points to improve

- ▶ Rolling-window-based estimation
- ▶ Liquidity constraints - LIBRO (Liquidity Bounded Risk-return by Trimborn et al. (2017))
- ▶ p-values or other robustness check



Literature Sources

- ▣ Guo, L., Tao, Y., Hardle, W. K., (2019): "Dynamic Network Perspective of Cryptocurrencies"
- ▣ Klein, T., H. P. Thu, and T. Walther (2018): "Bitcoin is not the New Gold – a comparison of volatility, correlation, and portfolio performance"
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- ▣ Dyhrberg, A. H. (2016): "Bitcoin, gold and the dollar - A GARCH volatility analysis"
- ▣ Baur, D. G., Dimpfl, T., Kuck, L., (2017): "Bitcoin, Gold and the Dollar – A Replication and Extension"
- ▣ Feng, W., Wang, Y., Zhang, Z., (2018): "Can cryptocurrencies be a safe haven: a tail risk perspective analysis"

