

Louvain School of Management

Portfolio Risk Diversification Effects of Cryptocurrencies

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ABSTRACT

The main question of this thesis is to know the diversification effect of cryptocurrencies. The goal is to determine if it is a good idea/ beneficial to incorporate any cryptocurrency into a portfolio containing standard assets such as indexes. Through performance analysis and DCC-GARCH estimations, I aspire to exhibit which cryptocurrency can better reduce risk among traditional portfolios. The present work examines daily returns, volatility, and correlations of five cryptocurrencies along with six traditional assets from January 19th, 2018, to July 29th, 2020.

The main results show that GOLD is the only asset among the studied assets that outperformed the market given the risk undertaken. Besides, GOLD can be used to hedge against CAC40, SP500, and MSCIWOLRD, according to the negative correlation with them.

However, cryptocurrencies have, in general, less good risk-adjusted return measures than standard financial assets. Regarding the DCC-GARCH correlation estimations, the results show that the lowest correlation value is 0,0740 for GOLD-Ehereum Classic. This combination has the best potential to reduce portfolio risk. These results are interesting for investors who want to include cryptocurrencies into a portfolio with GOLD and the three indexes and reduce the portfolio risk.

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TABLE OF CONTENTS

ABSTRACT	I
ACKNOWLEDGEMENT	III
TABLE OF CONTENTS	V
LIST OF FIGURES	IX
LIST OF TABLES	XI
LIST OF EQUATIONS	XII
1. INTRODUCTION	1
2. LITERATURE REVIEW.....	3
2.1. Markowitz Portfolio Selection Theory	3
2.2. Modern Portfolio Theory	4
2.3. Portfolio Risk Diversification	5
2.4. Diversifier, hedge, and safe haven assets.....	6
2.5. Risk-Adjusted PerformanceMeasurements	6
2.5.1. Theory.....	6
2.5.2. Literature consideraions.....	8
2.6. Volatility and Correlation Estimation modeling	9
2.6.1. Theory.....	9
2.6.2. Literature considerations.....	12
2.6.2.1. Bitcoin relative to other financial assets	12
2.6.2.2. Leading cryptocurrencies VS other financial assets	14
3. DATA	17
3.1. Description of the datasets	17
3.2. Data cleaning	18
3.3. Preliminary analysis – Descriptive statistics	19
3.3.1. Descriptive statistics of the cryptocurrencies	20
3.3.2. Descriptive statistics of the standard's financial assets.....	22
3.3.3. Descriptive statistics: The two types of assets comparison	24

4. METHODOLOGY	28
4.1. Hypotheses and research questions	28
4.1.1. Performance analysis using risk-adjusted measurements	28
4.1.2. Volatility and Correlation Estimation modeling	29
4.2. Description of the methodology	31
4.2.1. Performance Analytics	31
4.2.1.1. Simple Risk Measures	31
4.2.1.2. Capital Asset Prices Model (CAPM)	33
4.2.1.3. Partial Moments Measures	35
4.2.1.4. Extreme Risk Measures	36
4.2.1.5. Risk-adjusted Return	37
4.2.1. Volatility and Correlation Estimation Modeling	37
4.2.1.1. Previsualization - Rolling windows	38
4.2.1.2. Descriptive analysis	39
4.2.1.3. Multivariate DCC-GARCH	39
5. EMPIRICAL RESULTS	43
5.1. Performance Analysis	43
5.1.1. Absolute performances measures	43
(measures relative to the total risk)	43
5.1.2. Relative performances measures	45
(measures relative to systematic risk)	45
5.1.3. Performance analytics summary	48
5.2. Volatility and Correlation Estimation Modeling	50
5.2.1. Previsualization - Rolling windows	50
5.2.1.1. Returns Volatility	50
5.2.1.2. Correlation	54
5.2.2. Correlation Descriptive Analysis	62
5.2.3. Multivariate DCC-GARCH Estimations	63
5.2.3.1. GOLD-	64
5.2.3.2. CAC40-	65
5.2.3.3. SP500-	67
5.2.3.4. MSCIWORLD-	69
5.2.3.5. DCC-GARCH Correlation Estimations	70

6. CONCLUSION	72
6.1. Results interpretation and conclusion.....	72
6.2. Limits of the study.....	74
7. APPENDIX.....	77
7.1. Description of the cryptocurrency's dataset.....	77
7.1.1. Bitcoin (BTC).....	77
7.1.2. Ethereum (ETH).....	78
7.1.3. Litecoin (LTC)	78
7.1.4. Ethereum Classic (ETC)	79
7.1.5. Ripple (XRP).....	80
7.2. Description of the standard's financial assets dataset.....	80
7.2.1. Gold	81
7.2.2. The CAC40	82
7.2.3. The S&P500 Index (SP500).....	82
7.2.4. The MSCI World Index (MSCIWORLD)	83
7.2.5. 10-Years U.S. Treasury Bonds (TBOND10US)	84
7.2.6. The Currency Pair EUR/USD(EURUSD)	84
7.3. Plots and density histograms of cryptocurrencies	86
7.3.1. Bitcoin (BTC).....	86
7.3.2. Ethereum (ETH).....	86
7.3.3. Litecoin (LTC)	87
7.3.4. Ethereum Classic (ETC)	87
7.3.5. Ripple (XRP).....	87
7.4. Plots and density histograms of standard financial assets	88
7.4.1. Gold	88
7.4.2. CAC40	88
7.4.3. SP500	89
7.4.4. MSICWORLD.....	89
7.4.5. TBOND10US	89
7.4.6. EURUSD.....	90
7.5. Boxplots: The weekdays and weekend prices for cryptocurrency data	91
7.6. Jarque-Bera Normality Test.....	92

7.7.	DCC-GARCH Estimations Results	92
7.7.1.	Correlation GOLD-	93
7.7.2.	Correlation CAC40-	96
7.7.3.	Correlation SP500-	99
7.7.4.	Correlation MSCIWORLD-	102
8.	BIBLIOGRAPHY	106

LIST OF FIGURES

Figure 2: Negative Cumulative Returns	26
Figure 1: Positive Cumulative Returns	26
Figure 3: Graphic of Ethereum Returns Volatility	52
Figure 4: Graphic of Bitcoin Returns Volatility	52
Figure 5: Graphic of Ethereum Classic Returns Volatility	52
Figure 6: Graphic of Litecoin Returns Volatility	52
Figure 7: Graphic of Ripple Returns Volatility	52
Figure 8: Graphic of CAC40 Returns Volatility	53
Figure 9: Graphic of GOLD Returns Volatility	53
Figure 10: Graphic of MSCIWORLD Returns Volatility	53
Figure 11: Graphic of SP500 Returns Volatility	53
Figure 12: Graphic of TBOND10US Returns Volatility	53
Figure 13: Graphic of EURUSD Returns Volatility	53
Figure 14: Graphic of GOLD-ETH correlation	56
Figure 15: Graphic of GOLD-BTC correlation	56
Figure 16: Graphic of GOLD-ETC correlation	56
Figure 17: Graphic of GOLD-LTC correlation	56
Figure 18: Graphic of GOLD-BTC correlation	56
Figure 19: Graphic of CAC40-ETH correlation	57
Figure 20: Graphic of CAC40-BTC correlation	57
Figure 21: Graphic of CAC40-ETC correlation	57
Figure 22: Graphic of CAC40-LTC correlation	57
Figure 23: Graphic of CAC40-GOLD correlation	57
Figure 24: Graphic of CAC40-XRP correlation	57
Figure 25: Graphic of SP500-ETH correlation	58
Figure 26: Graphic of SP500-BTC correlation	58
Figure 27: Graphic of SP500-LTC correlation	58
Figure 28: Graphic of SP500-ETC correlation	58
Figure 29: Graphic of SP500-GOLD correlation	58
Figure 30: Graphic of SP500-XRP correlation	58
Figure 31: Graphic of MSCIWORLD-BTC correlation	59
Figure 32: Graphic of MSCIWORLD-ETH correlation	59
Figure 33: Graphic of MSCIWORLD-LTC correlation	59
Figure 34: Graphic of MSCIWORLD-ETC correlation	59
Figure 35: Graphic of MSCIWORLD-GOLD correlation	59
Figure 36: Graphic of MSCIWORLD-XRP correlation	59
Figure 37: Graphic of TBOND10US-BTC correlation	60
Figure 38: Graphic of TBOND10US-ETH correlation	60
Figure 39: Graphic of TBOND10US-ETC correlation	60
Figure 40: Graphic of TBOND10US-LTC correlation	60
Figure 41: Graphic of TBOND10US-GOLD correlation	60
Figure 42: Graphic of TBOND10US-XRP correlation	60
Figure 43: Graphic of EURUSD-ETH correlation	61

Figure 44: Graphic of EURUSD-BTC correlation.....	61
Figure 45: Graphic of EURUSD-ETC correlation.....	61
Figure 46: Graphic of EURUSD-LTC correlation	61
Figure 47: Graphic of EURUSD-GOLD correlation.....	61
Figure 48: Graphic of EURUSD-XRP correlation.....	61
Figure 49: Correlation plots of all assets	62
Figure 50: Density histogram of Bitcoin Return	86
Figure 51: Plot of Bitcoin Return.....	86
Figure 52: Density histogram of Ethereum Return.....	86
Figure 53: Plot of Ethereum Return	86
Figure 54: Plot of Litecoin Return	87
Figure 55: Density histogram of Litecoin Return.....	87
Figure 56: Density histogram of Ethereum Classic Return	87
Figure 57: Plot of Ethereum Classic Return.....	87
Figure 58: Density histogram of Ripple Return	87
Figure 59: Plot of Ripple Return	87
Figure 60: Density histogram of Gold Return.....	88
Figure 61: Plot of Gold Return	88
Figure 62: Descriptive Statistics of CAC40 Return	88
Figure 63: Plot of CAC40 Return	88
Figure 64: Density histogram of SP500 Return	89
Figure 65: Plot of SP500 Return.....	89
Figure 66: Plot of MSCIWORLD Return	89
Figure 67: Density histogram of MSCIWORLD Return.....	89
Figure 68: Plot of TBOND10US Return	89
Figure 69: Descriptive Statistics of TBOND10US Return	89
Figure 70: Density histogram of EURUSD Return	90
Figure 71: Plot of EURUSD Return	90
Figure 72: Boxplot of Ethereum.....	91
Figure 73: Boxplot of Bitcoin.....	91
Figure 74: Boxplot of Litecoin	91
Figure 75: Boxplot of Ethereum Classic	91
Figure 76: Boxplot of Ripple	91

LIST OF TABLES

Table 1: Student's t-test for cryptocurrencies	19
Table 2: Summary Statistics of the cryptocurrencies	20
Table 3: Summary Statistics of the standard's financial assets	22
Table 4: Absolute performances measures	45
Table 5: Relative performances measures	48
Table 6: Relative performance measures - M-squared excess return ranking.....	50
Table 7: Unconditional Return Volatility	51
Table 8: Unconditional Volatility on Rolling Correlation 30D	54
Table 9: Correlations comparison - GOLD.....	65
Table 10: Correlations comparison - CAC40	67
Table 11: Correlations comparison - SP500	68
Table 12: Correlations comparison - MSCIWORLD	70
Table 13: DCC-GARCH Correlation Estimations $R(1,2)$	71
Table 14: Jarque-Bera results of the cryptocurrency returns distribution.....	92
Table 15: Jarque-Bera results of the traditional asset returns distribution	92
Table 16: DCC-GARCH Correlation Estimation GOLD-BTC	93
Table 17: DCC-GARCH Correlation Estimation GOLD-ETH	93
Table 18: DCC-GARCH Correlation Estimation GOLD-ETC	94
Table 19: DCC-GARCH Correlation Estimation GOLD-LTC.....	94
Table 20: DCC-GARCH Correlation Estimation GOLD-XRP	95
Table 21: DCC-GARCH Correlation Estimation CAC40-ETH.....	96
Table 22: DCC-GARCH Correlation Estimation CAC40-BTC.....	96
Table 23: DCC-GARCH Correlation Estimation CAC40-ETC.....	97
Table 24: DCC-GARCH Correlation Estimation CAC40-LTC	97
Table 25: DCC-GARCH Correlation Estimation CAC40-GOLD.....	98
Table 26: DCC-GARCH Correlation Estimation CAC40-XRP.....	98
Table 27: DCC-GARCH Correlation Estimation SP500-ETH.....	99
Table 28: DCC-GARCH Correlation Estimation SP500-BTC.....	99
Table 29: DCC-GARCH Correlation Estimation SP500-LTC	100
Table 30: DCC-GARCH Correlation Estimation SP500-ETC.....	100
Table 31: DCC-GARCH Correlation Estimation SP500-XRP	101
Table 32: DCC-GARCH Correlation Estimation SP500-GOLD.....	101
Table 33: DCC-GARCH Correlation Estimation MSCIWORLD-ETH	102
Table 34: DCC-GARCH Correlation Estimation MSCIWORLD-BTC	102
Table 35: DCC-GARCH Correlation Estimation MSCIWORLD-ETC	103
Table 36: DCC-GARCH Correlation Estimation MSCIWORLD-LTC	103
Table 37: DCC-GARCH Correlation Estimation MSCIWORLD-GOLD	104
Table 38: DCC-GARCH Correlation Estimation MSCIWORLD-XRP	104

LIST OF EQUATIONS

Equation 1: Total Risk	4
Equation 2: Sharpe Ratio	32
Equation 3: Adjusted Sharpe Ratio.....	32
Equation 4: Tracking error	33
Equation 5: Information Ratio	33
Equation 6: Capital Asset Prices Model.....	34
Equation 7: Beta-Systemic Risk	34
Equation 8: Jensen's Alpha	35
Equation 9: TreynorRatio.....	35
Equation 10: Downside Risk.....	36
Equation 11: M-squared excess return.....	37
Equation 12: M-squared	37
Equation 13: Correlation	39
Equation 14: Correlation	39
Equation 15: log-likelihood function	40
Equation 16: Conditional variance-covariance matrix.....	41
Equation 17: Symmetric positive definite variance-covariance matrix	41
Equation 18: Conditional variance-covariance matrix.....	41
Equation 19: Return Correlation Equations System	42

1. INTRODUCTION

These recent years, there has been a disrupting innovation that is subject to multiple controversial debates. At this point, it is deemed as a perilous technology. Public and governmental regulators do not know how to manage it. It seems that this innovation is going on a dangerous stage and may become an evident aspect of our society. However, this subject is worth analyzing and clarifying some of the myths. This innovative idea is linked to Blockchain technology and, more particularly, cryptocurrencies.

Bitcoin and, more generally, cryptocurrencies have entered a new stage of consideration. Although their current roles are relatively ambiguous (currencies or assets), they have a non-negligible weight in financial investment. Built on blockchain technology, Bitcoin has established itself as the leader of cryptocurrencies and shows no signs of slowing down despite the few declines. Following the success of Bitcoin, many cryptocurrencies began to enter the market. In July 2021, there are slightly less than 5600¹ cryptocurrencies, according to the CoinMarketCap (2021). A number of cryptocurrencies have recently experienced increased speculative demand beyond their role as digital currency, placing some of them into the category of investment assets.

Following this idea, my thesis analysis is embedded in investment management, especially risk analysis. Although there are several types of risk within asset and investment management, the focus is on portfolio risk. It can be defined as the exposure to the uncertainty of meeting client expectations based, among others, on financial asset performances (Bacon, 2012). This work contributes to the ongoing debate on the utility and effectiveness of cryptocurrencies for portfolio investments. Besides, it aims to understand the benefits of cryptocurrencies to the financial market participants who seek to hedge their portfolios or even protect against market turmoil and downward movements.

¹ There are exactly 5595 cryptocurrencies on the day of July 10, 2020

This thesis aims to know the diversification effect of cryptocurrencies and to determine if any of them can reduce the risk of a traditional portfolio. Indeed, this study may contribute to investors building a portfolio based on standard assets classes who want to incorporate cryptocurrencies to hedge the portfolio's volatility. The problem beyond this work is to know the correlation values between a pair of cryptocurrencies and standard assets and then to exhibit the less correlated pairs. In other words, which cryptocurrencies are better to hedge against standard assets such as GOLD or SP500?

First, my work centers on the first moment, the return, through ex-post risk-adjusted-performance measurements. It tackles two aspects, the return over a period and the total risk of that return measured by the variability of return represented by the standard deviation. The idea is to classify the assets studied in terms of return adjusted by the risk undertaken. The results show that GOLD represents investors' most appealing asset, being the only asset that outperformed the market given the risk undertaken. However, cryptocurrencies have less good measure values than standard financial assets.

Then, my thesis concentrates on modeling volatility and correlation between pairs of cryptocurrency and traditional assets. The rolling volatility and correlation curves attest to the dynamic aspects as opposed to the unconditional version. This observation suggests that portfolio decisions should not be based on unconditional volatility and correlation due to the marked variation.

Following this idea, I use the multivariate model DCC-GARCH. The idea is to estimate the volatility via a GARCH (Generalised Autoregressive Conditionally Heteroscedastic) model and then depict the time-varying correlation of assets pairs studied through a Dynamic Conditional Correlation model.

The critical observation for the correlation estimations is that only correlations with GOLD and the three indexes are negative. They are slightly negatively correlated, indicating that GOLD act as a hedge against them. Besides, pairs of cryptocurrencies with GOLD and the three indexes are slightly correlated. The lowest correlation value is 0,0740 for GOLD-ETC. It implies that these two assets are the least correlated, and thus this combination has the best potential to reduce the portfolio risk.

The remainder of this thesis is divided into five parts as follow:

First, 2. LITERATURE REVIEW provides theoretical financial concepts essential to comprehend my various analysis. In addition, I integrate a literature review of empirical papers' in which I compare several pieces of research related to my question for section 2.5 Risk-Adjusted PerformanceMeasurements and 2.6 Volatility and Correlation Estimation modeling.

Then, 3. DATA gives a description in section 3.1 and an explanation in section 3.2 of the datasets related to the five cryptocurrencies and six standard financial assets. In addition, I am going to depict descriptive statistics.

In part 4. METHODOLOGY, I am going to expose the research questions and hypothesis in section 4.1 and explain how I conducted my analyses in section 4.2.

In part 5. EMPIRICAL RESULTS, the analysis of the results of the 5.1 Performance Analysis and 5.2 Volatility and Correlation Estimation Modeling are presented.

In the end, I am going to summarize the main results and lay out the limits of my study in section 6. CONCLUSION.

2. LITERATURE REVIEW

2.1. Markowitz Portfolio Selection Theory

In investment decisions, there is invariably a trade-off between returns gained and risk undertaken (Chandra, 2017). On the one hand, return represents the reward for engaging funds in a financial asset and is thus the primary motivating force that drives investment. On the other hand, risk concerns the likelihood that the concrete outcome of an investment will diverge from its predicted outcome. The most commonly used measure of risk in finance is variance or its square root, the standard deviation. Based on Markowitz's fundamental principle (Mangram, 2013; Markowitz, 1952), investors will only keep a risky asset if the expected return is high enough to offset them for assuming the risk. Generally speaking, the riskier the investment, the greater the required potential return.

Nobel Prize laureate Harry Markowitz is well known for his innovative theoretical contributions to financial economics and corporate finance. Pioneer in this field, his work instituted the foundations of Modern Portfolio Theory (MPT), notably through his essay "*Portfolio Selection*" (Markowitz, 1952). He established an investment framework for selecting and constructing investment portfolios to maximize expected portfolio returns and minimize investment risk (Mangram, 2013; Markowitz, 1952).

Using complex mathematical/statistical models, the most critical aspect of Markowitz's findings was its characterization of the effect on portfolio diversification by the number of assets in a portfolio and their covariance relationships (Markowitz, 1952). He demonstrated that under certain conditions, portfolio selection should be based on overall risk-reward characteristics. Indeed, he showed that the risk portfolio can be reduced by adequately selecting a weighted compilation of investment assets that together exhibit lower risk factors than investment in any specific asset or particular asset class (Mangram, 2013; Markowitz, 1952).

Finally, it is worth noting that Markowitz's portfolio selection theory is a "*normative theory*" that aims to depict a standard or norm of behavior that investors should follow in building an asset portfolio (Fabozzi, Gupta, & Harry, 2002). It contrasts with a

“*positive theory*” that conjectures how investors actually behave, such as the Capital Asset Pricing Model.

2.2. Modern Portfolio Theory

As mentioned above, my thesis concentrates on the risk side and, more specifically, the portfolio risk. Aside from other risk perspectives, the modern portfolio theory considers the total risk of equity as the combination of unsystematic risk and systematic risk (Tan, 2019; Chandra, 2017; Mangram, 2013; Markowitz, 1952).

Equation 1: Total Risk

$$\text{TOTAL RISK} = \text{UNSYSTEMATIC RISK} + \text{SYSTEMATIC RISK}$$

First, the unsystematic risk is related to company-specific factors that would likely only impact the company. It is a micro-level form of risk which is local or limited to a particular asset or industry. Therefore, unsystematic risk can be (almost entirely) avoided through diversification by forming a portfolio of assets that are not highly correlated with one another.

Then, systematic risk affects almost the entire market and cannot be avoided. It is a macro-level form of risk inherent to the overall market and thus cannot be diversified away. Global economic conditions, such as inflation, interest rates, are few examples of systematic risk factors. The entire portfolio would probably suffer from these factors. Usually, the systematic risk is represented by the measure of beta β .

Finally, the total risk is the sum of these two types of risk. Investing in assets involves exposure to simultaneously unsystematic risk and systematic risk. The portfolio distribution is crucial in order to obtain the best balance between return and risk. It is commonly accepted that as the number of assets increases, the portfolio will become more well-diversified. Indeed, the Efficient Frontier, which denotes the efficient allocations of diversified assets for variable risks, will significantly improve.

However, a low correlation value will lower the number required. Indeed, the more significant the proportion of uncorrelated assets in a portfolio, the more significant the

risk reduction. Intuitively, the correlation acts also as a critical measurement in building a portfolio of assets.

2.3. Portfolio Risk Diversification

The concept of diversification consists of risk reduction that implicates the allocation of investments among various financial instruments, industries, and other investment classes (Lioudis, The Importance of Diversification, 2021). Being the centerpiece between Markowitz's portfolio selection theory and Modern Portfolio Theory, the diversification effect relates to the relationship between correlations and portfolio risk. It is the result of the non-perfect correlation (positive or negative) between assets. Diversification represents an essential and effective risk reduction strategy since this latter can be achieved without compromising returns (Mangram, 2013; Markowitz, 1952).

Nevertheless, this strategy cannot eliminate all risk, or more precisely, it cannot impact one type of risk (Tan, 2019; Chandra, 2017; Mangram, 2013; Markowitz, 1952). As stated in the Modern Portfolio Theory, diversification only affects unsystematic risks due to the limited effect on a specific asset or industry. Conversely, it is doubtful that any diversification degree can effectively eliminate all systematic risk since it arises from external factors touching a majority of assets.

However, the critical benefit of diversification is that it can increase expected portfolio returns without increasing the risk, the unsystematic risk. The Efficient Frontier, also called Markowitz's Efficient Frontier, portrays the best combination of assets within an investment portfolio (Ganti, 2021). It is constituted by assets allocation producing the maximum expected return for a given risk level. Usually depicted in graphic form as a curve on a graph comparing risk against the expected return of a portfolio, the Efficient Frontier outlines the highest expected return on investment attainable for the given amount of risk. Being a fundamental concept of MPT, it describes the relationship between expected portfolio returns and the riskiness or volatility of the portfolio.

2.4. Diversifier, hedge, and safe haven assets

In the context of risk diversification and risk protection, three terms are worth defining. It refers to the role an investment can play in comparison to an asset portfolio. As mentioned above, diversification implicates portfolio risk and correlations across the portfolio assets. The more significant the proportion of uncorrelated assets in a portfolio, the more significant the risk reduction. Thus, the investor behavior consists of seeking a combination of assets with low correlations value for a given expected return. For that, some assets classes are deemed acting as to facilitate the risk reduction.

A diversifier relates to an asset that is positively (but not perfectly correlated) with another asset or portfolio on average (Stensås, Nygaard, Kyaw, & Treepongkaruna, 2019; Baur & McDermott, 2010). The particularity is to have assets relatively correlated that fluctuate in the same direction while reducing the unsystematic risk.

A hedge is an uncorrelated asset or negatively correlated with another asset or portfolio on average (Baur & McDermott, 2010). The typical utility consists of taking an opposite position or offsetting a related asset or portfolio (Downey, 2021). By holding an asset on average, it can be compared to taking out an insurance policy.

A safe haven refers to an uncorrelated asset or negatively correlated with another asset or portfolio in specific periods only, such as times of market stress or turmoil (Baur & McDermott, 2010). The expected utility is to restrain the portfolio's exposure to losses in the event of market downturns. (Chen, 2021). Only required to hold in particular periods, safe haven assets are expected to hold or gain value during market turmoil. For example, the financial media frequently mention gold as a “safe haven asset”. While most asset classes suffer losses, gold presents relatively good performance during adverse market conditions (Baur & McDermott, 2010).

2.5. Risk-Adjusted PerformanceMeasurements

2.5.1. Theory

As mentioned above, my thesis analysis is embedded in portfolio risk. The first part of my work refers to ex-post risk-adjusted-performance measurements. It tackles two aspects, the return over a period and the risk measured by the return variability.

The preliminary step consists of descriptive statistics that depict the return and the shape of the return distribution. The essential components of classical ex-post risk measures are the first, second, third, and fourth moments of the return distribution, respectively, to the mean, variance, skewness, and kurtosis (Bacon, 2012). There is a distinction between statistics providing insights about the location of the data and those that give comprehension about the data's dispersion (Soetewey, 2020).

Following the preliminary steps, performance analytics consists of comparing, and most of the time, ranking stock returns included in a portfolio to a benchmark. The process implicates composing a risk measure that specifies if the reward obtained balanced the risk undertaken by the portfolio manager (Bacon, 2012). There are several types of risk measures depending on the aspects and the goal needed:

- ❖ Simple risk measures appraise the performance in a general manner and take into account the whole return distribution. There are, to name a few, the Sharpe Ratio, Skewness-kurtosis Ratio, Tracking error.
- ❖ The Capital Asset Prices Model is a linear regression used to investigate the relationship between portfolio return and the risk-free market rate. It allows determining the systematic risk/volatility represented by Beta (β) and the excess return adjusted for systematic risk represented by Jensen's Alpha (α).
- ❖ Partial moments measures are semi-standard deviations that consider return under or above a specific target rate (0, the risk-free rate or a benchmark rate). It permits an investor to focus on undesirable risks (mostly the case) or desirable risks. Downside and upside risk are some examples, as well as the Omega ratio (Ω).
- ❖ Extreme risk measures concentrate on the shape of returns in the distribution tails rather than on the entire distribution. It allows apprehending extreme events that have low probability but potentially high impact. Evidently, there is more disquietude about extreme negative events. The Value at Risk is a good example.
- ❖ The risk-adjusted Return concept is sometimes erroneously related to ratios such as Sharpe Ratio. As the name indicates, ratios are not returns because

they do not tell the relative performance quantity. Conversely, risk-adjusted returns convert ratios to a return metric entirely understandable and valuable to assess relative performance. The most common one is Modigliani-squared (M^2).

2.5.2. Literature considerations

Regarding portfolio management using risk-adjusted measurements, the literature lacks research that includes cryptocurrency markets (Ankenbrand & Bieri, 2018). Since there is no consensus yet on whether cryptocurrencies constitute an individual asset class, it would be beneficial to evaluate this market via performance analysis compared to the others. Therefore, this section aims to exhibit the performance and levels of risks associated with investments in the cryptocurrency market. Then, the idea is to depict the impact of diversification in a traditional portfolio to construct an optimal model containing a combination of cryptocurrencies and standard assets.

To begin with, two authors, Dobrynskaya (2020) and Keenan (2020) conclude that cryptocurrencies do not appear to be markedly distinct from standard assets in terms of some risk-adjusted measurements. The former shows that the cryptocurrency market does not differ from traditional asset markets regarding downside risk pricing. It is pretty intriguing, considering that cryptocurrencies are characterized by unusual return dynamics, bubbles, and idiosyncratic risk. Besides, Dobrynskaya (2020) reports a notable heterogeneity in the exposure to downside market risk across a sample of more than 500 coins. Generally, a higher downside risk exposure is associated with higher subsequent returns.

The Keenan (2020) analysis shows that the inclusion of cryptocurrencies did not necessarily increase the risk-adjusted returns of an already well-diversified portfolio. He also suggests attributing a very moderate proportion of cryptocurrencies (e.g., 5% of the total portfolio) to a diversified portfolio in conjunction with a disciplined rebalancing strategy (e.g., weekly). According to him, it can support the increase of the risk-adjusted returns.

However, three papers share the same results: cryptocurrencies can lead to better portfolio diversification and better risk-adjusted measurements than the stock index.

First, Ma, Ahmad, & Liu (2020) study shows that crypto-diversification enhances the returns in most cases and decreases portfolio volatility in all portfolios. Also, including cryptocurrencies provides higher returns than the traditional portfolios for the same level of risk, as measured by the standard deviation of the portfolios.

Second, Hu, Rache, & Fabozzi (2019) demonstrate that the compounding of extremely volatile single cryptocurrencies in a minimum-risk portfolio often outperforms a leading stock market index like the S&P 500. By building optimal portfolios with risk budgeting based on two risk measures, the authors also find that minimize variance, and Conditional Value at Risk outperform a traditional stock market index via crypto portfolio optimizations. They conclude that the minimum Conditional VaR portfolio has the highest risk-adjusted return while the minimum Variance portfolio and the benchmark (the S&P 500) have similar performance.

Furthermore, Borri (2019) analysis points out that cryptocurrencies are highly exposed to tail-risk within crypto-markets while not exposed to tail-risk for other global assets, like the US equity market or gold. Moreover, he shows that idiosyncratic risk can be significantly diminished and that portfolios of cryptocurrencies offer better risk-adjusted and conditional returns than individual cryptocurrencies. Therefore, these outcomes implicate that including cryptocurrencies in traditional investors' portfolios could offer attractive returns and hedging properties. In addition, Håberg & Klungland (2019) provide evidence that each cryptocurrency's investment percentage should be treated individually. For example, based on the Sharpe ratio, the optimal percentage for the cryptocurrencies/gold starts from 0.5% to 10% of the portfolio.

2.6. Volatility and Correlation Estimation modeling

2.6.1. Theory

The second part of my thesis concerns volatility and correlation modeling, arguably one of the most critical concepts in whole finance. Over the past decade, a vast empirical and theoretical investigation has been made on modeling and forecasting stock market volatility, both by academics and practitioners (Brooks, 2019). As

measured by the standard deviation or variance of returns, volatility is often used as a raw measure of the total risk of financial assets. Indeed, the estimation or forecast of this latter parameter is demanded in measuring market risk for any value-at-risk models.

Beforehand, there are explicit justifications for considering non-linear models in various circumstances that better capture the data's relevant features. The reasons lie in the fact that many relationships in finance are likely inherently non-linear. More specifically, linear structural (and time series) models are, among others, unfit to explain a number of essential features common to many financial data, such as leptokurtosis², volatility clustering or volatility pooling³, and leverage effects⁴ (Brooks, 2019).

A few non-linear models have been constructed to capture better volatility models, helping model financial data. The most widespread non-linear financial models are the ARCH (AutoRegressive Conditionally Heteroscedastic) or GARCH (the Generalised ARCH). These models are employed for modeling and forecasting volatility and switching models. It allows a series to follow different processes at different points in time (Brooks, 2019).

ARCH and GARCH models' particularity consists of integrating the possibility for the variance of the errors to be non-constant, also known as heteroscedasticity. It represents a suitable property for a volatility forecasting model to strive for the unconditional variance of the series as the prediction horizon increases. It can be explained by the fact that volatility series are "mean-reverting", with an up move in volatility being offset by a down move. Also, it is implausible that the variance of the errors will be constant over time in financial time series. Therefore, it is reasonable to examine a model that does not assume that the variance is constant (Brooks, 2019).

Nevertheless, it should be noted that GARCH models are extremely more widely used than ARCH models due to the latter's limitations. Indeed, the ARCH(q) model presents some difficulties that make it not practical to employ. The GARCH model represents a natural extension of an ARCH(q) model, which overtakes some problems. The former

² It consists of the disposition for financial asset returns to have distributions that present fat tails and excess peakedness at the mean.

³ It represents the penchant for volatility in financial markets to appear in bunches.

⁴ It results in the susceptibility for volatility to increase more after a large price fall than following a price rise of the same magnitude.

is more parsimonious and prevents overfitting. Thus, the model is less likely to breach non-negativity constraints and allows the conditional variance to depend upon its own previous lags (Brooks, 2019).

Besides, there are many extensions to the basic one due to perceived problems with standard GARCH(p, q) models. The various types of GARCH models allow obtaining more complex 'hybrid' models that can account for several essential features of financial series simultaneously. Moreover, another primary usage of GARCH-type models is forecasting volatility by expressing movements in the conditional variance of an error term u_t (Brooks, 2019).

Simultaneously, a significant limitation of the standard GARCH models is that they are exclusively univariate in nature. It means that they model the conditional variance of each series wholly independently of all other series. This limitation has two main reasons at the source. The first is the tendency for volatility to change in one market or asset following a change in the volatility of another, often named "volatility spillovers". Secondly, it is frequently the case in finance that the covariances among series are of interest, as well as the variances of the individual series themselves (Brooks, 2019).

Therefore, using a multivariate model has the potential to surmount both of these shortcomings with their univariate counterparts. Multivariate extensions to GARCH models can be used to forecast the volatilities of the component series, just as with univariate models. Since the volatilities of financial time series commonly move together, a joint modeling approach may be more efficient than treating each separately (Brooks, 2019).

To finish, there is, theoretically, an infinite number of various kinds of non-linear models due to the immense possibility of combinations. Indeed, the linearity may be present in the mean but not in the variance, or inversely, linear in variance but not in the mean. Also, the model may be linear or non-linear in both mean and variance. Besides, the choice and construction of models depend on data nature and structure. It is essential to know what characteristics to depict based on the constraints such as the time-varying, cross-correlation, dynamic conditionality, to name a few (Brooks, 2019).

2.6.2. Literature considerations

Since the thesis aims to model the volatility of cryptocurrencies relative to traditional assets, I am going to review a more significant number of quantitative researches that tackle this theme. In this section, the purpose is to regroup papers that share quite the same relation between all asset classes and cryptocurrencies used. Although the different authors have different approaches and take different aspects, it is still interesting to point out the potential similarities and disparities.

This section is separated into two parts. Firstly, I regroup articles that compare only Bitcoin against other financial assets. Then, the second part joins my thesis problem by making an empirical examination of the correlation between leading cryptocurrencies and other financial assets.

2.6.2.1. Bitcoin relative to other financial assets

In this part, I analyze six papers based only on Bitcoin for the correlation analysis. Results and conclusions of this group of articles are divided between two insights. On the one hand, some articles affirm the link between Bitcoin and some financial assets. On the other hand, others attest isolation of Bitcoin. While three papers seem to validate the first hypothesis, one has the opposite point of view.

The findings of Bouri, Gupta, Lau, Roubaud, & Wang (2018) and Selmi, Mensi, Hammoudeh, & Bouoiyour (2018) establish a negative correlation between Bitcoin and GFSI for the first paper and oil for the second one. In the first paper, the marginal and copula models show that the Bitcoin market is wealthy while the GFSI is very low and inversely. Following this idea, the quantile-on-quantile regression results of Selmi, Mensi, Hammoudeh, & Bouoiyour (2018) reveal a positive and strong correlation between oil returns and Bitcoin returns when the oil price is meager.

Furthermore, the papers of Bouri, Gupta, Lau, Roubaud, & Wang (2018) and Selmi, Mensi, Hammoudeh, & Bouoiyour (2018) have a similar inference about Bitcoin's status as a safe haven. The directional predictability test of Bouri, Gupta, Lau, Roubaud, & Wang (2018) exhibits evidence that Bitcoin can act as a safe haven when

there is an alarm in the global financial market (particularly in the medium term). Indeed, the results present a complete quantile-to-quantile relationship between financial stress and Bitcoin return. As for Selmi, Mensi, Hammoudeh, & Bouoiyour (2018), the gold results imply that Bitcoin could serve the function of a hedge, a safe haven, and a diversifier for oil price movements. Nevertheless, this property should be nuanced along with different market conditions, given that these outcomes are confirmed in the medium term.

Nevertheless, Kim, Seong-Tae, & Sangjin (2020) find, through four models, that there is a positive time-varying relationship between Bitcoin, Gold, and S&P 500 markets since the COVID-19 occurrence. The Gaussian Copula Marginal Regression (GCMR) model exposes that the S&P 500 and Gold prices are statistically significant to Bitcoin regarding log-return and volatility.

However, outcomes from Ji, Bouri, Gupta, & Roubaud (2018) contemporaneous analysis show that the Bitcoin market is relatively insulated. Indeed, the Vector AutoRegression (VAR) model lacks cointegration between Bitcoin and the other financial asset classes. It appears that the Bitcoin volatility is primarily self-explanatory, seen that the most considerable contribution made by each of the seven financial assets deem for roughly 4% of Bitcoin's total volatility. Nevertheless, these results must be relativized because it concerns two out of three specific sub-periods.

As for Al-Yahyaee, Mensi, & Yoon (2018) and Gajardo, Kristjanpoller, & Minutolo (2018), results show cross-correlations and multifractal between Bitcoin, major global currencies, and other financial assets, but without any precision of the direction. The former assesses the multifractality and time-varying efficiency of Bitcoin against the stock, gold and currency markets and finds that Bitcoin is the most inefficient among the four markets. Although there is vital evidence of multifractal behavior in all four return series, the Bitcoin market presents a very observable long-memory feature (Al-Yahyaee, Mensi, & Yoon, 2018). Therefore, investors can foresee eventual prices and raise anomalous returns. Following this idea, the results of Gajardo, Kristjanpoller, & Minutolo (2018), through a multifractal asymmetric detrended cross-correlation analysis method, exhibit that all currencies studied, including Bitcoin, present multifractality in every cross-correlation and there is an asymmetry in the cross-correlation exponents under different trends.

To conclude, this second group seems to have no consensus. While Bouri, Gupta, Lau, Roubaud, & Wang (2018) and Selmi, Mensi, Hammoudeh, & Bouoiyour (2018) reach the same conclusion that Bitcoin may serve as a safe haven for investors as well as gold, Kim, Seong-Tae, & Sangjin (2020) affirm a positive time-varying relationship. Besides, Al-Yahyaee, Mensi, & Yoon (2018) and Gajardo, Kristjanpoller, & Minutolo (2018) show evidence of cross-correlations and multifractal. Nevertheless, this result should be taken with caution because the contemporaneous analysis of Ji, Bouri, Gupta, & Roubaud (2018) reveals Bitcoin markets' isolation.

2.6.2.2. Leading cryptocurrencies VS other financial assets

The second part contains six papers analyzing the time-varying correlations, conditional correlations, conditional volatilities, and the causality between a number of cryptocurrencies and a number of financial asset classes. This group's results generally tend to the same conclusion, which affirms no or low correlation between cryptocurrencies and financial asset classes.

First, Milunovich (2018) and Rehman & Apergis (2019) find evidence of a correlation between cryptocurrencies and different financial asset classes. The former outcomes exhibit connectedness through a Granger causality analysis both within and across the cryptocurrencies and standard financial assets. As for Rehman & Apergis (2019), the results show that the returns and the volatility behavior of certain commodities futures are accounted for the cryptocurrencies being helpful drivers, and vice versa. This predictive capacity occurs either symmetrically (across all quantiles) or asymmetrically (in specific quantiles)(Rehman & Apergis, 2019). It is noteworthy to specify that these authors shift towards the primary model of non-parametric causality in quantiles, which examines all quantiles of the distribution rather than only the center of the distribution.

Indeed, Rehman & Apergis (2019) first performed a linear Granger causality analysis based on a linear framework, indicating a weak causality link between Bitcoin and Ethereum and individual commodity futures. This joint the dynamic cross correlations model (DCC) of Aslanidis, Bariviera, & Martínez-Ibañez (2019) exhibiting very low correlations between cryptocurrencies and traditional assets, implying that the cryptocurrencies' returns are not connected to main financial markets. Also, the results

of Charfeddine, Benlagha, & Maouchi (2020), using various time-varying copula approaches and bivariate dynamic conditional correlation GARCH models, show that the cryptocurrencies cross-correlation with traditional assets is changing over time but weak. In addition to that, Tiwari, Raheem, & Kang (2019) find, based on the copula-DCC-EGARCH and copula-ADDC-EGARCH models, the presence of low time-varying correlations close to zero, pointing out that cryptocurrency serves as a hedge asset against the risk of the S&P 500 stock market. Whereas these articles effectively find evidence of correlation at a low level, Corbet, Meegan, Larkin, Lucey, & Yarovaya (2018) are the only ones who conclude a correlation. The Frequency Domain Analysis (FDA) using the Barunik and Krehlik methodology show that all selected digital currencies are somewhat insulated from other financial markets.

Moreover, some articles further conclude a correlation within the group of digital currencies and standard assets groups. Indeed, Corbet, Meegan, Larkin, Lucey, & Yarovaya (2018) find, through a time-domain analysis, that most of the significant linkages are within the group of cryptocurrencies and other financial asset classes. In addition to that, the time-varying conditional correlations model of Aslanidis, Bariviera, & Martínez-Ibañez (2019) shows that, on average, the correlation between cryptocurrencies is positive. Besides, the connectedness analysis of (Milunovich, 2018), using the (standardized) generalized forecast error variance decompositions (SGVD), shows that the performance of digital currencies is strongly interconnected to one another.

However, several correlation studies evince other curious results related to spillover and conditional volatility behavior. First, The time-domain analysis of Corbet, Meegan, Larkin, Lucey, & Yarovaya (2018) based on a generalized variance decomposition framework reveals that the spillovers' intensity varies over time according to the analysis of the dynamics of pairwise spillovers. This links up the dynamic conditional correlation outcomes of Tiwari, Raheem, & Kang (2019), which states that the correlation coefficients fluctuate considerably with the time change in the pairwise cases S&P 500 index and cryptocurrency markets. Then, some results concern the reaction of conditional volatility to shocks. Tiwari, Raheem, & Kang (2019) find, based on the copula-DCC-EGARCH and copula-ADDC-EGARCH models, that volatility seems to depend more on previous shocks and conditional variances. Adverse shocks have a greater effect on conditional volatility than positive shocks of the same

magnitude, given asymmetric volatility. Following this idea, the Charfeddine, Benlagha, & Maouchi (2020) outcomes demonstrate that the relationship between cryptocurrencies and conventional assets is sensitive to external economic and financial shocks. It is shown that cryptocurrencies are low hedging instruments in most cases, based on portfolio analysis.

In conclusion, the majority of the papers conclude that cryptocurrencies are interlinked. Conversely, the correlation between digital and non-digital assets appears to be low and to vary over time. Nevertheless, these conclusions ought to be nuanced given the spillover fluctuation over time and depending on the shocks. It seems clear that the methodology's choice and the estimation models employed impact the analysis outcomes. Thus, it is beneficial to use several models in order to apprehend the correlation better.

3. DATA

In this section, the datasets used for the performance analytics and the correlation analysis are outlined. Also, I provide some insights that I learned by cleaning and exploring them. The programming and statistical software, RStudio, allowed me to perform all the analyses. This software is deemed as time-efficient as it requires little time to have the statistics of series computed along with risk measurements modeling volatility. The code regrouping all the workflows used in this thesis framework can be found in the workspace I build on the RStudio website⁵.

This section is divided into three sections. First, there is section 3.1 Description of the datasets. Next, I discussed the steps I went through to compute the final datasets utilized for the analysis in section 3.2 Data cleaning. Finally, I review the preliminary analysis of the datasets through a descriptive statistical analysis in section 3.3 Preliminary analysis – Descriptive statistics.

3.1. Description of the datasets

For the analysis, I analyzed the daily returns computed⁶ from the daily prices (U.S. Dollar) of five cryptocurrencies and six standard financial assets from January 19th to 2018 July 29th, 2020. The period consists of two and a half years, with a total number of observations of 659. The data of the daily prices of cryptocurrencies and standard financial assets used have been collected from the sites (Investing, 2020) for the former and (Refinitiv, 2020) for the latter.

First, the cryptocurrency dataset includes Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ethereum Classic (ETC), and Ripple (XRP), which are some of the most actively traded digital assets. Then, the standard financial assets comprise gold (GOLD), stocks indexes such as CAC 40 total return index (CAC40), the S&P 500 total return index (SP500) used as the benchmark. There is the risk-free rate represented by the government debt as captured by the US benchmark 10-year government bond index

⁵<https://rstudio.cloud/project/1655150>

⁶ Further explanations about the computation is in the next section, Data cleaning.

(TBOND10US), then the MSCI world-market-cap-weighted stock market index (MSCIWORLD), and finally the currency pair EUR/USD or in other words, the exchange rate between the Euro and the US Dollar(EURUSD). A short description and historical insights of all assets utilized are presented in Appendix 7.1 for the cryptocurrencies and Appendix 7.2 for the standard's financial assets.

3.2. Data cleaning

In order to perform the empirical analysis, a preliminary cleaning of the datasets was necessary. First, it was needed to synchronize the cryptocurrencies' daily price data and the standard financial assets due to the divergence in the prices' recording process. Indeed, the cryptocurrencies' prices are recorded each day, during the week and even the weekend, while the standard's financial asset prices are recorded only on the weekdays.

Therefore, the datasets of the cryptocurrencies have to be separated into two categories, weekdays and weekends. Another variable (*weekend dummy*) was added to determine if the day of price recording is on a weekday (0) or if it is on the weekend (1). Excel allowed to distinguish between these two groups and keep the prices linked to a weekday for the synchronization with the datasets of the standard's financial assets.

However, a preliminary question emerged regarding the cryptocurrency returns: *Do the weekend returns differ significantly from those recorded on the weekdays?* I ran a bilateral student's t-test on RStudio, more precisely, a Welch test to answer this question. The null hypothesis of the student's t-test is that the means of the two samples are equal, and consequently, the alternative hypothesis state that the means are different. The idea is to verify if these two samples are significantly dissimilar or not by comparing their means values.

Before doing the student's t-test, I extracted a boxplot for each cryptocurrency regarding the variable *weekend dummy* to visualize the data by group (see Appendix 7.3). These reveal that the two-sample statistics overlapped each other, which not rejecting the first hypothesis. Furthermore, the test results in Table 1revealed that, for

all cryptocurrencies, the hypothesis that the two samples' means are equal could not be rejected with a significance level of 5%. In other words, there is no sufficient evidence in the data to conclude that the weekdays' returns (0) and the weekend returns (1) are different. Indeed, the p-value of the student's t-test for the five cryptocurrencies is above the threshold of 0.05. It means that it is plausible to observe the two-sample statistics under the first hypothesis that their means are equal.

Table 1: Student's t-test for cryptocurrencies

T-Test	Bitcoin	Ethereum	Litecoin	Ethereum Classic	Ripple
Value of T	0.32946	-0.67646	-0.66279	-0.21413	0.15382
P-value	0.7419	0.499	0.5077	0.8305	0.8778

To finish, the daily return variable needed to be computed based on the daily price data gathered. The real return formula is used to consider and adjust prices due to inflation or other external factors. It consists of taking first the price of a day (n) and subtracted it by the previous day's price (n-1) to have the dollar return. After that, I divided the dollar return by the previous day's price (n-1), corresponding to the initial dollar investment. Thanks to a few manipulations on Excel, I was able to do so for all the period's daily values.

3.3. Preliminary analysis – Descriptive statistics

Before the empirical analysis, it is essential to perform a preliminary analysis of the datasets to gain insights into the various returns' values during the studied period. To do so, I computed summary statistics, compounded arithmetically, on the software RStudio. I presented the results in two tables: Table 2: Summary Statistics of the cryptocurrencies t for the cryptocurrencies and Table 3 for the standard's financial assets. For information, there are plots representing the return evolution during the period studied and density histograms, in Appendix 7.3 for the cryptocurrencies and Appendix 7.4 for the standard financial assets. In this section, I am going to outline and

analyze the descriptive statistics of the two groups of assets, first separately, before giving a general conclusion.

3.3.1. Descriptive statistics of the cryptocurrencies

Table 2: Summary Statistics of the cryptocurrencies⁷

Statistics	Bitcoin	Ethereum	Litecoin	Ethereum Classic	Ripple
Annualized Return	0.0348	-0.4049	-0.4522	-0.3862	-0.4052
Globa Return	0.0937	-0.7427	-0.7928	-0.7210	-0.7429
Minimum	-0.3818	-0.4470	-0.3849	-0.4217	-0.3465
Maximum	0.1740	0.2472	0.3368	0.2718	0.3720
1st Quartile	-0.0179	-0.0232	-0.0294	-0.0273	-0.0257
Median	-0.0001	-0.0027	-0.0042	-0.0011	-0.0032
3rd Quartile	0.0178	0.0230	0.0264	0.0256	0.0215
Mean⁸	0.0011	-0.0005	-0.0008	-0.0002	-0.0006
Standard Deviation	0.0429	0.0544	0.0555	0.0590	0.0552
Annualized Standard Deviation	0.6814	0.8628	0.8817	0.9364	0.8766
Fisher's Skewness	-0.7394	-0.5937	0.4750	-0.2223	0.7399
Pearson's Kurtosis	10.7191	8.4988	7.8758	5.9204	7.7460

Based on t, it is noticeable that there is more discrepancy between the maximum's values than the minimum ones among the cryptocurrencies. The lowest maximum return is +17.50% for Bitcoin, and the highest maximum return is +37.20% for ripple, while the values of the minimum returns start from -44.70% forEthereum and go to -

⁷ The values have been rounded to the fourth decimal place

⁸Arithmetic Mean

34.65 for % for ripple. It seems to have more variations in the maximum's returns than the minimum's return measure. It implicates that the cryptocurrency returns do not follow a normal distribution.

The Jarque-Bera test for normality confirms these. Indeed, the test results in Appendix 7.6 revealed that, for all cryptocurrencies, the null hypothesis that the kurtosis value is three and the skewness value is zero is rejected with a significance level of less than 1%. More precisely, the χ^2 values are far from zero (the least value is 967.87991 for Ethereum Classic), indicating that the sample data do not have a normal distribution. Also, the p-value of all is 2.2204E-16 which is negligible. Therefore, there is sufficient evidence to say that the cryptocurrency datasets are not normally distributed. These conclusions will be further discussed through other statistics, such as the skewness and the kurtosis.

However, there is a divergence among the annualized standard deviation values of cryptocurrencies. Based on Table 2, Bitcoin is the least risky with the lowest value of 68.14%, meaning that Bitcoin's returns deviate over a year from the mean by 68.14%. Concerning the highest annualized standard deviation, Ethereum Classic presents the most variability with a total risk value of 93.64%, signifying that Ethereum Classic's returns deviate over a year from the mean by 93.64%. Nevertheless, the annualized standard deviation does not indicate if the volatility is positive or negative. Indeed, a high variability mainly resulting in positive gains can be considered "good", whereas high variability mainly caused by negative gains would be unfavorable. Therefore some additional volatility measurements taking into account this distinction will be analyzed in the Performance Analytics section (5.1) using Risk-Adjusted measurement.

To finish the descriptive analysis, the skewness and the kurtosis values provide more precision about the shape of the several return distributions. First, the values of degree of skewness in Table 2 are relatively close to 0 for all cryptocurrencies (between -1 and 1), meaning that the return distributions are moderately or approximatively symmetric like a normal distribution. Bitcoin, Ethereum and Ripple are considered moderately skewed since the degree of skewness is between -1 and -0.5 and between 0.5 and 1. The Litecoin and Ethereum Classic distributions are approximately symmetric because the skewness value is between -0.5 and 0.5. In addition to that, I noticed that Bitcoin, Ethereum, and Ethereum Classic present a

negative value of skewness. It implicates that there are moderately more extreme returns extending to the left tail. Inversely Litecoin and Ripple present a positive skewness degree characterized by relatively more extreme returns extending to the right tail. Then, kurtosis values above 3 in Table 2 indicate that all cryptocurrencies distributions are leptokurtic, characterized by a peaked distribution with fat tails. These results regarding the return distribution can be seen in Appendix 7.3.

3.3.2. Descriptive statistics of the standard's financial assets

Table 3: Summary Statistics of the standard's financial assets⁹

Statistics	GOLD	CAC40	SP500	MSCIWORLD	TBOND10US	EURUSD
Annualized Return	0.1590	-0.0072	0.0803	0.0459	0.1005	0.0149
Global Return	0.4709	-0.0188	0.2239	0.1245	0.2846	0.0394
Minimum	-0.0476	-0.1228	-0.1198	-0.0990	-0.0244	-0.0174
Maximum	0.0509	0.0847	0.0939	0.0878	0.0211	0.0181
1st Quartile	-0.0036	-0.0045	-0.0038	-0.0036	-0.0018	-0.0022
Median	0.0005	0.0007	0.0008	0.0006	0.0002	0.0001
3rd Quartile	0.0043	0.0061	0.0065	0.0051	0.0026	0.0024
Mean	0.0006	0.0001	0.0004	0.0003	0.0004	0.0001
Standard Deviation	0.0081	0.0136	0.0151	0.0125	0.0043	0.0039
Annualized Standard Deviation	0.1279	0.2160	0.2400	0.1982	0.0678	0.0621
Fisher's Skewness	0.0925	-1.4172	-0.6056	-1.1182	-0.1315	-0.1284
Pearson's Kurtosis	5.9572	15.8982	15.0874	18.1770	6.5550	2.0121

⁹ The values have been rounded to the fourth decimal place

Based on Table 3, there is relatively more divergence between the minimum values than the maximum's values among the standard's financial assets. The minimum return values start from -12.28% for CAC40 and go to -1.74% for EURUSD, while the lowest maximum return is +1.81% for EURUSD, and the highest maximum return is +9.39% for SP500. It seems to have moderately more fluctuations in the minimum's returns than in the maximum's returns. It suggests that financial asset returns do not follow a normal distribution.

The Jarque-Bera test for normality confirms these. Indeed, the test results in Appendix 7.6 revealed that, for all traditional assets, the null hypothesis that the kurtosis value is three and the skewness value is zero is rejected with a significance level of less than 1%. More precisely, the χ^2 values are far from zero (the least value is 112.97274 for EURUSD), indicating that the sample data do not have a normal distribution. Also, the p-value of all is 2.2204E-16 which is negligible. Therefore, there is sufficient evidence to say that the traditional datasets are not normally distributed. These conclusions will be further discussed through other statistics, such as the skewness and the kurtosis.

However, there is a divergence among the annualized standard deviation values of the standard's financial assets. Based on 2, EURUSD presents the lowest variability with a total risk of 6.21%, meaning that EURUSD 's returns deviate over a year from the mean by 6.21%. Concerning the highest annualized standard deviation, SP500 is the riskiest variability of 24.00%, signifying that SP500's returns deviate from the mean by 24.00% over a year. As for cryptocurrencies, the annualized standard deviation does not indicate if the volatility is positive or negative. Therefore, further discussion will be in the Performance Analytics section (5.1).

Besides, it seems to have a tendency for the standard's financial assets to split into two groups. On the one side, the standard deviation values for GOLD, TBOND10US, and EURUSD are of the order of tenth in return percentage. On the other side, the ones for CAC40, SP500, and MSCIWORLD are of the order of unity in return percentage. Nevertheless, GOLD seems, in terms of annualized standard deviation, to distinguish itself from the TBOND10US and EURUSD without having the same behavior as the stock indexes.

To finish the descriptive analysis, the skewness and the kurtosis values provide more precision about the shape of the several return distributions. First, there is relative

heterogeneity regarding the degree of skewness of the financial asset classes in Table 3. While only GOLD has a positive skewness close to 0 (0.0925), the others are negatively skewed. For the former, this suggests that its return distribution is approximately symmetric, as well as TBOND10US and EURUSD, and tends to follow a normal distribution since the degree of skewness is between -0.5 and 0.5. As for CAC40, SP500 and MSCIWORLD, their distribution is highly skewed due to a skewness less than -1 and thus presents more extreme returns extending to the left tail but not at the same degree.

Second, the kurtosis values in Table 3 are quite heterogeneous among the financial asset classes. It appears to have three separations. EURUSD is the only one having a kurtosis value below three but close to it (2.0121). It indicates that its return distribution follows quite well a normal one. However, GOLD and TBOND10US present positive kurtosis values and are relatively close to 3 (5.9572 for the former and 6.5550 for the latter). Regarding the stock indexes (CAC40, SP500 and MSCIWORLD), the kurtosis values are greater than 15. To sum up, all the asset classes except GOLD have a leptokurtic distribution, some more pronounced than others. These results regarding the return distribution can be seen in Appendix 7.4.

3.3.3. Descriptive statistics: The two types of assets comparison

To begin, I am going to compare the annualized returns and the global returns of the two groups directly in this section, along with two charts of the cumulative returns. I distinguish assets with cumulative returns in Figure 1 and those with positive ones in Figure 2. I found it relevant to separate it like this to emphasize the rentability of the assets visually.

Based on Figure 1, almost all cryptocurrencies (except Bitcoin) have a negative cumulative return as well as CAC40. Inversely, Figure 2 shows that the four remainder standard financial assets plus Bitcoin exhibit a positive cumulative return. It is confirmed by the global returns in Table 2 and Table 3. More precisely, the lowest global return is -79.28% for Litecoin, and the highest value is 47.09% for GOLD. In between, CAC40 is the only standard financial asset that presents a negative global

return of -1.88%, and reciprocally, Bitcoin is the only cryptocurrency with a positive global return of 9.37%. The same comments can be extrapolated to the annualized returns.

Furthermore, it is explicit from the two charts that the two groups of assets have disparate performances. On the one hand, the six standard financial asset returns seem to exhibit slight growth with relatively low variability over the period. On the other hand, the five cryptocurrency returns seem unstable and decline significantly during the defined time (except for Bitcoin). Indeed, the range of global returns for cryptocurrencies without Bitcoin starts from -79.28% to -72.10%. As for standard financial assets without GOLD, the global returns range is broader, from -1.88% to 28.46%. It appears that Bitcoin and GOLD can be deemed as outliers in their respective groups.

However, two significant generalized and significant decreases over the period, one in late 2018 and the other in early 2020, depict several reactions to the bear situation. In effect, the returns of cryptocurrencies and the three stock indexes decline suddenly and intensely due to a global crisis before increasing right away but not at the same level (deeper for the former group). Following this idea, cryptocurrencies do not suit as a safe haven asset in the sense that their values do not remain stable or do not increase during market turbulence. On the contrary, GOLD, TBOND10US, and EURUSD seem to be less impacted by the crisis and mostly recover well better than the others. It is generally accepted that they are considered safe havens when there is a recession. Thus, investors switch to these financial asset classes to hedge and secure their funds.

To sum up the chart analysis, these outcomes are pretty intriguing based on Bitcoin and cryptocurrencies' popularity. They tend to be considered an alternative to standard financial assets but seem to perform less efficiently than the latter and seem not to be good choices for an investor. However, I am going to put in opposition to the comments made in the two previous parts (3.3.1 and 3.3.2) to apprehend better the discrepancies and similarities between the two groups of assets.

Figure 1: Negative Cumulative Returns

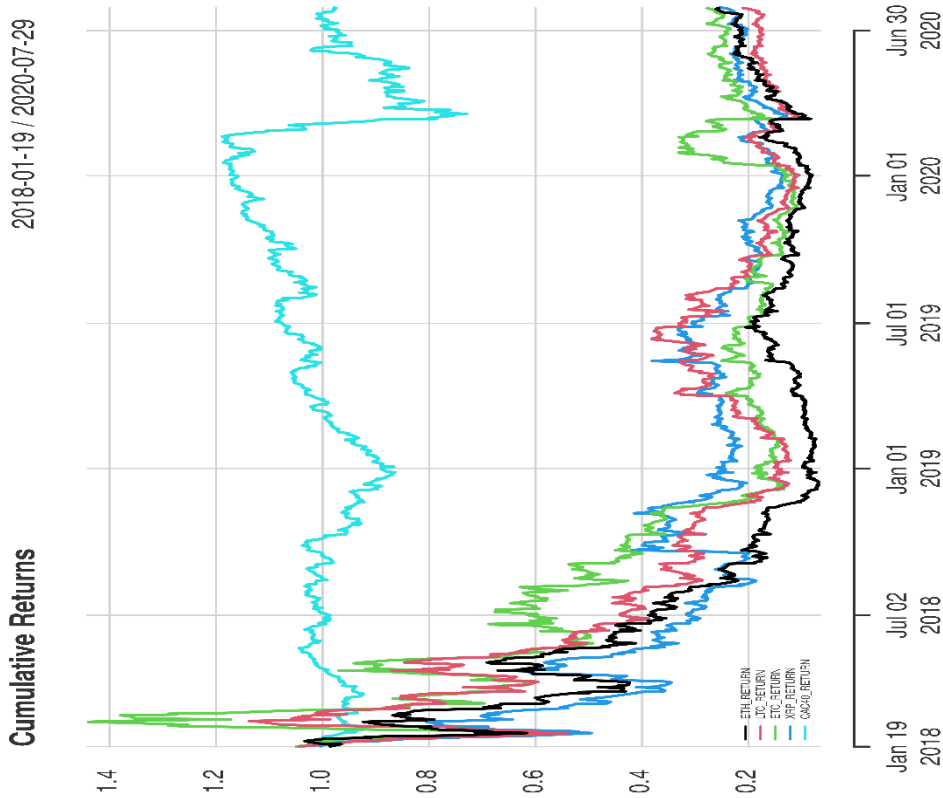
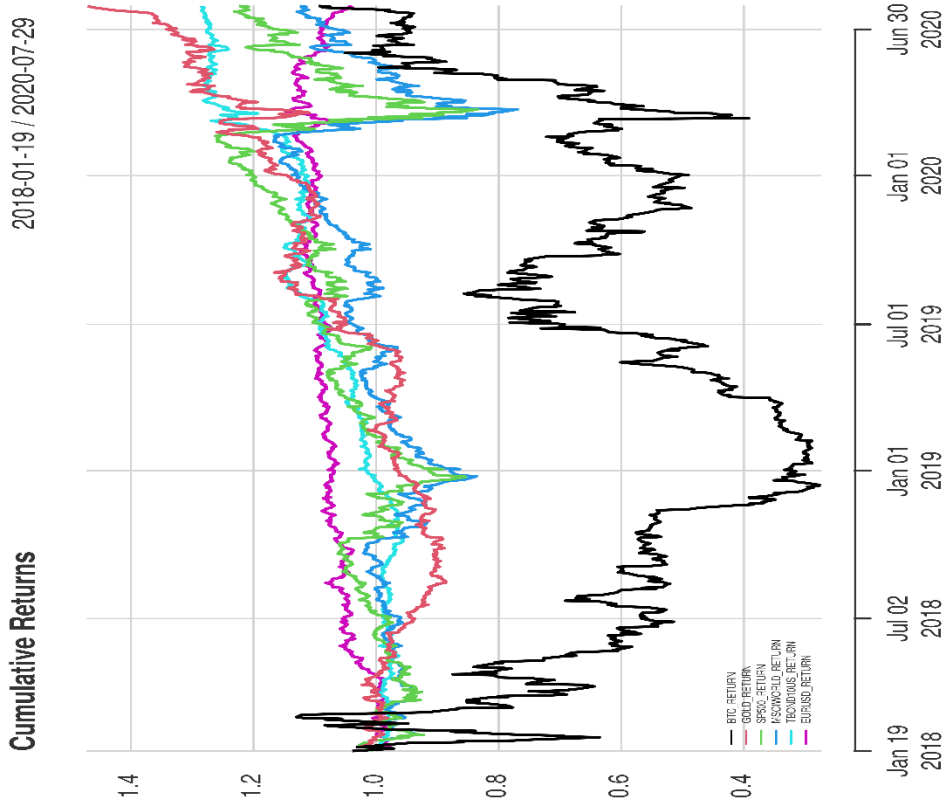


Figure 2: Positive Cumulative Returns



Concerning the maximum and minimum, there is a significant gap between cryptocurrencies and standard financial asset performances. The behavior of the two types of assets seems to not correspond with each other. Indeed, the scope of the values for the two groups is quite different. While the highest maximum and lowest minimum returns are +37.20% and -44.70% for cryptocurrencies, the standard financial assets are +9.39% and -12.28%. Obviously, the returns performed dissimilarly depending on whether it is a cryptocurrency or another financial asset class. The return of the former tends to vary more in the high and low values implicating more uncertainty.

Furthermore, I am going to compare the results of the annualized standard deviation of the two types of assets based on the comments made earlier. First, the cryptocurrencies' values are significantly higher than standard financial assets. The former's lowest value is 68.14%, while the highest one is 24.00% for the latter. Second, I noticed a divergence in the performances of the two kinds of assets. While there is no apparent trend amid cryptocurrencies, the standard's financial assets seem to fall apart into two groups. TBOND10US and EURUSD form the group presenting annualized standard deviation values less than 10%. As for CAC40, SP500, and MSCIWORLD, their values range from 19.82% to 24.00%. Then, GOLD seems to distinguish itself from the other and does not fit into one category with an annualized standard deviation of 12.79%.

To finish the descriptive analysis, the Jarque-Bera test for normality confirms that all the distributions do not perfectly follow a normal distribution characterized by a kurtosis value of three and a skewness value of zero. The skewness and the kurtosis values provided more precision about the several distributions' shapes. Among the 11 assets studied, only CAC40 and MSCIWORLD distribution are highly skewed with a skewness value less than -1. While all the other standard financial assets are negatively skewed, the cryptocurrencies groups contain three negative skewness and two positive ones. All cryptocurrencies distributions are leptokurtic regarding the kurtosis value, whereas the standard financial asset classes are quite heterogeneous. Only the EURUSD distribution follows quite well a normal one with a kurtosis value close to 3 (2.0121). The other financial asset distributions are leptokurtic, some more marked than the others.

4. METHODOLOGY

The aim of the present section is to explain the inherent approach to the EMPIRICAL RESULTS. It also gives a justification for the methods I used to address the research problem. Concretely, this section is divided into two parts. In light of the literature review, I sharpen the problem into several research questions and empirical hypotheses in section 4.1. In section 4.2., I exhibit the methods I followed to test the hypotheses and answer the research questions.

4.1. Hypotheses and research questions

As explained in the INTRODUCTION section, this thesis aims to determine if, via diversification, any cryptocurrency can reduce the risk of a traditional portfolio. Thus, the two main questions are expressed as follows:

Research question 1: Is it a good idea/ is it beneficial to incorporate any cryptocurrency to a portfolio containing standard assets such as indexes?

Research question 2: Which cryptocurrency has the better potential to reduce risk among traditional portfolios?

To answers these overall questions, I will proceed in two steps. First, my work tackles the first moment, the return, through ex-post risk-adjusted-performance measurements. Then, my thesis concentrates on modeling asset volatility and the correlation between pair of cryptocurrency and traditional assets. However, several questions and hypotheses emerged based on the literature review made in section 2. LITERATURE REVIEW.

4.1.1. Performance analysis using risk-adjusted measurements

Four out of six papers share similar results that cryptocurrencies can lead to better portfolio diversification and risk-adjusted measurements than the stock indexes (Ma,

Ahmad, & Liu, 2020; Hu, Rache, & Fabozzi, 2019; Borri, 2019, and Håberg & Klungland, 2019). Ma, Ahmad, & Liu (2020) show that including cryptocurrencies provide higher returns than the traditional portfolios for the same level of risk, as measured by the standard deviation of the portfolios. Crypto-diversification enhances the returns in most cases and decreases the portfolio volatility in all portfolios.

Besides, Hu, Rache, & Fabozzi (2019) outcomes demonstrate that minimizing variance and Conditional Value at Risk via crypto portfolio optimizations outperform a traditional stock market index. Also, according to Borri (2019), cryptocurrencies are highly exposed to tail-risk within crypto-markets, while they are not exposed to tail-risk for other global assets. He finds that including cryptocurrencies in traditional investors' portfolios can significantly diminish idiosyncratic risk and offer attractive returns and hedging properties.

Nevertheless, the papers of Dobrynskaya (2020) and Keenan (2020) reach the conclusion that the crypto market does not appear to be markedly distinct from traditional financial markets in terms of some risk-adjusted measurements. The first author exhibits that the former market is not substantially different from the latter asset markets regarding downside risk pricing. Moreover, (Keenan, 2020) finds that including cryptocurrencies did not necessarily increase risk-adjusted returns of an already well-diversified portfolio.

Hypothesis 1: Some cryptocurrencies offer better risk-adjusted measurements, such as Conditional Value at Risk. Following this idea, diversification via cryptocurrencies enhances the returns while decreasing portfolio volatility in all portfolios.

Research question 3: Which assets present the best risk-adjusted return?

Research question 4: What is the ranking in terms of risk-adjusted return?

4.1.2. Volatility and Correlation Estimation modeling

The first part results and conclusions are divided between affirming the link between Bitcoin and some financial assets and attesting to the isolation of Bitcoin. While two papers seem to validate the first hypothesis, one has the opposite point of view. Firstly,

Bouri, Gupta, Lau, Roubaud, & Wang (2018) and Selmi, Mensi, Hammoudeh, & Bouoiyour (2018) reach the same conclusion. Given the negative correlation, Bitcoin may serve as a safe haven when there is an alarm in the global financial market, as well as gold for investors. The results of (Selmi, Mensi, Hammoudeh, & Bouoiyour, 2018) with gold imply that Bitcoin could serve the function of a hedge, a safe haven, and a diversifier for oil price movements.

Furthermore, Kim, Seong-Tae, & Sangjin (2020) affirm a positive time-varying relationship. Besides, Al-Yahyaee, Mensi, & Yoon (2018) and Gajardo, Kristjanpoller, & Minutolo (2018) show evidence of asymmetric cross-correlations and multifractal. Nevertheless, this result should be taken with caution because the contemporaneous analysis of Ji, Bouri, Gupta, & Roubaud (2018) reveals Bitcoin markets' isolation.

Hypothesis 2: Significant time-varying correlation and asymmetric cross-correlation between Bitcoin and financial asset classes.

Research question 5: What are the nature and the direction of the correlation between Bitcoin and financial asset classes?

Research question 6: Can Bitcoin act as a safe haven or hedge for certain traditional assets, based on the correlation estimation modeling?

However, the correlation between the two groups of assets is not generally shared by scholars. Indeed, papers studied attest to the low correlation between the group of cryptocurrencies and financial asset classes. First, two out of six studies Milunovich (2018) and Rehman & Apergis (2019) find evidence of a correlation between cryptocurrencies and different financial asset classes. Their analysis confirms connectedness both within and across the cryptocurrencies and standard financial assets Milunovich (2018) and points out a significant causality running from cryptocurrency markets to commodity futures in terms of their mean, as well as their volatility (Rehman & Apergis, 2019).

Nevertheless, the results of Aslanidis, Bariviera, & Martínez-Ibañez (2019), Charfeddine, Benlagha, & Maouchi (2020), and Tiwari, Raheem, & Kang (2019) exhibit very low correlations and time-varying correlations between cryptocurrencies and traditional assets. It implies that the cryptocurrencies' returns are not connected to the

main financial markets. Besides, Tiwari, Raheem, & Kang (2019) pointed out that, given the low time-varying correlations close to zero, cryptocurrency serves as a hedge asset against the risk of the S&P 500 stock market. Finally, the paper of Corbet, Meegan, Larkin, Lucey, & Yarovaya (2018) is the only one that has the conclusion of the isolation of all selected digital currencies from other financial markets.

Hypothesis 3: Significant but weak correlations, cross-correlations, and time-varying correlations between the cryptocurrencies and standard financial asset classes.

Research question 7: What are the nature, direction, and intensity of these linkages?

Research question 8: Which pair of cryptocurrencies and traditional assets present fewer correlation values?

4.2. Description of the methodology

4.2.1. Performance Analytics

The first hypothesis and research questions 3 and 4 are related to the return performance of cryptocurrencies compared to a benchmark during the given period. In that case, I elaborate a code using the Performance Analytics package in RStudio¹⁰. This package is a powerful tool to retrieve the essential risk ratios and measures that I need to analyze performances. Below, I am going to explain all of those I use based on the categorization of Bacon (2012). Note that all metrics are calculated given the arithmetical method. Besides, I employed SP500 as the benchmark and TBOND10US as the risk-free rate.

4.2.1.1. Simple Risk Measures

¹⁰<https://rstudio.cloud/project/1655150>

➤ Adjusted Sharpe ratio (reward to variability)

The adjusted Sharpe ratio is retrieved by incorporating penalty factors for negative skewness and excess kurtosis to the initial Sharpe ratio. This version considers the fact that returns are not normally distributed and takes into account the skewness and kurtosis

William Sharpe introduced the Sharpe ratio in 1966 to measure the reward received (the stock or portfolio return minus the risk-free rate) in balance with the risk undertaken (the variability). It represents the reward to variability.

The greater the Sharpe ratio, the better is the combination of risks. It means that the risk-reward balance is better for this portfolio through better risk-adjusted performance.

The two ratios are calculated with annualized metrics as follow:

Equation 2: Sharpe Ratio

$$SR = ((r_P) - (r_F)) / (\sigma_P)$$

Equation 3: Adjusted Sharpe Ratio

$$ASR = SR \times \left[1 + \left(\frac{\widetilde{\zeta}_P}{6} \right) \times SR - \left(\frac{\widetilde{\kappa}_P - 3}{24} \right) \times SR^2 \right]$$

Where:

$\widetilde{r}_P$ = annualized portfolio return $\widetilde{\zeta}_P$ = annualized portfolio skewness

$\widetilde{r}_F$ = annualized risk-free rate¹¹ $\widetilde{\kappa}_P$ = annualized portfolio kurtosis

$\widetilde{\sigma}_P$ = annualized portfolio risk (variability, the standard deviation of return)

➤ Tracking Error or Relative Risk (ex-post)

The tracking error represents the relative variability via the calculation of the standard deviation using the excess return. The term relative refers to the excess return obtained through the portfolio's subtraction by that benchmark.

It permits the detection of the degree of congruity in which a portfolio tracks a benchmark's performance. If the tracking error is close to 0, it indicates that the portfolio

¹¹ In the purpose of having absolute measure, the risk-free rate in the SR and ASR calculation is zero

outperformed the benchmark consistently over time. Conversely, a high value would translate that the portfolio returns are more volatile over time.

For my analysis, the arithmetic excess return is employed, which gives the arithmetic tracking error as follow:

Equation 4: Tracking error

$$\sigma_A = \sqrt{\frac{\sum_{i=1}^n (a_i - \bar{a})^2}{n}}$$

Where:

σ_A = ex-post tracking of arithmetic excess return $\bar{a}$ = mean arithmetic excess return

a_i = arithmetic excess return in month i, $(r_i - b_i)$ b_i = benchmark return

➤ Information Ratio

The information ratio is comparable to the Sharpe ratio except that instead of absolute return and risk (standard deviation), the excess return and the tracking error are utilized in the calculation as follows:

Equation 5: Information Ratio

$$IR_A = \frac{\tilde{a}}{\tilde{\sigma}_P}$$

As for the Sharpe ratio, the higher the information ratio, the higher the level of consistency, and thus the better is the combination of risks.

Where:

IR_A = Information ratio using arithmetic excess return

$\tilde{a}$ = annualized Excess Return $(\tilde{r}_P - \tilde{r}_B)$ $\tilde{\sigma}_P$ = annualized Tracking Error

4.2.1.2. Capital Asset Prices Model (CAPM)

The Capital Asset Prices Model is a linear regression used to investigate the relationship between portfolio return and the risk-free market rate.

The Capital Asset Prices Model can be written as follows:

Equation 6: Capital Asset Prices Model

$$r_p - r_F = \alpha + \beta \times (b - r_F) + \varepsilon$$

Where:

r_p = portfolio return r_F = risk-free rate b = benchmark return
 α = Jensen's alpha β = Beta-systematic risk or volatility ε = error term

➤ **Beta-Systemic Risk**

The beta in the CAPM corresponds initially to the volatility of a portfolio in comparison to the market. Concretely, the beta consists of comparing the excess return of the portfolio against the risk-free rate, on the one hand, and the excess return of benchmark against the same risk-free rate, on the other hand. It is written as follows:

Equation 7: Beta-Systemic Risk

$$\beta = \frac{\sum_{i=1}^n \left[((r_i - r_{Fi}) - (\bar{r} - \bar{r}_F)) \times ((b_i - r_{Fi}) - (\bar{b} - \bar{r}_F)) \right]}{\sum_{i=1}^n \left((b_i - r_{Fi}) - (\bar{b} - \bar{r}_F) \right)^2}$$

Where:

$\bar{r}_F$ = risk-free rate in month i $\bar{r}_F$ = mean risk-free rate $\bar{b}$ = mean benchmark

➤ **Jensen's Alpha or ex-post alpha**

Introduced by Michael Jensen in 1968, Jensen's measure corresponds to the regression equation's alpha for the capital asset pricing model (CAPM). The model's average return on an asset is above or below expected, given the asset's beta and the average market return. More particularly, it is the excess return adjusted for systematic risk. Note that all the metrics are observed and not anticipated regarding my analysis.

If the alpha is >0 , it is generally said the asset has beaten the market, and inversely, if the alpha is <0 , it is considered that the asset has underperformed the market.

From the CAPM Equation 8, Jensen's alpha can be retrieved as follows:

Equation 8: Jensen's Alpha

$$\alpha = \bar{r}_P - \bar{r}_F + \beta \times (\bar{b} - \bar{r}_F)$$

Where:

$\bar{r}_P$ = mean portfolio return $\bar{r}_F$ = mean risk-free rate $\bar{b}$ = mean benchmark return

➤ **Treynor ratio (reward to volatility)**

Introduced by J.L. Treynor, this ratio is comparable to the Sharpe ratio except that instead of total risk (the standard deviation) in the denominator, the systematic risk calculated by beta is used. This ratio assumes that the portfolio is well-diversified and, therefore, ignores the non-systematic risk. As for the Sharpe ratio, the higher the Treynor ratio, the better the portfolio's risk-adjusted performance.

The Treynor ratio is written as follow:

Equation 9: TreynorRatio

$$TR = \frac{\tilde{r}_P - \tilde{r}_F}{\beta}$$

4.2.1.3. *Partial Moments Measures*

From the point of view of the Post-modern Portfolio Theory, the distinction between bad and good variability is recognized. Following this idea, investors privilege upside risk rather than downside risk and thus employed semi-standard deviation.

➤ Downside Risk

The downside risk is the second lower partial moment of return that appraises underperformance variability below a minimum target rate (risk-free rate, the benchmark return or zero). It captures the potential deterioration in the value of a portfolio if the market conditions change. The lower the downside risk, the better the investor he has exposed to a lower potential loss.

The calculation of the downside risk considers all returns above the target as zero so that they are not taken into account as follows:

Equation 10: Downside Risk

$$\sigma_D = \sqrt{\sum_{i=1}^n \frac{\min[(r_i - r_T), 0]^2}{n}}$$

Where:

r_T = minimum target return

4.2.1.4. *Extreme Risk Measures*

➤ Value at Risk (Ex-post non-parametric)

Initially developed in the 1900s by investment banks, the Value at Risk (VaR) measures the maximum loss when investing in a portfolio over a given time interval under normal market conditions at different confidence levels (usually 95% or 99%). Return at risk or performance at risk would be a more appropriate term because it gauges and controls the level of risk exposure. The lower the VaR, the better for the investor that will have a less maximum loss.

In the empirical analysis, the ex-post historical non-parametric is employed and is retrieved by merely re-organizing actual historical portfolio returns putting them in order from best to worst. The VaR is then determined at the percentile chosen related to the confidence level (e.g., the percentile 95th when using a 95% confidence level).

➤ Conditional VaR or Expected Shortfall

Contrary to the VaR, the conditional VaR gives insight into the tail's shape and the expected loss beyond the confidence level. Considering the remainder of the tail returns, the CVaR is the average return conditional on the return exceeding the value at risk.

4.2.1.5. Risk-adjusted Return

Risk-adjusted return is sometimes erroneously associated with the Sharpe ratio, whereas it is “just” a ratio and not a return. Although ratios allow sorting portfolios in preference, they do not provide information about relative performance quantity. Indeed, the goal of a risk-adjusted return is to compare different levels of risk assets.

➤ The Modigliani-squared (M^2) excess return

Introduced in 1997 by Leah Modigliani and her grandfather Professor Franco Modigliani, the M-squared is an authentically risk-adjusted return. The M^2 is a valuable tool to evaluate the theoretical performance if it had a similar risk to the market. The higher the M-squared, the better is the performance for the same level of risk. The formulas of the M^2 and the M^2 excess return are written as follows:

Equation 11: M-squared excess return

$$M^2 \text{ excess return} = M^2 - \tilde{b}$$

Equation 12: M-squared

$$M^2 = \tilde{r}_p + SR \times \tilde{\sigma}_b - \tilde{\sigma}_p$$

Where:

$\tilde{\sigma}_b$ = annualized standard deviation of benchmark return (market risk, variability)

4.2.1. Volatility and Correlation Estimation Modeling

This section of volatility and correlation estimation modeling tackles hypotheses 2 and 3 along with research questions 5 to 8. This analysis is divided into two steps: the descriptive analysis and the volatility estimation models.

The volatility estimation and, more particularly, the correlation estimation serve to determine to what extent an investor can diversify his portfolio by integrating an asset linked to the initial elements of the portfolio. It gives insights into the diversification effects in order to potentially reduce the unsystematic, which is diversifiable. It contributes to establishing a hedging strategy for the portfolio.

There are several approaches and methods to construct estimation models. Depending on the complexity, models are more or less accurate and reliable. A portfolio manager needs to choose suitable estimation models to build an efficient portfolio that can overperform the market. It is hazardous to rely on unconditional correlation since it can also be highly volatile over time.

4.2.1.1. Previsualization - Rolling windows

A first and basic approach is to take a rolling window with a defined number of days and calculate values by moving the window. This technique allows to previsualize, to some extent, the time-varying aspects of the return volatility and the correlation value. Also named the “baby GARCH”, it is an effortless way to exhibit and model time-series dynamics compared to static/unconditional calculations.

I build a rolling window of 30 days for my work, which I applied to all my data series for the given period regarding the return volatility and correlation values. This window of 30 days implicates that the dependence is strictly limited to 30 days. However, The choice of the window lengths is arbitrary. There are no specific rules to know the number of days suitable to fit the estimation better. It depends on several factors: the assets type, industry, region, and many others. It would be necessary to try several different lengths to determine the optimal one.

Therefore, this technique presents a significant limitation. It may miss critical elements that impact the volatility of the correlation randomly in time. Indeed, it does not take into account the dynamics of volatility between pairs of assets. It is more pertinent to

estimate via more complex models such as multivariate DCC-GARCH. It uses likelihood maximization to obtain the minimum squared error values. Thus, it would consider better the volatility and the correlation dynamics. The results will fit better the actual volatility and correlation values.

4.2.1.2. Descriptive analysis

Another preliminary step consists of a descriptive analysis of correlation values and the significance level and correlation plots that visually show the linkages.

The correlation is the standardized version of the covariance between portfolio and benchmark returns. It is retrieved by dividing the covariance by the portfolio standard deviation and the benchmark standard deviation. Besides, correlation can be defined as the measure of variability in the portfolio that systematically compares to total variability (Bacon, 2012).

A negative/positive correlation indicates that the two variables under consideration vary in opposite/same directions. Besides, a low correlation value may be an indicator for a potential diversification effect (Bacon, 2012). In other words, the correlation value specifies the degree of hedging between two assets.

The correlation is written as follow (Pearson method):

Equation 14: Correlation

$$\rho_{P,b} = \frac{COVARIANCE}{\sigma_p \times \sigma_b}$$

Equation 13: Correlation

$$\rho_{P,b} = \frac{\beta \times \sigma_b}{\sigma_p}$$

Where:

$\rho_{P,b}$ = correlation between the portfolio and the benchmark

σ_p = standard deviation of the portfolio σ_b = standard deviation of the benchmark

4.2.1.3. Multivariate DCC-GARCH

The preliminary steps give reason to employ a more complex model considering the dynamics of volatility for each asset. One of the most frequently used methodologies in capturing the time-varying structure of the correlations is the Dynamic Conditional Correlation (DCC) model. It assumes that the conditional correlation evolves linearly according to a simple GARCH (1,1)-type structure (Engle, 2002). GARCH models have the advantage of formulating an explicit dynamic model of volatility.

The DCC-GARCH framework has become popular among academics and practitioners. In a multivariate framework, the basic DCC-GARCH may be too restrictive. In particular, this model implies that all correlations pairs have the same response to news and decay parameters (Brooks, 2019).

To examine the time-varying correlations, I apply the DCC-GARCH model for the given period via Eviews. It integrates the flexibility of univariate GARCH models and the harmony of correlation estimation functions. Besides, this model allows for correlation-specific news parameters, while the decay parameter is assumed to be the same across correlation pairs to keep the model tractable (Engle, 2002); (Brooks, 2019).

The first step in modeling the DCC-GARCH consists of estimating GARCH through a technique known as maximum likelihood. Fundamentally, the method operates by finding the most likely values of the parameters given the actual data. More specifically, a log-likelihood function (LLF) is formed, and the values of the parameters that maximize it are sought. In this case of multivariate models, a diagonal approach using positive definite correlation matrices is employed. The Maximizing the log-likelihood function for multivariate GARCH models is written as follow (Brooks, 2019):

Equation 15: log-likelihood function

$$\ell(\theta) = -TN/2 \log 2\pi - \frac{1}{2} \sum_{t=1}^T (\log |H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t)$$

Where:

θ = all the unknown parameters to be estimated

N = the number of assets

H_t = $N \times N$ conditional variance-covariance matrix

T = the number of observation

ε_t = $N \times 1$ innovation (disturbance) vector matrix

Then, define the conditional variance-covariance matrix as follow:

Equation 16: Conditional variance-covariance matrix

$$H_t = D_t R_t D_t$$

Where:

D_t = N × N conditional standard deviations¹² matrix on the leading diagonal

R_t = N × N conditional time-varying correlation matrix

Finally, the generalized DCC model estimates the correlation between pairwise assets. The correlation coefficients between pairwise compose the off-diagonal elements in the covariance matrix Q_t . The model is generated by these two equations as follow (Aslanidis, Bariviera, & Martínez-Ibañez, 2019):

Equation 17: Symmetric positive definite variance-covariance matrix

$$Q_t = (\bar{Q} - A' \bar{Q} A - \beta \bar{Q}) + A' \varepsilon_{t-1} \varepsilon'_{t-1} A + \beta Q_{t-1}$$

Equation 18: Conditional variance-covariance matrix

$$R_t = \text{diag} \{Q_t^*\}^{-1} Q_t \text{diag} \{Q_t^*\}^{-1}$$

Where:

A = 3×3 parameter matrix

β = decay parameter

Q_t^* = N × N matrix that takes the square roots of each element in Q ¹³

$\varepsilon_{t-1} = D_{t-1}^{-1} r_{t-1}$ = Denotes the standardized returns

Concretely on Eviews, I first computed a system of 2 equations for the returns modelization between a cryptocurrency and a traditional asset. The equations modelization is a function of the dependent and the independent variables for the precedent period (-1). Following the model AR(1), a dependency of order 1 in the

¹² Diagonal matrix containing the square roots of the conditional variances from univariate GARCH model estimations on each of the N individual series

¹³ This operation is effectively taking the covariances in Q_t and dividing them by the product of the appropriate standard deviations in Q_t^* to create a matrix of correlations.

returns is assumed for the correlation modelization. The generalization of the equations is written as follow:

Equation 19: Return Correlation Equations System

$$AssetA_RETURN = C(1) + C(2) * AssetA_RETURN(-1) + C(3) * AssetB_RETURN(-1)$$

$$AssetB_RETURN = C(4) + C(5) * AssetB_RETURN(-1) + C(6) * AssetA_RETURN(-1)$$

Then, I estimate this system via the ARCH – Conditional Heteroskedasticity. I apply the model specification type of Constant Conditional Correlation, which integrates the time-varying dynamic via the equations system AR(1) described in Equation 19. The auto-regressive order 1 is employed for the ARCH and the GARCH (for the residual terms). Besides, I use the multivariate normal error distribution.

Even though return dependency is not confirmed, this modelization allows the volatility of Asset A returns to depend on the volatility of Asset B returns and thus allows the correlation modelization.

5. EMPIRICAL RESULTS

The following section presents the results obtained by applying the methodologies detailed in 4.2 on the datasets overviewed in part 3. The results of my research questions are divided into two parts; 5.1 Performance Analysis and 5.2 Volatility and Correlation Estimation Modeling

5.1. Performance Analysis

This section is focused on the analysis of the return performances divided into two parts. First, the absolute risk performance measures (section 5.1.1) within the returns and risks of asset and benchmark are calculated separately and used for comparison. Note that for that part, the risk-free rate equals zero. Secondly, the relative performance measures (section 5.1.2) focus on the asset's excess return against the benchmark. Finally, a summary of the performance analytics ranks the assets based on the M-squared excess return. In the thesis case, the benchmark is the stock index SP500, and the risk-free rate is TBOND10US.

5.1.1. Absolute performances measures (measures relative to the total risk)

Given the descriptive statistics made in section 3.3, it appears that all assets, except EURUSD, present a leptokurtic distribution. Besides, the majority of them are moderately or highly skewed. Following this idea, the Adjusted Sharpe Ratio (ASR) is used, correcting the Sharpe Ratio (SR) skewness and kurtosis. It is noticeable that the five cryptocurrencies and the six standard financial assets present, overall, dissimilar ASM. On the one hand, the former group exhibits ASM value starting from 4.29% for Bitcoin to 5.90% for Ethereum Classic. It implicates that Bitcoin has the most minor risk-reward balance among cryptocurrencies. Inversely, Ethereum Classic provides the best combination of risks through better risk-adjusted performance.

On the other hand, the latter group's ASM values were lower, from 0.39% for EURUSD to 1.51% for SP500. Obviously, EURUSD offers the worst reward to variability amid all assets, even less than TBOND10US, globally considered the risk-free rate. To sum up, the curious outcome is that the returns of cryptocurrencies compensate for the total risk undertaken at a larger scale than the standard financial assets returns.

Regarding the pure downside risk, the two groups exhibit discrepancy in the values again, but standard financial assets are better off in that case. Indeed, the latter group presents globally less potential deterioration in the return if the market conditions change. The pure downside risk values start from 0.28% for TBOND10US and EURUSD to 1.11% for SP500. It suggests that the two formers are exposed to a lower potential loss. Besides, the three stock indexes' returns share approximately the same behavior as well as TBOND10US and EURUSD between them. As for GOLD returns, it is situated in between. However, the cryptocurrencies are exposed to higher potential loss with downside risk values starting from 3.02% for Bitcoin and 4.19% for Ethereum Classic. It does not seem to have a particular tendency or regrouping amid the currencies.

To pursue the analysis, it is interesting to concentrate on the shape of returns in tails through extreme risk measures such as the Value at Risk (VaR) and Conditional VaR, also called Expected Shortfall (ES), at a level of confidence of 99%. First, the analysis of the pure downside risk previously made can be transposed to the former metric. Indeed, TBOND10US and EURUSD present the lowest maximum loss under normal market conditions (respectively -0.94% and 1.07%). GOLD follows closely with a VaR of -1.881%. The stock indexes shift slightly away with -3.69% for MSCIWORLD, -4.18% for SP500 and -4.40% for CAC40. Regarding cryptocurrencies, VaR values are lower and ten order (in terms of return percentage). Again, Bitcoin presents the lowest maximum loss among the cryptocurrencies with 10.66%, while Ethereum Classic exhibits the highest maximum loss with 15.75%.

However, all assets' ES values have decreased due to skewness and kurtosis but not the same magnitude causing few changes in the ranking. Indeed, EURUSD becomes the asset presenting the lowest average return conditional on the return exceeding the value at risk with an ES of -1.28%. TBOND10US is then second with -1.58%. As for the cryptocurrencies, Bitcoin stays the highest ES value with -16.41%, while Ethereum takes the least place with -21.08%.

Table 4: Absolute¹⁴ performances measures¹⁵

Statistics	Adjusted Sharpe Ratio	Pure Downside Risk	Value at Risk ¹⁶ (Ex-post non-parametric)	Conditional VaR / Expected Shortfall ¹⁷
Bitcoin	0.0429	0.0302	-0.1066	-0.1641
Ethereum	0.0544	0.0393	-0.1542	-0.2108
Litecoin	0.0555	0.0375	-0.1241	-0.1829
Ethereum Classic	0.0590	0.0419	-0.1575	-0.2104
Ripple	0.0552	0.0363	-0.1322	-0.1834
GOLD	0.0081	0.0053	-0.0188	-0.0292
CAC40	0.0136	0.0105	-0.0418	-0.0651
SP500	0.0151	0.0111	-0.0440	-0.0706
MSCIWORLD	0.0125	0.0094	-0.0369	-0.0634
TBOND10US	0.0043	0.0028	-0.0094	-0.0158
EURUSD	0.0039	0.0028	-0.0107	-0.0128

5.1.2. Relative performances measures

(measures relative to systematic risk)

Concerning the betas, all the values are positive and inferior to 1, meaning that all assets have a smaller risk level than the market (SP500). Besides, the ranking does not join the ones for the other metrics and exhibits some curious aspects. First, the worst podium is shared by Ethereum (90.82%), Litecoin (84.74%) and MSCIWORLD (83.41%). This intriguing outcome suggests that the stock index presents more volatility, based on the market, than the three other cryptocurrencies. Moreover, Bitcoin has a systematic risk lower than CAC40 (64.69% for the former and 66.87% for the latter) and takes place just before GOLD and EURUSD. Indeed, GOLD presents the

¹⁴In the purpose of having absolute measure, the risk-free rate in calculations is zero

¹⁵ The values have been rounded to the fourth decimal place

¹⁶ With 99% confidence

¹⁷With 99% confidence

second-lowest systemic risk (17.20%), closely followed by EURUSD (15.41%). It is noteworthy that these two betas are moderately apart from the other assets, even from the ones for CAC40 and MSCIWORLD that get closer to cryptocurrencies' ones.

Furthermore, Jensen's alpha and the annualized Alpha values do not conclude the same ranking as the absolute performance measures or the betas. Indeed, Bitcoin and GOLD exhibit the highest Jensen's alpha with positive values of, respectively, 0.07% and 0.02%. It is pretty intriguing that these two are the only ones that, given the systematic risk (Beta), have beaten the market (SP500). The other assets have negative values, with the lowest one for Litecoin (-0.13%). It suggests that these assets underperformed the market, given the systematic risk (Beta).

However, Jensen's alpha of the assets is globally close to zero. Concerning the annualized alpha, the ranking still holds with Bitcoin and GOLD at the top (positive value of 18.65% and 5.75%) and Litecoin latest (-27.25%). Nevertheless, it is clear that the differential is not the same in comparison to the alpha. Moreover, the contrast between cryptocurrencies and standard financial assets is more marked. While the former group's annualized alpha values are in the order of ten in terms of return percentage, the latter groups are in the unity order.

Regarding the tracking error, the discrepancy between cryptocurrencies and standard financial assets is quite apparent, with the former group exhibiting more relative risk and thus being more volatile based on the benchmark. First, Except for Bitcoin, with the lowest tracking error among cryptocurrencies (67.12%), all the others have a value above 80%, with Ethereum Classic presents the highest one (91.43%). It implies that Bitcoin performed relatively better than the other cryptocurrencies through tracking more consistent benchmark performance (SP500). On the other hand, the standard financial assets' tracking error starts from 6.65% for MSCIWORLD to 25.99% for GOLD. It indicates that the former outperformed very well the benchmark consistently over time.

Compared to the Sharpe ratio discussed in the previous part, the information ratio provides an entirely different ranking. First, only GOLD presents a positive value of 30.27%, meaning that it is the only one that outperformed the benchmark with a better combination of risks consistently over time. Besides, Bitcoin has an information ratio of -6.78% higher than the other assets, even the standard ones, and takes second

place after GOLD. It is worth pointing out that MSCIWORLD exhibits a similar information error value to the four remainders of cryptocurrencies with a value of -51.82% that is even lower than the one for Ethereum Classic (-51.03%). To finish, the lowest information ratio is -62.12% for Litecoin, implicating that this cryptocurrency underperformed the benchmark with the worst combination of risks consistently over time.

The ranking, according to the Treynor ratio, presents some similarities with the Information ratio one. First, GOLD is again the only asset with a positive value (29.34%) and thus takes the first place. Also, Litecoin has the lowest Treynor ratio among all assets, with a value of -59.79%. It implicates that GOLD exhibits the best combination of systematic risks, while Litecoin obtained the worst reward for systematic risk. However, the places between these two assets are quite different in comparison to the Information ratio ranking. Indeed, MSCIWORLD takes second place ahead of Bitcoin (-7.17% for the former against -10.31% for the latter). This time, the EURUSD has a comparable Treynor ratio value to the four remainders of cryptocurrencies with a value of -53.48% that is even lower than the one for Ethereum (-51.10%). This curious change reveals that EURUSD is volatile regarding systematic risk related to the benchmark risk (SP500).

To finish this analysis, M-squared (M^2) excess return is an authentically risk-adjusted return. Based on this metric, the ranking is useful for an investor to evaluate the theoretical performance if it had a similar risk to the benchmark (SP500). Once again, GOLD is the only asset with a positive value of 21.81%, giving it first place. It suggests that GOLD has beaten the market and represents the most profitable asset given the same level of risk over the period. Since the other assets exhibit a negative value of M^2 , they underperformed the market considering the same risk undertaken. More precisely, EURUSD and MSCIWORLD follow with respectively -2.28% and -2.48%. Then, Bitcoin takes fourth place in front of CAC40 (-6.81% against 8.84%). Regarding the four remainders of cryptocurrencies, the last one is Litecoin with -20.34%, and the better off is Ethereum Classic with (-17.93%). Again the discrepancy in terms of range is clearly defined between the cryptocurrencies and the standard financial assets.

Table 5: Relative performances measures¹⁸

Statistics	Beta	Jensen's Alpha	Annualized Alpha	Tracking error (relative risk)	Information Ratio	Treynor Ratio	M-squared excess return ¹⁹
Bitcoin	0.6469	0.0007	0.1865	0.6712	-0.0678	-0.1031	-0.0681
Ethereum	0.9082	-0.0009	-0.2104	0.8318	-0.5834	-0.5110	-0.1930
Litecoin	0.8474	-0.0013	-0.2725	0.8573	-0.6212	-0.5979	-0.2034
Ethereum Classic	0.8243	-0.0006	-0.1333	0.9143	-0.5103	-0.5421	-0.1793
Ripple	0.7859	-0.0010	-0.2167	0.8573	-0.5663	-0.5904	-0.1913
GOLD	0.1720	0.0002	0.0579	0.2599	0.3027	0.2934	0.2181
CAC40	0.6687	-0.0003	-0.0835	0.1887	-0.4641	-0.1598	-0.0884
MSCIWORLD	0.8341	-0.0002	-0.0394	0.0665	-0.5182	-0.0717	-0.0248
EURUSD	0.1541	-0.0003	-0.0793	0.2503	-0.2614	-0.5348	-0.0228

5.1.3. Performance analytics summary

Based on the absolute performance measures related to the total risks, cryptocurrencies and standard financial assets perform in two distinct ways. The former group exhibits globally more risks and more potential losses than the latter. Nevertheless, it appears that the reward compensates for the total risk undertaken at a larger scale than the standard financial assets returns based on the Sharpe ratio.

¹⁸ The values have been rounded to the fourth decimal place

¹⁹ The risk-free rate is zero instead of the TBOND10US rate

Besides, there seems to be some regrouping among the financial asset classes. On the one hand, EURUSD and TBOND10US act alike, presenting less risk along with few rewards. On the other hand, the stock indexes are a little apart in terms of ratio values without having the same performances as the cryptocurrencies. Finally, Bitcoin performance is in between these two small groupings.

Nevertheless, the performance measures relative to the market situation (SP500 as the benchmark and TBOND10US as the risk-free rate) do not provide a common classification of several assets. In general, cryptocurrencies present less good measure values than standard financial assets during the period studied. Although the two groups of assets exhibit globally distinct measures, some assets shift away a few times from the initial group, such as GOLD, MSCIWOLRD or Bitcoin.

The critical outcome is that GOLD represents the most appealing asset for investors, given the relative risk. Indeed, for most of the measures, it has the higher and thus the best values of risk-adjusted measures. Besides, GOLD is, overall, the only asset that outperformed the market given the risk undertaken. Following all these elements, GOLD is the best candidate for diversifying a portfolio thanks to its well good balance between returns and relative risks.

However, it is worth pointing out that Bitcoin presents better measures than some standard financial assets in a few aspects. It suggests that Bitcoin has, at some point, a better combination of reward in balance to the relative risk undertaken.

To finish this performance analytics, it is beneficial to rearrange the table based on the authentic risk-adjusted return, the M^2 excess return. Table 6 may be helpful for any investor who wants to compute a portfolio combining cryptocurrencies and standard financial assets. It would help better understanding the return performances considering the risk undertaken from different aspects (variability or volatility).

Table 6: Relative performance measures - M-squared excess return ranking

Rank	Statistics	M-squared excess return ²⁰	Beta	Jensen's Alpha	Annualized Alpha	Tracking error (relative risk)	Information Ratio	Treynor Ratio
1 st	GOLD	0.2181	0.1720	0.0002	0.0579	0.2599	0.3027	0.2934
2 nd	EURUSD	-0.0228	0.1541	-0.0003	-0.0793	0.2503	-0.2614	-0.5348
3 nd	MSCIWO RLD	-0.0248	0.8341	-0.0002	-0.0394	0.0665	-0.5182	-0.0717
4 nd	Bitcoin	-0.0681	0.6469	0.0007	0.1865	0.6712	-0.0678	-0.1031
5 nd	CAC40	-0.0884	0.6687	-0.0003	-0.0835	0.1887	-0.4641	-0.1598
6 nd	Ethereum Classic	-0.1793	0.8243	-0.0006	-0.1333	0.9143	-0.5103	-0.5421
7 nd	Ripple	-0.1913	0.7859	-0.0010	-0.2167	0.8573	-0.5663	-0.5904
8 nd	Ethereum	-0.1930	0.9082	-0.0009	-0.2104	0.8318	-0.5834	-0.5110
9 nd	Litecoin	-0.2034	0.8474	-0.0013	-0.2725	0.8573	-0.6212	-0.5979

5.2. Volatility and Correlation Estimation Modeling

5.2.1. Previsualization - Rolling windows

This section aims to exhibit the time-varying aspects of the return volatility and correlation of the assets studied. As a preliminary step, I chose to apply a rolling window of 30 days for the return volatility and correlation values. The goal is to see the dynamics of these two metrics in comparison with static/unconditional calculations.

5.2.1.1. Returns Volatility

²⁰The risk-free rate is zero instead of the TBOND10US rate

Based on all graphics (Figure 4 to Figure 13), the first constatation is that the rolling volatility curves effectively expose the dynamic aspects of the volatility as opposed to unconditional volatility. While the unconditional volatility curves remain static, the rolling volatility curves vary over time. Therefore, it confirms the time-varying characteristic of the return volatility. This observation suggests that portfolio decisions should not be based on unconditional volatility due to the marked variation. Otherwise, the investor would over or underestimate by not fitting the realized volatility.

Furthermore, the dynamic present within the rolling volatility is much stronger than that within returns. The curves of the rolling volatility present more irregularity than the return curves. It means that the return volatility fluctuates more than the return itself. All the graphs show that rolling volatility curves can jump or fall relatively more substantially than return curves. As volatility measures the dispersion of returns, it is easy to imagine that the volatility curve shifts more intensively when there is more return dispersion. For example, all the asset series exhibit a sudden increase in volatility during the pandemic crisis in March 2020. It is due to the economic turmoil caused by the Covid-19 and its repercussion.

Nevertheless, all assets do not follow the same pattern regarding returns and volatility. As described in section 3.3 Preliminary analysis – Descriptive statistics, cryptocurrencies and standard assets series have different performances. Table 7 shows that the five cryptocurrencies exhibit more pronounced volatility following the returns range. The scope of unconditional volatility values for cryptocurrencies starts from 68% to 94%, while the scope for traditional assets begins from 7% to 24%.

Table 7: Unconditional Return Volatility

Unconditional Return Volatility										
BTC	ETH	LTC	ETC	XRP	GOLD	CAC40	SP500	MSCIWORLD	TBOND10US	EURUSD
68%	86%	88%	94%	88%	13%	22%	24%	20%	7%	6%

Furthermore, the cryptocurrencies' rolling volatility goes up to more than 150% and even more than 200% for Ripple and Ethereum Classic. Inversely, the six standard financial asset rolling volatility generally fluctuates under 40% except for the pandemic crisis when the three stock indexes' volatilities rise and reach 80%. These outcomes confirm the marked variability and the risked character of cryptocurrencies relative to traditional assets.

Figure 4: Graphic of Bitcoin Returns Volatility

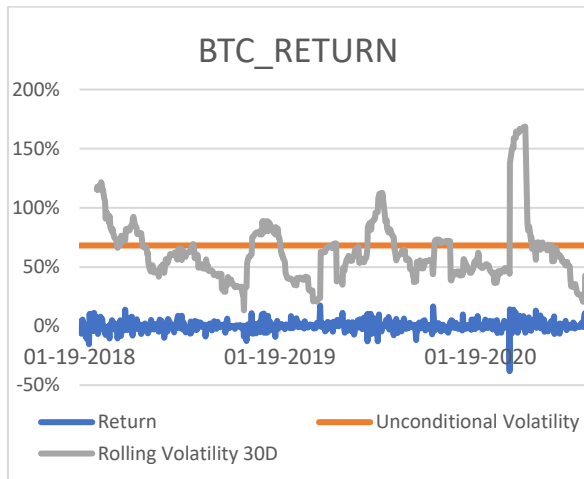


Figure 3: Graphic of Ethereum Returns Volatility

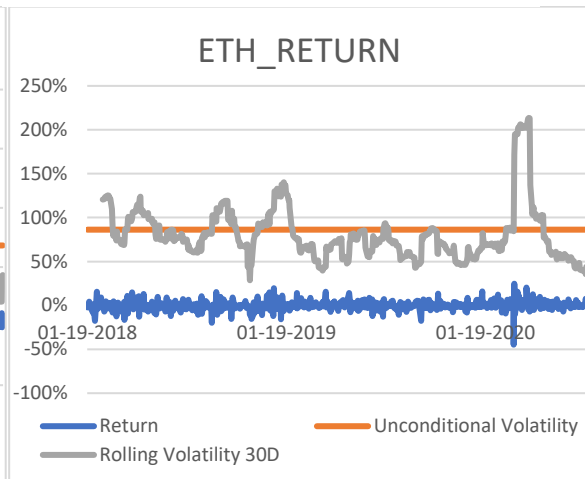


Figure 6: Graphic of Litecoin Returns Volatility

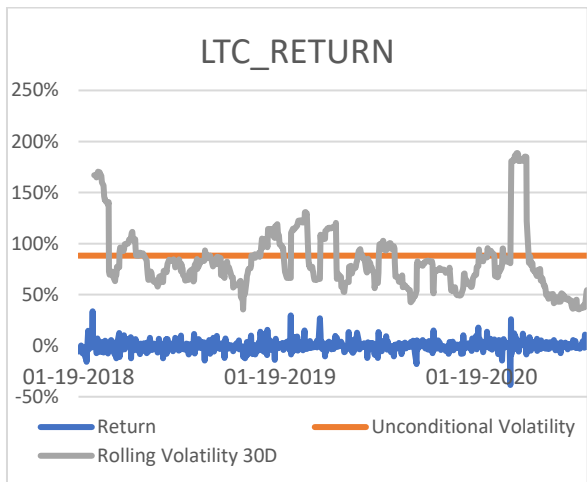


Figure 5: Graphic of Ethereum Classic Returns Volatility

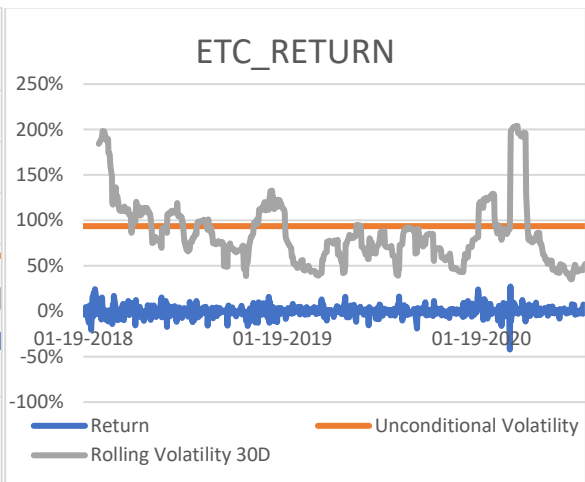


Figure 7: Graphic of Ripple Returns Volatility

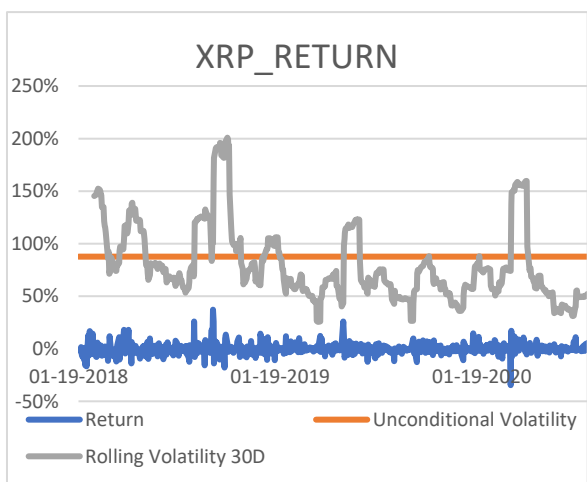


**Figure 9: Graphic of GOLD
Returns Volatility**

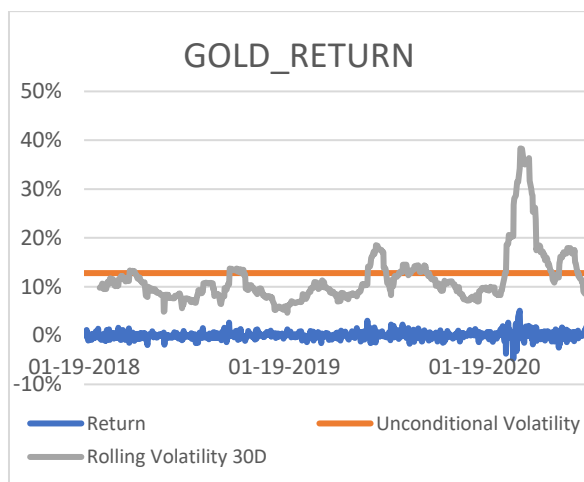


**Figure 8: Graphic of CAC40
Returns Volatility**

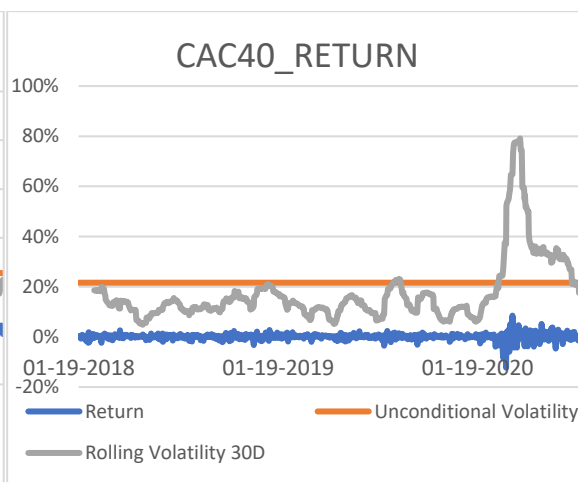


**Figure 11: Graphic of SP500 Returns
Volatility**

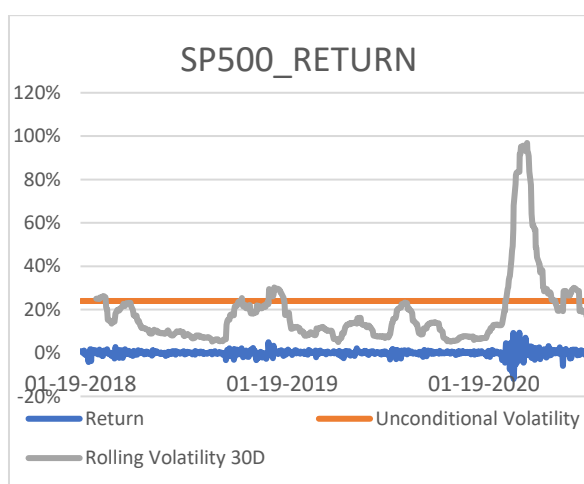


**Figure 10: Graphic of MSCIWORLD
Returns Volatility**

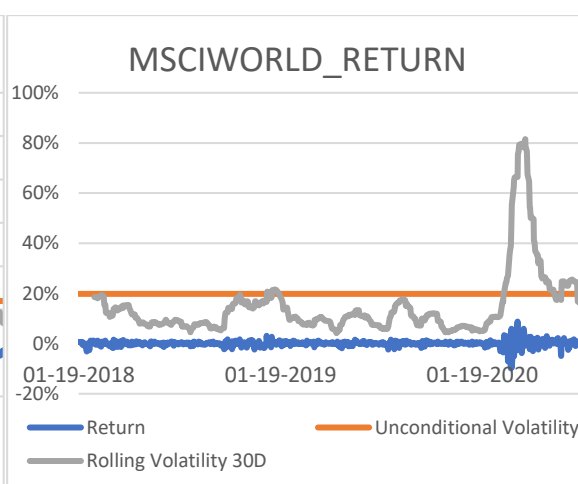


**Figure 12: Graphic of TBOND10US
Returns Volatility**

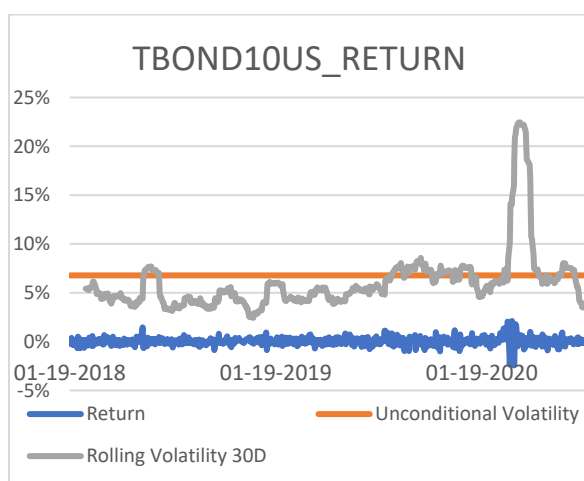
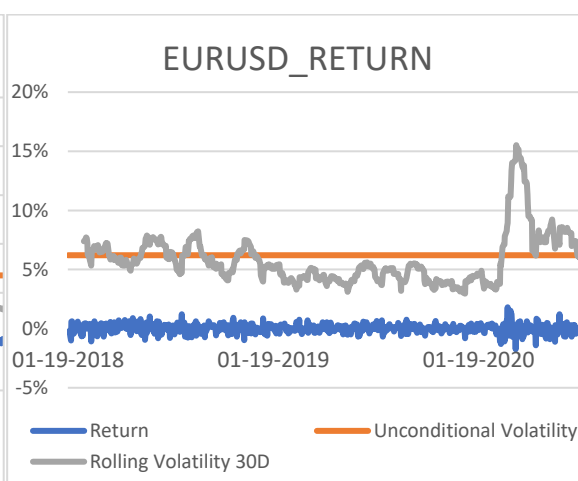


**Figure 13: Graphic of EURUSD Returns
Volatility**



5.2.1.2. Correlation

As for the rolling volatility curves, the rolling correlation curves based on all graphics (Figure 14 to Figure 48) exhibit the dynamic aspects of the correlation as opposed to unconditional correlation. While the unconditional correlation curves remain static, the rolling correlation curves fluctuate vastly over time. Therefore, it confirms the time-varying characteristic of the correlation.

Nevertheless, in that case, the variations are more marked and more sudden than for the return volatility. The correlation value can change in all directions, from a positive to a negative value from one day to the next. In other words, the correlation nature changes daily as well as the portfolio diversification effects.

It can be seen in Table 8 that the unconditional volatility values of the rolling correlation are relatively higher in comparison to the unconditional return volatility in Table 7. For example, the values of unconditional volatility on rolling correlation, including TBOND10US and EURUSD, are much more superior to unconditional return volatility for simply the two assets. The correlation is more “volatile” than the return volatile itself due to the dependence of return volatility between pairs of assets.

Besides, the unconditional volatility on rolling correlation, including GOLD in pair with traditional assets, seems to be the highest among cryptocurrencies. It is intriguing considering that the unconditional return volatility of GOLD only is lower than that for cryptocurrencies.

Table 8: Unconditional Volatility on Rolling Correlation 30D

Unconditional Volatility on Rolling Correlation 30D						
	BTC	ETH	LTC	ETC	XRP	GOLD
GOLD	80,25%	74,88%	86,41%	87,14%	75,18%	
CAC40	77,42%	78,83%	78,71%	78,07%	80,71%	120,30%
SP500	98,20%	99,37%	93,63%	91,03%	94,57%	107,21%
MSCIWORLD	99,11%	100,75%	92,82%	89,49%	97,18%	122,11%
TBOND10US	82,20%	86,09%	89,00%	79,23%	81,98%	98,22%
EURUSD	75,53%	71,43%	72,73%	69,13%	67,92%	87,44%

In conclusion, these results indicate that investors should not base portfolio decisions on simply unconditional correlation. It is particularly hazardous to calculate an unconditional correlation since it can also be extremely volatile over time. They should be highly cautious using correlation values by computing models that integrate volatility dynamics between pairs of assets. Otherwise, the investor would misestimate by ignoring the high volatility of the correlation and thus not fitting the realized volatility. The unconditional correlation, along with the significance level, will be analyzed deeper in the next section.

Figure 15: Graphic of GOLD-BTC correlation

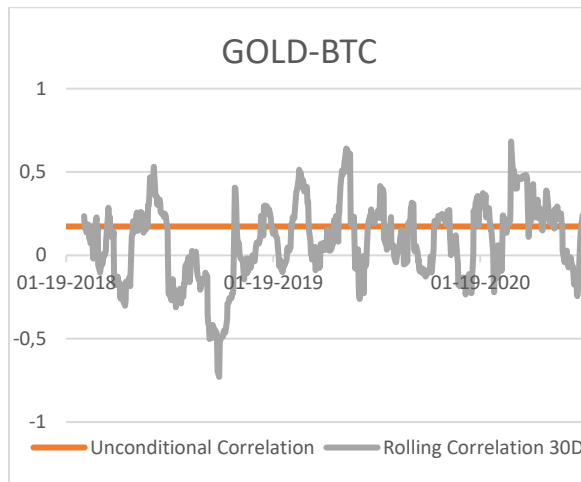


Figure 14: Graphic of GOLD-ETH correlation

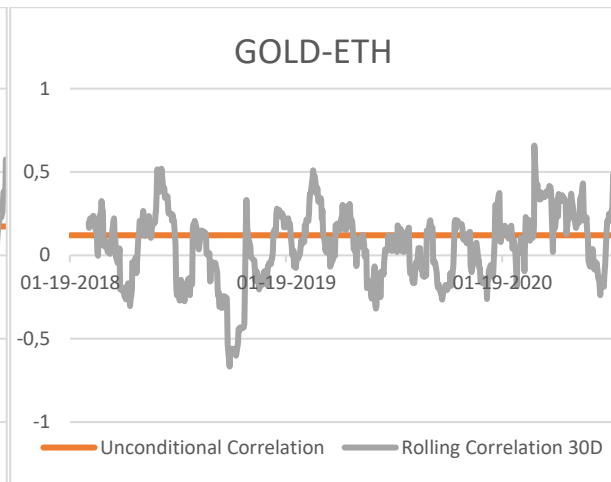


Figure 17: Graphic of GOLD-LTC correlation

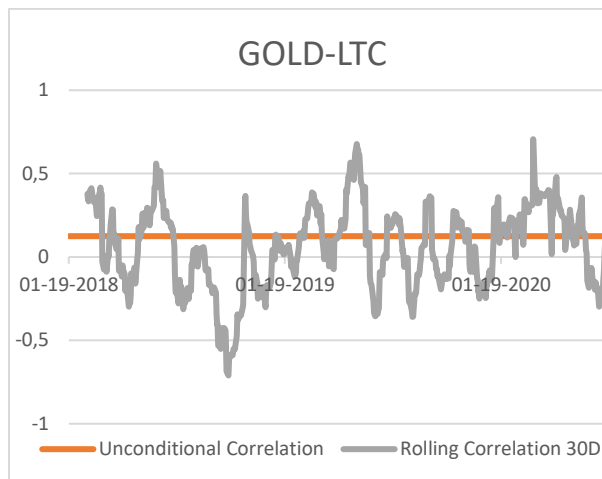


Figure 16: Graphic of GOLD-ETC correlation

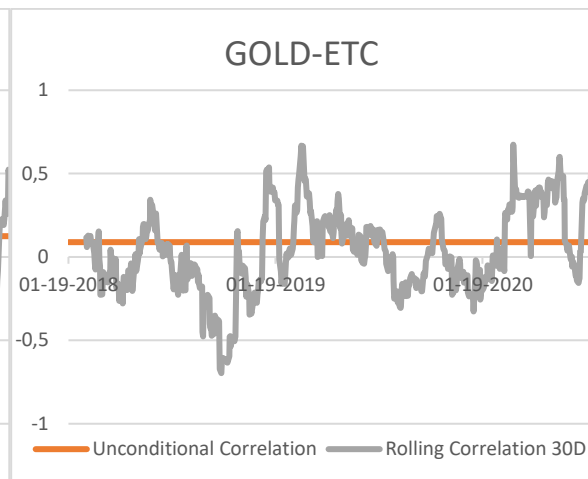


Figure 18: Graphic of GOLD-BTC correlation

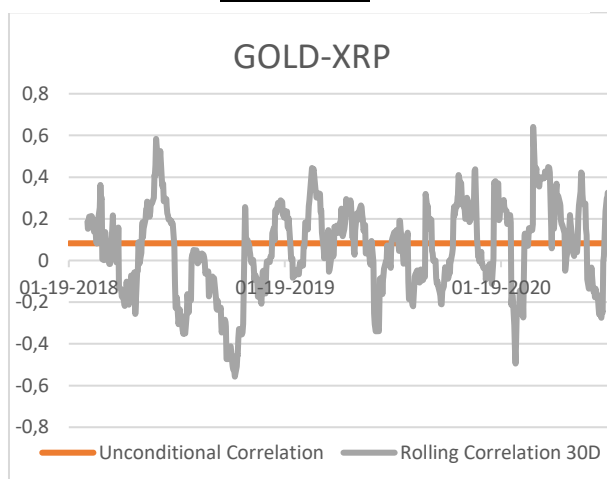


Figure 20: Graphic of CAC40-BTC correlation

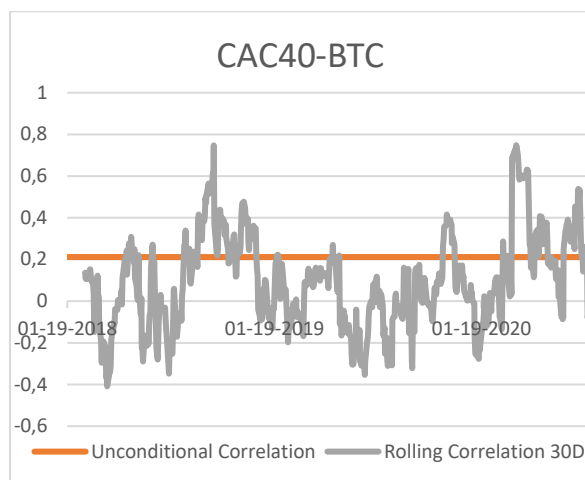


Figure 19: Graphic of CAC40-ETH correlation

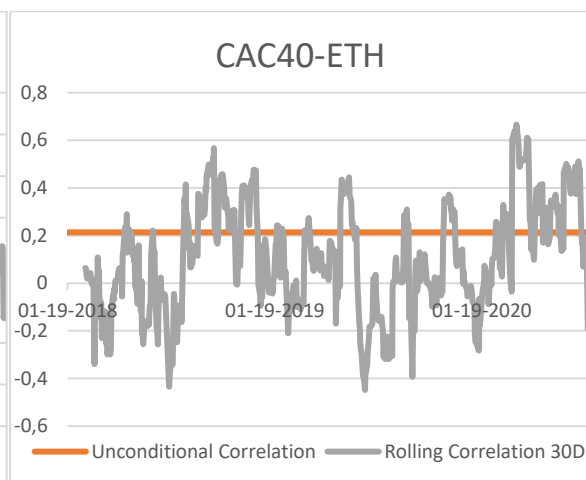


Figure 22: Graphic of CAC40-LTC correlation

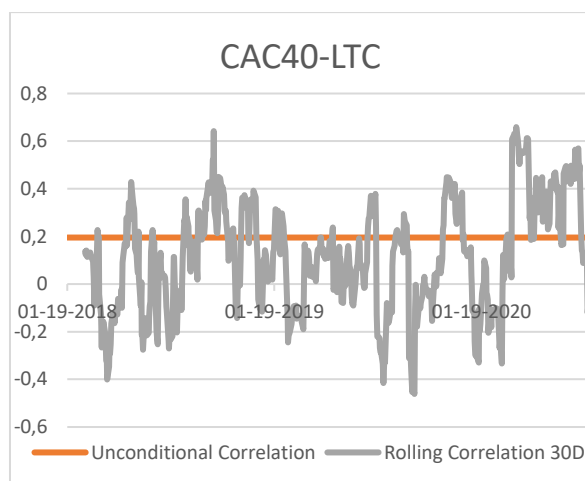


Figure 21: Graphic of CAC40-ETC correlation

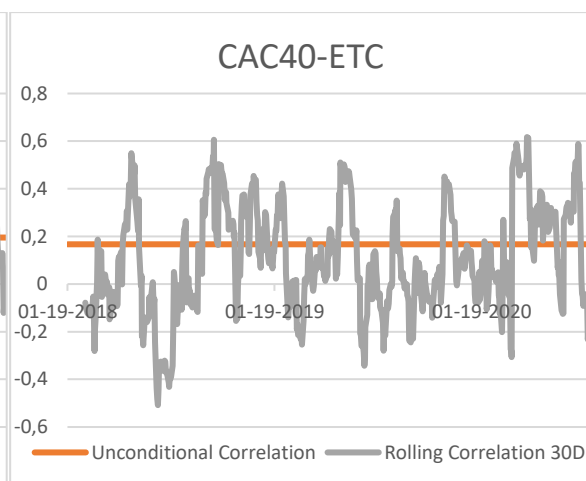


Figure 24: Graphic of CAC40-XRP correlation

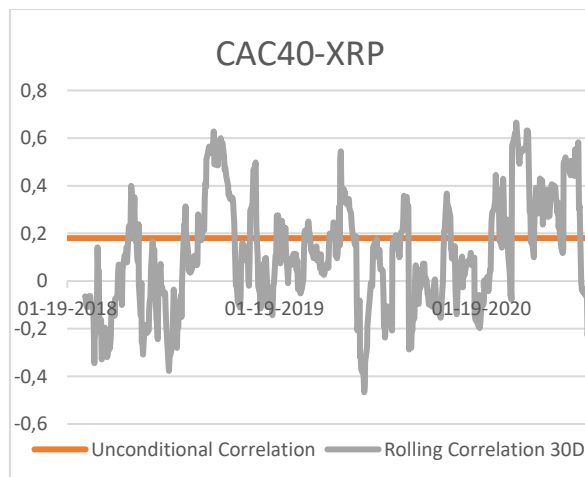


Figure 23: Graphic of CAC40-GOLD correlation

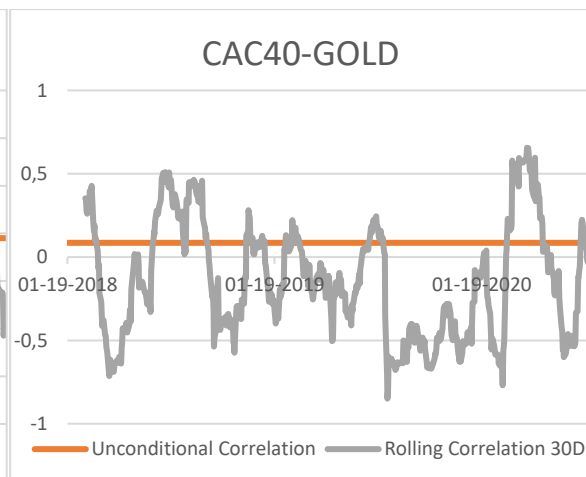


Figure 26: Graphic of SP500-BTC correlation

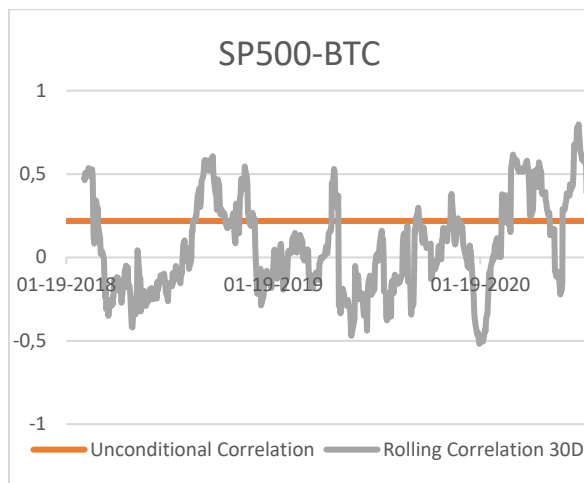


Figure 25: Graphic of SP500-ETH correlation

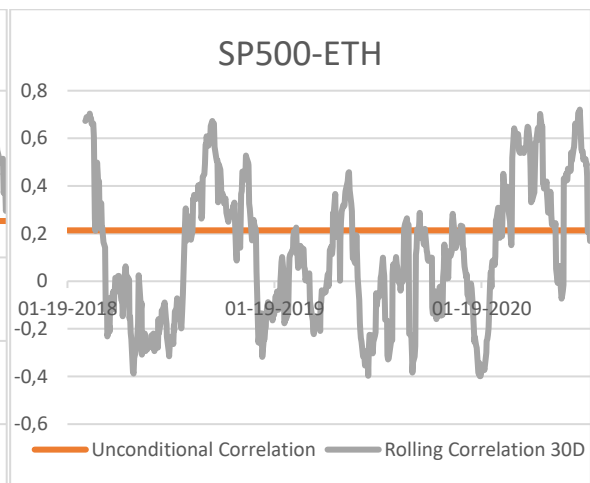


Figure 27: Graphic of SP500-LTC correlation

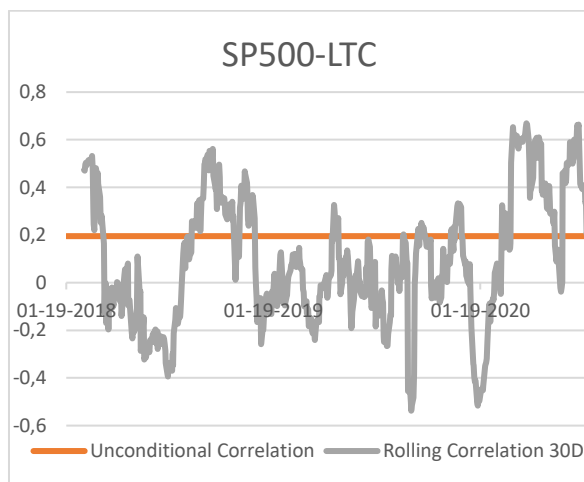


Figure 28: Graphic of SP500-ETC correlation

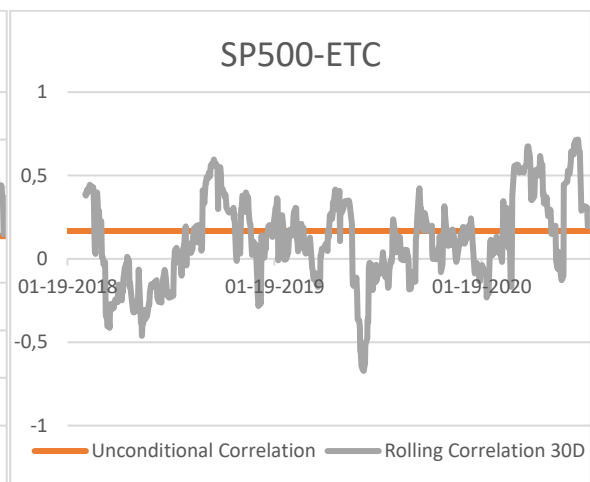


Figure 30: Graphic of SP500-XRP correlation

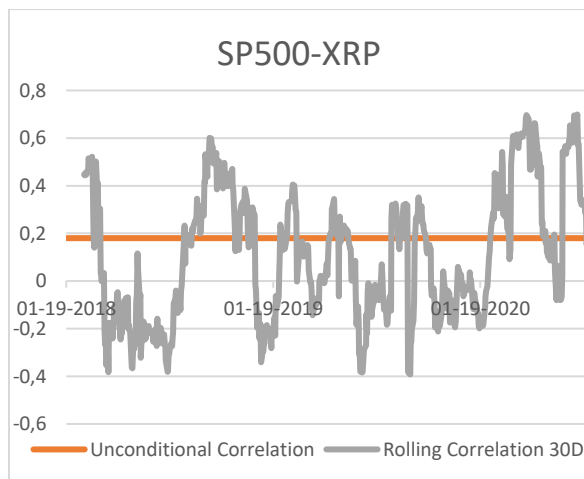


Figure 29: Graphic of SP500-GOLD correlation

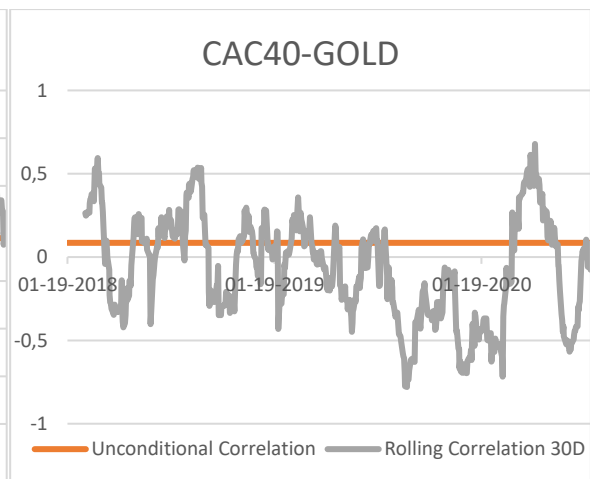


Figure 31: Graphic of MSCIWORLD-BTC correlation

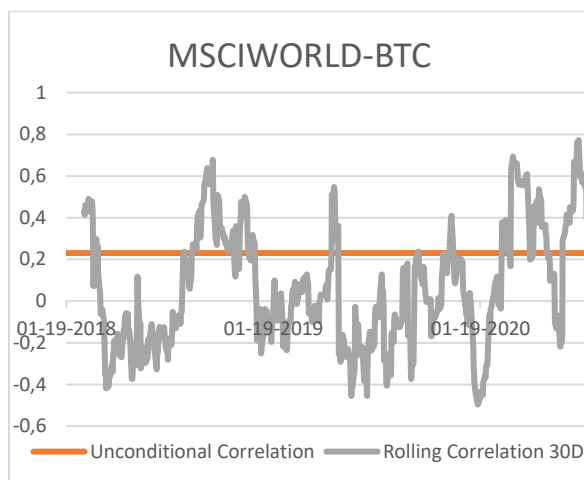


Figure 32: Graphic of MSCIWORLD-ETH correlation

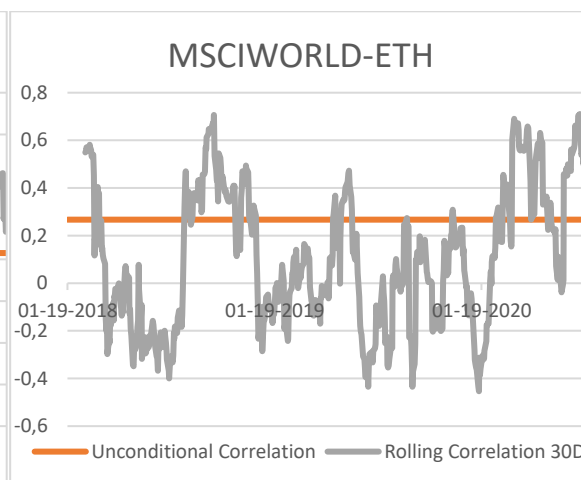


Figure 33: Graphic of MSCIWORLD-LTC correlation

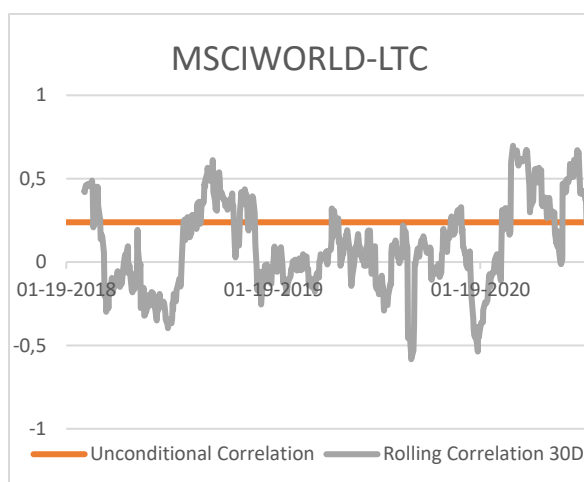


Figure 34: Graphic of MSCIWORLD-ETC correlation

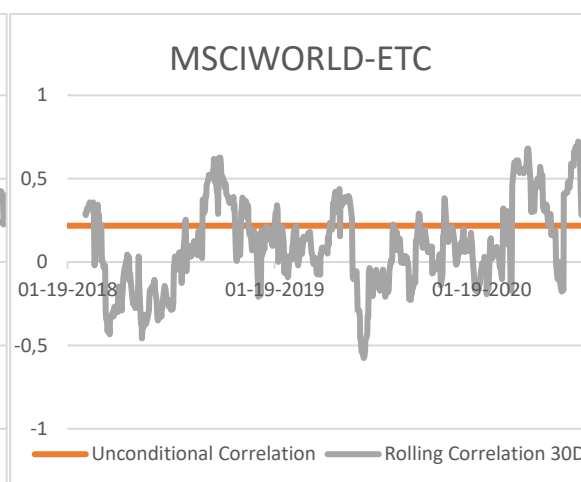


Figure 36: Graphic of MSCIWORLD-XRP correlation

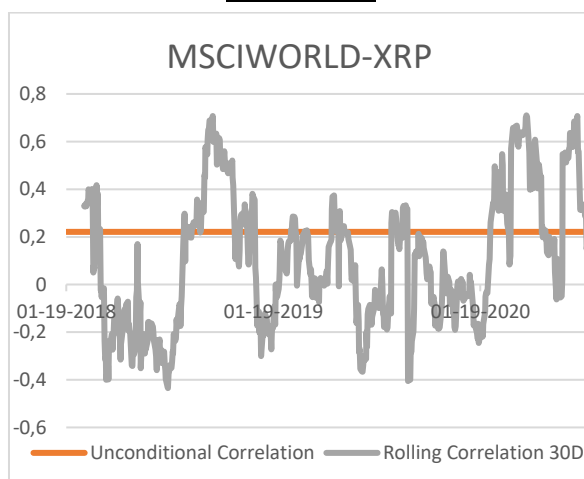


Figure 35: Graphic of MSCIWORLD-GOLD correlation

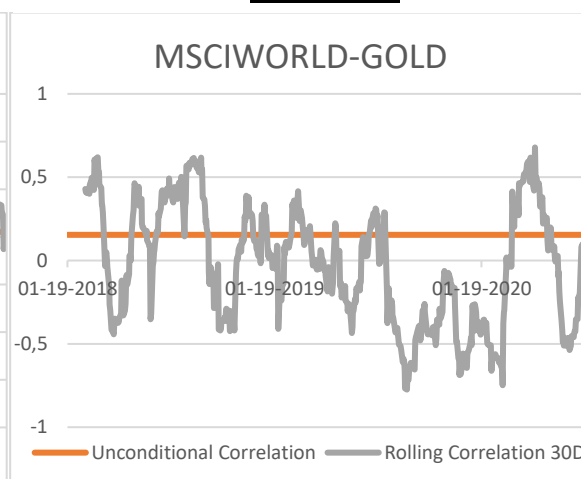


Figure 37: Graphic of TBOND10US-BTC correlation

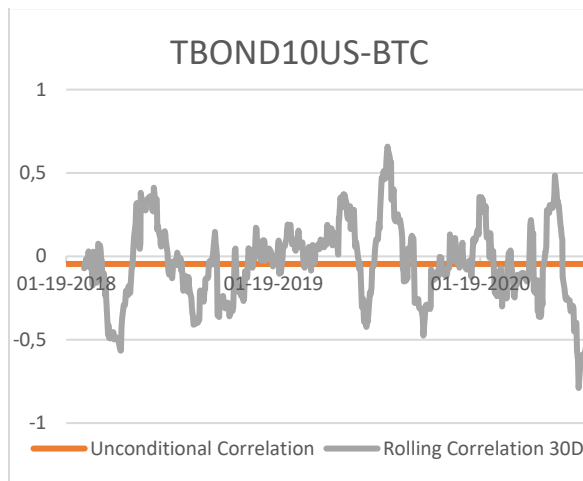


Figure 38: Graphic of TBOND10US-ETH correlation

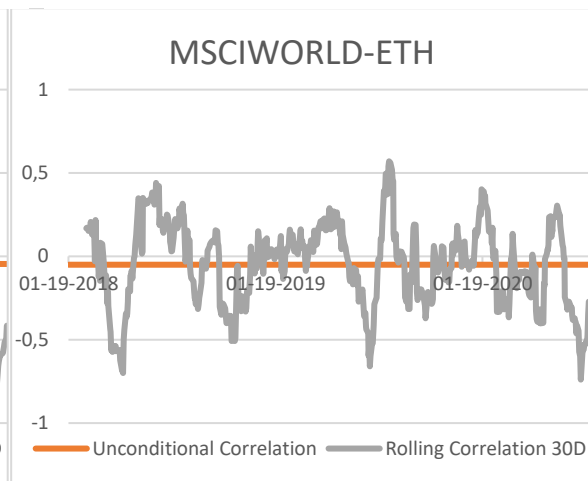


Figure 40: Graphic of TBOND10US-LTC correlation

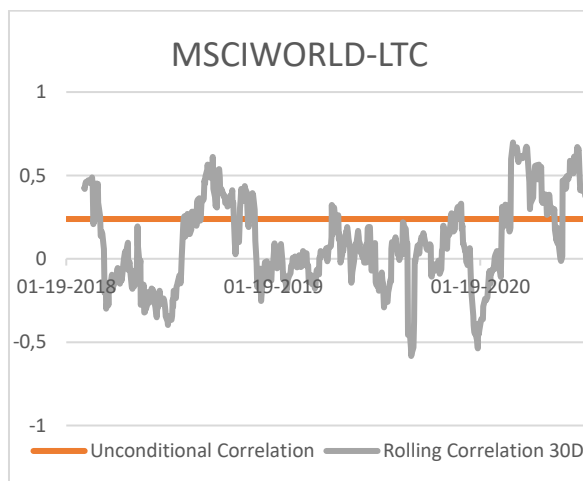


Figure 39: Graphic of TBOND10US-ETC correlation

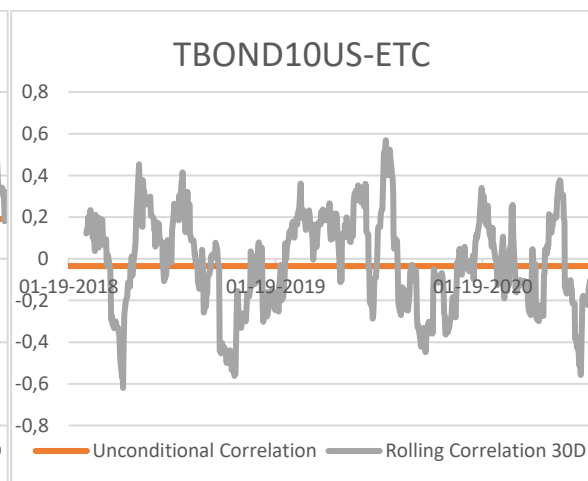


Figure 42: Graphic of TBOND10US-XR correlation

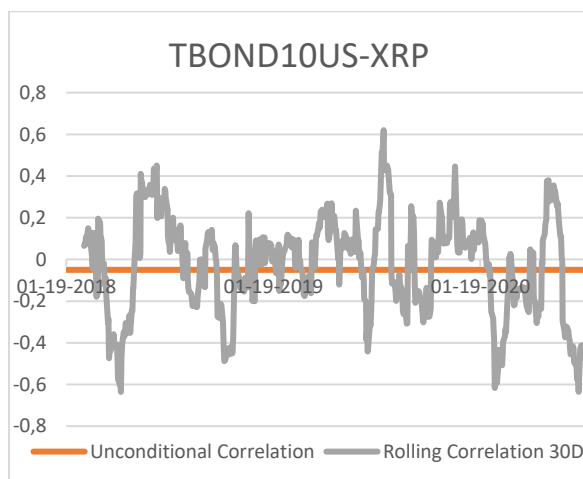


Figure 41: Graphic of TBOND10US-GOLD correlation

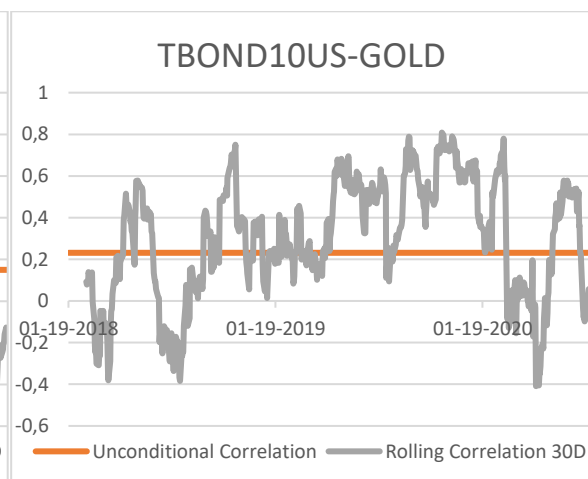


Figure 44: Graphic of EURUSD-BTC correlation

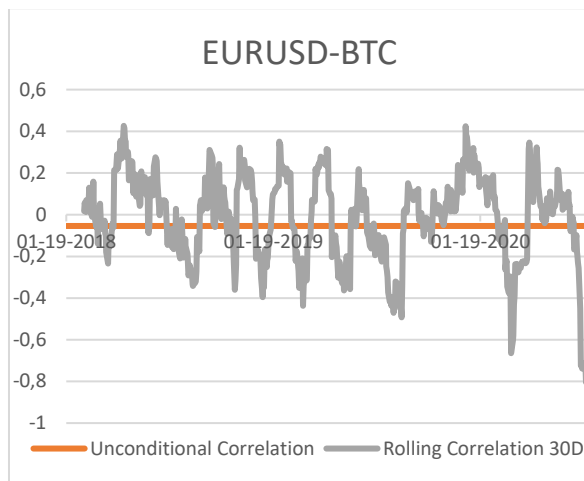


Figure 43: Graphic of EURUSD-ETH correlation

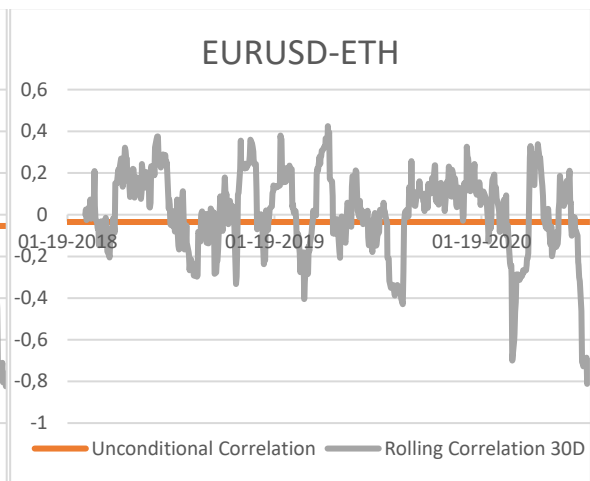


Figure 46: Graphic of EURUSD-LTC correlation

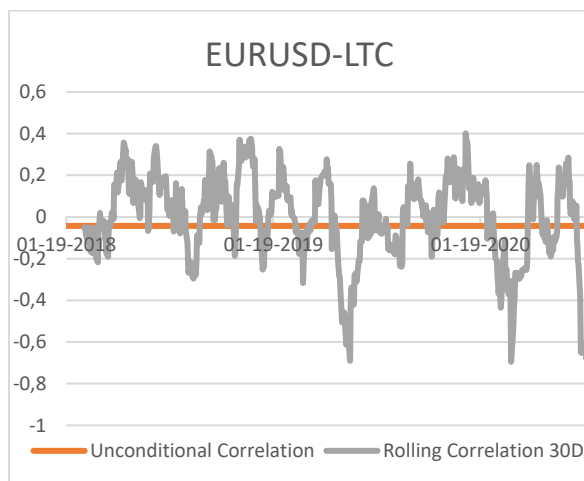


Figure 45: Graphic of EURUSD-ETC correlation

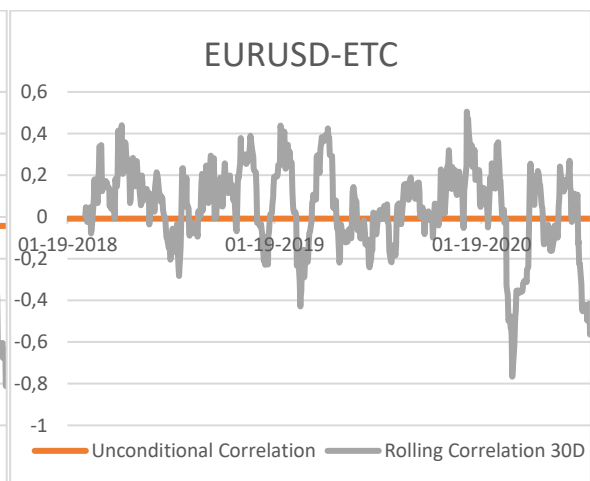


Figure 48: Graphic of EURUSD-XRP correlation

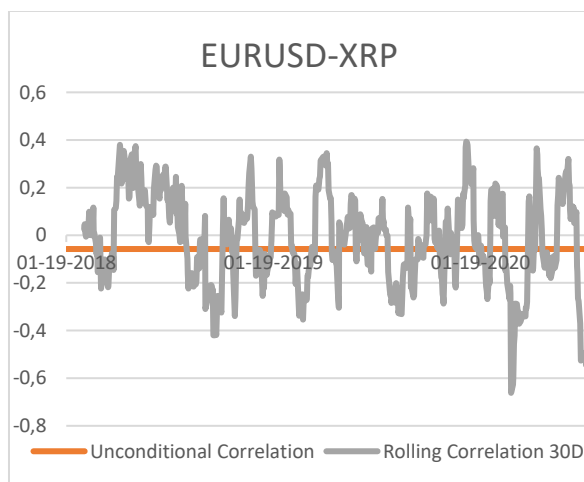
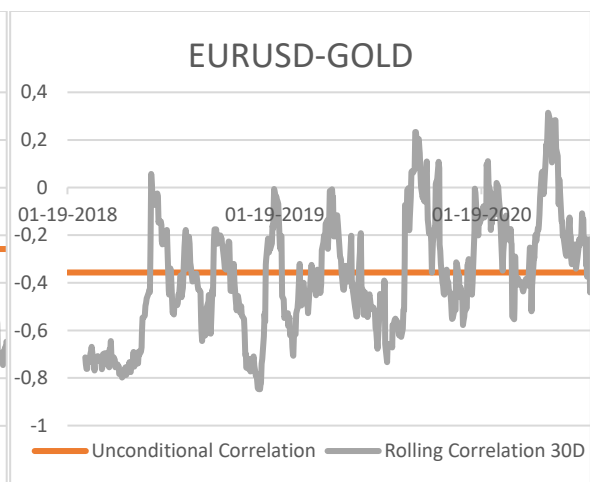


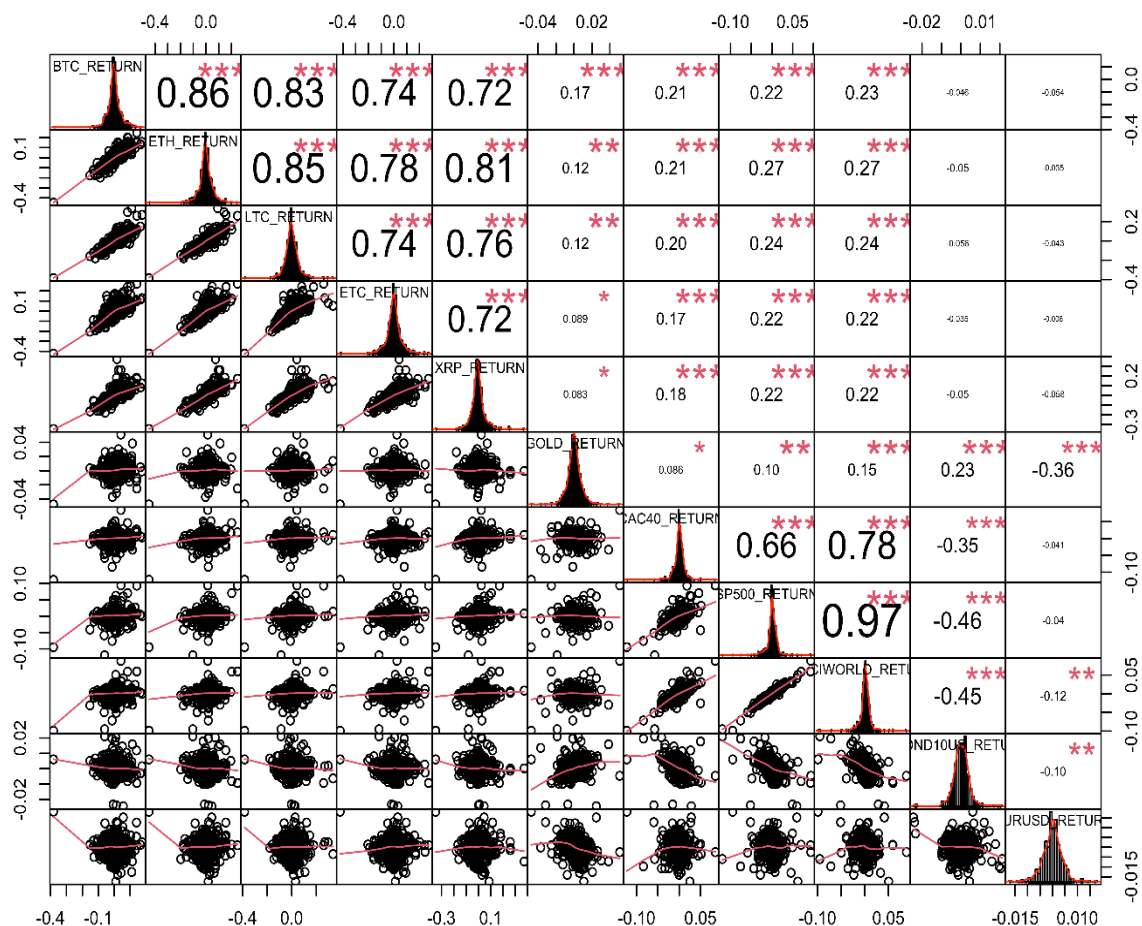
Figure 47: Graphic of EURUSD-GOLD correlation



5.2.2. Correlation Descriptive Analysis

Figure 49 provides information about the several relationships among all the assets studied. There are the unconditional correlation value, the significance level, and the correlation plots that visually show the linkages. Several relationships can be seen on the correlation plots through the position of the points around the lines. Indeed, the strong correlations are translated by regrouping the points along a straight line, whereas a scattered point cloud represents a weak correlation. Nevertheless, it is noteworthy to point out outliers in the plot with cryptocurrencies, which skew the results. The plots show one extreme point at the bottom left.

Figure 49: Correlation plots of all assets



First, all the cryptocurrencies are strongly positively correlated with each other exhibiting correlation values starting, on the one hand, from 72% for the combinations Ripple with Ethereum Classic and Ripple with Bitcoin, and on the other hand, going to 86% for Bitcoin and Ethereum. It means that the first group of assets varies in the same direction, at a confidence level of 99%. Consequently, these cryptocurrencies do not present the potential to hedge against each other and reduce the portfolio risk.

Inversely, the group of standard financial assets does not present homogeneity in terms of correlation. The SP500 and MSCIWORLD are almost perfectly correlated with the highest positive correlation value of 97%, meaning the two vary in the same direction and exhibit a low possibility of diversification effect.

TBOND10US shares the lowest negative correlation value with SP500 (-46%), indicating a potential risk reduction as a hedge via diversification. Being strongly positively correlated, the three stock indexes have a weak positive correlation value with GOLD (less than 15%), implicating a capacity for GOLD to act as a diversifier or safe haven. Besides, EURUSD has the least number of significant correlations, being weakly negatively correlated with only TBOND10US, GOLD, and MSCIWORLD.

Between the two groups of assets, all the cryptocurrencies share quite similar positive correlations with the three stock indexes. The values are between 18% and 27%, implicating that the two kinds of assets fluctuate weakly in the same direction. In addition, TBOND10US and EURUSD do not exhibit a significant correlation with all five cryptocurrencies suggesting that the linkage cannot be confirmed. Regarding GOLD, the correlation values with cryptocurrencies are positively low but significant (at a different confidence level). The results joint the idea that Bitcoin and cryptocurrencies do not suit as safe-haven assets. It would not be appropriate to incorporate it into a portfolio to diversify during market turbulence. A priori, cryptocurrencies do not limit exposure to losses in the event of market downturns.

5.2.3. Multivariate DCC-GARCH Estimations

This section is divided into five subsections according to the four traditional assets studied (GOLD, CAC40, SP500, and MSCIWORLD) along with a resume. I will analyze the results of each traditional asset correlation separately before comparing to exhibit

the most appealing DCC-GARCH correlation estimations. All the results extracted via Eviews are presented in Appendix 7.7 DCC-GARCH Estimations Results.

I decide to compute the DCC-GARCH correlation estimations for a pair of cryptocurrency and traditional assets. I do not integrate TBOND10US and EURUSD due to their no significant correlations with all cryptocurrencies. There is no evidence to reject the null hypothesis that the actual value of these correlations is equal to 0.

Besides, I find it interesting to incorporate the GOLD correlations with the three indexes to compare its diversification effect to cryptocurrencies. The idea is to determine if the latter ones can offer better diversification benefits than GOLD.

5.2.3.1. GOLD-

➤ Dynamic Return modelization

The results in Appendix 7.7 (Table 16 to Table 20) show that the p-value of all coefficients (1 to 6) for all pairs is above 5%, meaning that they are not significant. There is no evidence to reject the null hypothesis that the actual value of these coefficients is equal to 0. Therefore, there is no dynamic to capture in the return modelization of GOLD and the five cryptocurrencies. In other words, GOLD and the five cryptocurrencies are not significantly dependent.

➤ Dynamic Volatility modelization

The results in Appendix 7.7 (Table 16 to Table 20) show that the p-value of all coefficients (7 to 12) for all pairs is below 5%, meaning that they are significant. It attests to the strong dynamic in the volatility modelization. This modelization exhibits the dependence in the volatility inside the correlation between GOLD and the five cryptocurrencies.

Besides, it appears that LTC volatility negatively impacts GOLD volatility. The negative value of coefficient 12 represents it. Moreover, the GARCH model is particularly effective for GOLD as coefficients 7, 8, and 9 are higher than coefficients 10, 11, and 12. It means that there is more dynamic in the volatility of GOLD than in the volatility

of cryptocurrencies. Due to the pronounced cryptocurrency volatility, it is hard to capture it.

➤ Dynamic Correlation modelization

This subsection compares the three different correlation estimations for the end of the period studied (2018 July 29th, 2020). Table 9 shows that the DCC-GARCH correlation values for GOLD with the five cryptocurrencies are globally lower than the unconditional and rolling correlation values. The pairs of assets with GOLD are slightly correlated, indicating that it is possible to combine cryptocurrencies with GOLD and reduce the portfolio's risk as diversifiers.

Nevertheless, unconditional and DCC-GARCH correlations for each pair are similar with the same range, while the values of the rolling correlation are considerably higher.

Table 9: Correlations comparison - GOLD

Correlations comparison - GOLD					
	GOLD-BTC	GOLD-ETH	GOLD-LTC	GOLD-ETC	GOLD-XRP
Unconditional Correlation	0,1734	0,1204	0,1249	0,0891	0,0825
Rolling Correlation 30D	0,5715	0,4840	0,5050	0,5107	0,4119
DCC-GARCH $R(1,2)$	0,1524	0,1159	0,1251	0,0740	0,0904

5.2.3.2. CAC40-

➤ Dynamic Return modelization

The results in Appendix 7.7 (Table 21 to Table 26) show that the p-value of almost all coefficients (1 to 6) for all pairs is above 5%, meaning that they are not significant. There is no evidence to reject the null hypothesis that the actual value of these coefficients is equal to 0.

Nevertheless, the return modelization of the CAC40 with GOLD presents one significant coefficient. It appears that the return of CAC40 from the precedent period

partly explains the variation of GOLD return for the present period. In financial reality, it is not difficult to imagine that implication.

However, there is no dynamic to capture in the return modelization of CAC40 and the five cryptocurrencies. CAC40 and the five cryptocurrencies are not significantly dependent, but there is still a slight dependence between CAC40 and GOLD.

➤ Dynamic Volatility modelization

The results in Appendix 7.7 (Table 21 to Table 26) show that the p-value of all coefficients (7 to 12) for all pairs is below 5%, meaning that they are significant. It attests to the strong dynamic in the volatility modelization. This modelization exhibits the dependence in the volatility inside the correlation of CAC40 with the five cryptocurrencies and GOLD.

Besides, it appears that LTC volatility negatively impacts CAC40 volatility. The negative value of coefficient 12 represents it. Moreover, the GARCH model is particularly effective for CAC40 as coefficients 7, 8, and 9 are higher than coefficients 10, 11, and 12. It means that there is more dynamic in the volatility of CAC40 than in the volatility of cryptocurrencies. Due to the pronounced cryptocurrency volatility, it is hard to capture it.

Nevertheless, the volatility of GOLD is more impacted by the volatility of CAC40 than inversely represented by a higher value of coefficient 12 than coefficient 9.

➤ Dynamic Correlation modelization

This subsection compares the three different correlation estimations for the end of the period studied (2018 July 29th, 2020). Table 10 shows that the DCC-GARCH correlation values for CAC40 with the five cryptocurrencies and GOLD are globally lower than the unconditional correlation values. The pairs of assets with CAC40 are slightly correlated, indicating that it is possible to combine cryptocurrencies with CAC40 and reduce the portfolio's risk as diversifiers.

Nevertheless, the DCC-GARCH correlation for CAC40-GOLD is negative, implicating the hedging potential against CAC40. Moreover, the rolling correlations for each pair

are also negatives indicating, in this case, that the five cryptocurrencies could act as hedging for CAC40.

Table 10: Correlations comparison - CAC40

Correlations comparison - CAC40						
	CAC40-BTC	CAC40-ETH	CAC40-LTC	CAC40-ETC	CAC40-XRP	CAC40-GOLD
Unconditional Correlation	0,2115	0,2137	0,1954	0,1671	0,1800	0,0856
Rolling Correlation 30D	-0,0776	-0,1976	-0,0946	-0,1619	-0,1528	-0,0799
DCC-GARCH R(1,2)	0,1278	0,1477	0,1347	0,1119	0,1430	-0,1396

5.2.3.3. SP500-

➤ Dynamic Return modelization

The results in Appendix 7.7 (Table 27 to Table 32Table 21) show that the p-value of almost all coefficients (1 to 6) for all pairs is above 5%, meaning that they are not significant. There is no evidence to reject the null hypothesis that the actual value of these coefficients is equal to 0.

Nevertheless, the return modelization of the SP500 with BTC and XRP presents one significant coefficient each. First, it appears that the return of BTC from the precedent period partly explains the variation of SP500 return for the present period. Then, it seems that the return of SP500 from the precedent period partly explains the variation of XRP return for the present period. These statistical implications are not easy to defend from an economic perspective.

However, there is no dynamic to capture in the return modelization of SP500 with ETH, LTC, ETC, and GOLD. They are not significantly dependent, but there is still a slight dependence of SP500 with BTC and XRP.

➤ Dynamic Volatility modelization

The results in Appendix 7.7 (Table 27 to Table 32) show that the p-value of all coefficients (7 to 12) for all pairs is below 5%, meaning that they are significant. It attests to the strong dynamic in the volatility modelization. This modelization exhibits the dependence in the volatility inside the correlation of SP500 with the five cryptocurrencies and GOLD.

Besides, it appears that LTC volatility negatively impacts SP500 volatility. The negative value of coefficient 12 represents it. Moreover, the GARCH model is particularly effective for SP500 as coefficients 7, 8, and 9 are higher than coefficients 10, 11, and 12. It means that there is more dynamic in the volatility of SP500 than in the volatility of cryptocurrencies. Due to the pronounced cryptocurrency volatility, it is hard to capture it.

Nevertheless, the volatility of GOLD is more impacted by the volatility of SP500 than inversely represented by a higher value of coefficient 12 than coefficient 9.

➤ Dynamic Correlation modelization

This subsection compares the three different correlation estimations for the end of the period studied (2018 July 29th, 2020). Table 11 shows that the DCC-GARCH correlation values for SP500 with the five cryptocurrencies and GOLD are globally lower than the unconditional and rolling correlation values. The pairs of assets with CAC40 are slightly correlated, indicating that it is possible to combine cryptocurrencies with CAC40 and reduce the portfolio's risk as diversifiers. Nevertheless, the DCC-GARCH correlation for CAC40-GOLD is negative, implicating the hedging potential against CAC40.

Table 11: Correlations comparison - SP500

Correlations comparison - SP500						
	SP500-BTC	SP500-ETH	SP500-LTC	SP500-ETC	SP500-XRP	SP500-GOLD
Unconditional Correlation	0,2184	0,2137	0,1954	0,1671	0,1800	0,0856
Rolling Correlation 30D	0,3134	0,2100	0,2769	0,2121	0,2439	-0,0768
DCC-GARCH R(1,2)	0,0969	0,1521	0,1200	0,1171	0,1328	-0,0799

5.2.3.4. *MSCIWORLD-*

➤ Dynamic Return modelization

The results in Appendix 7.7 (Table 33 to Table 38) show that the p-value of almost all coefficients (1 to 6) for all pairs is above 5%, meaning that they are not significant. There is no evidence to reject the null hypothesis that the actual value of these coefficients is equal to 0.

Nevertheless, the return modelization of the MSCIWORLD with XRP and GOLD presents significant coefficients. First, it appears that the return of XRP from the precedent period partly explains the variation of MSCIWORLD return for the present period. Then, it seems that the return modelization of the MSCIWORLD with XRP and GOLD makes significant the dependence of MSCIOWRLD return from the precedent period with itself for the present period. It is curious to observe these statistical results from an economic perspective.

However, there is no dynamic to capture in the return modelization of MSCIWORLD with BTC, ETH, LTC, and ETC. They are not significantly dependent, but there is still a slight dependence of MSCIWORLD with XRP and GOLD.

➤ Dynamic Volatility modelization

The results in Appendix 7.7 (Table 33 to Table 38) show that the p-value of all coefficients (7 to 12) for all pairs is below 5%, meaning that they are significant. It attests to the strong dynamic in the volatility modelization. This modelization exhibits the dependence in the volatility inside the correlation of MSCIWORLD with the five cryptocurrencies and GOLD.

Besides, it appears that LTC volatility negatively impacts MSCIWORLD volatility. The negative value of coefficient 12 represents it. Moreover, the GARCH model is particularly effective for SP500 as coefficients 7, 8, and 9 are higher than coefficients 10, 11, and 12. It means that there is more dynamic in the volatility of MSCIWORLD than in the volatility of cryptocurrencies. Due to the pronounced cryptocurrency volatility, it is hard to capture it.

Nevertheless, the volatility of GOLD is more impacted by the volatility of MSCIWORLD than inversely represented by a higher value of coefficient 12 than coefficient 9.

➤ Dynamic Correlation modelization

This subsection compares the three different correlation estimations for the end of the period studied (2018 July 29th, 2020). Table 12 shows that the DCC-GARCH correlation values for MSCIWORLD with the five cryptocurrencies and GOLD are globally lower than the unconditional and rolling correlation values. The pairs of assets with MSCIWORLD are slightly correlated, indicating that it is possible to combine cryptocurrencies with MSCIWORLD and reduce the portfolio's risk as diversifiers. Nevertheless, the DCC-GARCH correlation for CAC40-GOLD is negative, implicating the hedging potential against MSCIWORLD.

Table 12: Correlations comparison - MSCIWORLD

Correlations comparison - MSCIWORLD						
	MSCIWORLD-BTC	MSCIWORLD-ETH	MSCIWORLD-LTC	MSCIWORLD-ETC	MSCIWORLD-XRP	MSCIWORLD-GOLD
Unconditional Correlation	0,2306	0,2671	0,2386	0,2179	0,2210	0,1544
Rolling Correlation 30D	0,3576	0,2016	0,3148	0,2350	0,2330	-0,0303
DCC-GARCH R(1,2)	0,1055	0,1562	0,1282	0,1152	0,1435	-0,0426

5.2.3.5. DCC-GARCH Correlation Estimations

This subsection compares the DCC-GARCH correlation estimations for the end of the period studied (2018 July 29th, 2020). Beforehand, all the correlation coefficients R(1,2) are significant.

The first critical constatation is that only correlations with GOLD and the three indexes are negative. They are slightly negatively correlated, indicating that GOLD act as a hedge against them. The lowest correlation value is -0,1396 with CAC40, followed by SP500 with a -0,0799, and the highest value is -0,0426.

Regarding the correlation with cryptocurrencies, the lowest correlation value is 0,0740 for GOLD-ETC. It implicates that these two assets are the least correlated, and thus this combination has the best potential to reduce the portfolio risk. Also, the correlation for CAC40-ETC is the lowest among the other correlation between CAC40 and cryptocurrencies.

Moreover, it appears that for SP500 and MSCIWORLD, the correlations with BTC are the lowest among the other cryptocurrencies. The correlation for SP500-BTC is 0,0969 and for MSCIORLD-BTC is 0,1055.

However, the highest correlation value is the combination of GOLD-BTC with 0,1524. For the three indexes, the combinations with ETH present the highest correlation values for each of them.

These results are interesting for investors who want to include cryptocurrencies into a portfolio with GOLD and the three indexes and reduce the portfolio risk.

Table 13:DCC-GARCH Correlation Estimations $R(1,2)$

DCC-GARCH Correlation Estimations $R(1,2)$						
	BTC	ETH	LTC	ETC	XRP	GOLD
GOLD	0,1524	0,1159	0,1251	0,0740	0,0904	
CAC40	0,1278	0,1477	0,1347	0,1119	0,1430	-0,1396
SP500	0,0969	0,1521	0,1200	0,1171	0,1328	-0,0799
MSCIWORLD	0,1055	0,1562	0,1282	0,1152	0,1435	-0,0426

6. CONCLUSION

The last section of the thesis is dedicated to the interpretation and conclusion of the empirical results. The goal is to confirm or reject the hypotheses and answer the problem statement. Some financial implications will also be developed. Finally, the study's limits will exhibit potential amelioration and deepening about the subjects tackled in this work.

6.1. Results interpretation and conclusion

The main question of this thesis is to know the diversification effect of cryptocurrencies. The goal is to determine if it is beneficial to incorporate any cryptocurrency into a portfolio containing standard assets such as indexes. Through performance analysis and DCC-GARCH estimations, I aspire to exhibit which cryptocurrency can better reduce risk among traditional portfolios.

First, the absolute performance measures related to the total risks show that cryptocurrencies and standard financial assets present, overall, two distinct performances. The first group generally has more risks and more potential losses than the second one, but the reward seems to compensate for the total risk undertaken at a larger scale. Indeed, the Adjusted Sharpe ratio rank cryptocurrencies above the other assets. Nonetheless, the global return over the period shows that only Bitcoin has a positive value amid cryptocurrencies and the six standard financial assets. However, EURUSD and TBOND10US appear to act alike, presenting less risk along with few rewards. Bitcoin performance is between these two and the three stock indexes, which is a little apart in terms of ratio values without having the same performances as the cryptocurrencies.

Nevertheless, the relative performance measures do not conclude with the same categorization of the several assets studied. Although the two groups of assets exhibit globally distinct measures, some assets shift away a few times from the initial group, such as GOLD, MSCIWORLD, or Bitcoin. While cryptocurrencies have lower measure values than standard financial assets, GOLD represents investors' most appealing

asset, being the only asset that outperformed the market given the risk undertaken. Moreover, Bitcoin has, at some point, a better combination of reward in balance to the relative risk undertaken, compared to some standard financial assets. The M-squared excess return supports this outcome by ranking Bitcoin fourth place ahead of CAC40.

As for unconditional correlations between cryptocurrencies and standard financial assets, it appears that the first group is homogeneous. The five cryptocurrencies share quite a similar correlation with the different asset classes. While they are weakly positively correlated to the three stock indexes, there is no significant correlation with both EURUSD and TBOND10USD. Also, there is a weak positive correlation between GOLD and cryptocurrencies.

However, the rolling volatility and correlation curves exhibit the dynamic aspects as opposed to the unconditional version. The dynamic present within the correlation is much stronger than that within volatility and, in turn, much stronger than within returns. These observations attest to the use of the multivariate DCC-GARCH estimations model and suggest that portfolio decisions should not be based on unconditional volatility or correlation due to the marked variation. Otherwise, the investor would over- or underestimate by not fitting the realized volatility.

For the dynamic return modelization, it appears that only BTC, XRP, and GOLD present significant coefficients among the assets studied. XRP shares slight dependence with SP500 and MSCIWORLD. Then, GOLD shares slight dependence with CAC40 and MSCIWORLD. Finally, BTC shares slight dependence with SP500.

Furthermore, the critical result from the dynamic volatility modelization is that the GARCH model is particularly effective for traditional assets. There is more dynamic in the volatility of standard assets than in the volatility of cryptocurrencies. Nevertheless, it appears that LTC volatility negatively impacts all traditional assets. In addition, the volatility of GOLD is more impacted by the volatility of traditional assets than inversely.

Moreover, the three correlations method estimations present different ranges of values that can induce different portfolio management decisions. The DCC-GARCH correlation values for the four traditional assets with the five cryptocurrencies are globally lower than the unconditional and rolling correlation values. These results attest to the importance of building a suitable model to reduce the portfolio risk efficiently.

Finally, the critical constatation for the correlation estimations is that only correlations with GOLD and the three indexes are negative. They are slightly negatively correlated, indicating that GOLD act as a hedge against them. Besides, pairs of cryptocurrencies with GOLD and the three indexes are slightly correlated. The lowest correlation value is 0,0740 for GOLD-ETC. It implicates that these two assets are the least correlated, and thus this combination has the best potential to reduce the portfolio risk.

To conclude my thesis, GOLD is the only asset among the assets studied that outperformed the market given the risk undertaken. Besides, GOLD can be used to hedge against CAC40, SP500, and MSCIWOLRD, according to the negative correlation with them.

However, cryptocurrencies have, in general, less good risk-adjusted return measures than standard financial assets. Regarding the DCC-GARCH correlation estimations, the results show that the lowest correlation value is 0,0740 for GOLD-ETC. This combination has the best potential to reduce portfolio risk. These results are interesting for investors who want to include cryptocurrencies into a portfolio with GOLD and the three indexes and reduce the portfolio risk.

6.2. Limits of the study

One of these study limits relates to the datasets and, more specifically, on the period. The study period was limited to the length of a master's thesis. The period selected does not seize the whole impacts and variations caused by the sanitary crisis of COVID-19. The crisis that has started in February/March 2020 has not ended yet and still impacts every single aspect of the economy. However, it would be interesting to extend the study on a longer duration to capture even more insight about variations below this limit, given that external or internal shocks may not affect immediately.

Another limit lies in the equation system used to build the DCC-GARCH estimations. The statistical results indicate that the estimations present non-significant coefficients, suggesting remodeling the equation system by removing the variables with non-significant coefficients. It would also be interesting to pursue the research by refining the understanding of the coefficients in the idea of obtaining the best-fit models. There

is room to extend my thesis by applying other models such as the diagonal BEKK or VEC. It would constitute robustness tests for assessing the viability of the model I used. However, my thesis is an overview of the several possibilities to study the correlation between different assets for portfolio risk diversification.

7. APPENDIX

7.1. Description of the cryptocurrency's dataset

This Appendix provides a brief description of the five cryptocurrencies used in the research. Moreover, insights into their history are given. This section is based on the website (CoinMarketCap, 2020), specifically on each cryptocurrency's respective pages. The Appendix is organized into five sections, one for each cryptocurrency.

7.1.1. Bitcoin (BTC)

Bitcoin is defined as a peer-to-peer online currency, implying that all transactions occur directly between an equal and independent member in the network, without an intermediary authorizing or facilitating them. According to its founder (Nakamoto, 2008), the Bitcoin creation's goal is to allow *“online payments to be sent directly from one party to another without going through a financial institution.”* In other words, Bitcoin and cryptocurrencies at large represent money that can be transmitted by anybody, at any place in the world, without being dependent on trusted intermediaries, such as banks and financial services companies.

On October 31, 2008, a person or an organization named Satoshi Nakamoto²¹ published Bitcoin's whitepaper, explaining how a peer-to-peer, online currency could be implemented. The idea is to use a decentralized ledger of transactions grouped into batches (called “blocks”) and secured by cryptographic algorithms. On January 3, 2009, just two months later, the creator Nakamoto mined the Bitcoin network's first block, known as the genesis block, launching the world's first cryptocurrency. Bitcoin distinguishes being the first cryptocurrency to be actually used even though some conception for a similar decentralized electronic currency precedes it.

²¹ There is a mystery around the person or the organization behind the original inventor of Bitcoin. As of 2020, The true identity of Satoshi Nakamoto remains unknown.

However, Bitcoin has succeeded in establishing a worldwide community and giving birth to an entirely new industry of millions of devotees who create, contribute, invest in, trade, and use Bitcoin and other cryptocurrencies in their everyday lives. Over the years, cryptocurrency's software has evolved thanks to many people's help through patching vulnerabilities and adding new features.

7.1.2. Ethereum (ETH)

Ethereum is defined as a decentralized open-source blockchain system that offers its own cryptocurrency, Ether. Moreover, it operates as a platform for many other cryptocurrencies (called "tokens"), as well as for the implementation and accomplishment of decentralized smart contracts. The execution of smart contracts on the Ethereum platform constitutes its principal innovation, strengthening smart contract technology's prevailing benefits. However, this blockchain system's goal is to grow into a worldwide stage for decentralized applications, in which users around the world can write and run software that is resistive to censorship, downtime, and fraud.

In 2013, Ethereum was first portrayed in a white paper written by a Russian-Canadian named Vitalik Buterin, along with other co-founders. In fact, there are eight co-founders behind the Ethereum blockchain, which is a vast number for a crypto project. After a first meeting on June 7, 2014, in Zug, Switzerland, they succeeded in obtaining funding for the project in an online public sale in the summer of 2014.

Then, the official launched of the Ethereum blockchain was on July 30, 2015. The latter has pioneered the concept of a blockchain smart contract platform designed to reduce the need for trusted intermediates between contractors. It automatically executes the actions required to accomplish an agreement between several parties on the internet, thus reducing transaction costs and enhancing transaction reliability. Nowadays, Ethereum represents the first global platform for decentralized applications and smart contracts.

7.1.3. Litecoin (LTC)

Litecoin is a peer-to-peer cryptocurrency created by Charlie Lee, a former Google employee who intends to create a "light version of Bitcoin." The cryptocurrency was issued via an open-source client on GitHub on Oct. 7, 2011, and five days later, on Oct. 13, 2011, the Litecoin Network went live.

For the developers, Litecoin can be seen as the "silver" to Bitcoin's "gold." Indeed, the cryptocurrency was developed based on the Bitcoin protocol, with some differences in the hashing algorithm used, block transaction times, hard cap, and other factors. It is noteworthy to point out one of the divergences: its prioritization of transaction confirmation speed.

7.1.4. Ethereum Classic (ETC)

Ethereum Classic (ETC²²) is a hard fork of Ethereum (ETH) launched in July 2016 after a major hacking event led to 3.6 million ETH theft. At that time, the hard fork (ETC) was contentious due to disagreement between users of Ethereum over whether to retrovert the blockchain to revoke the effects of the significant hack. Ethereum Classic appeared to be the network that did not revert the chain without artificially countering the DAO hack.

The Ethereum Classic is the legacy chain of Ethereum with the aim to preserve the latter blockchain as it originally was. Technically, its actual creators are the original Ethereum developers, to name the most known, Vitalik Buterin. Therefore, Ethereum Classic has the same function as Ethereum, which consists of the host and supports decentralized applications (DApps) as a smart contract network.

Nevertheless, Ethereum Classic has strived to distinguish itself from Ethereum through the networks' technical roadmap, which has diverged further from Ethereum's one with time. With no "official" team attached to the project, the global community project does not aim to change its proof-of-work (PoW) mining algorithm into a proof-of-stake (PoS) mining algorithm, unlike Ethereum.

²²ETC is actually the name of the token that runs on the Ethereum Classic fork

7.1.5. Ripple (XRP)

First of all, it is crucial to distinguish between a few terms that may be confused. Ripple alone represents a company running a digital payment platform called RippleNet, which is on top of a distributed ledger database called XRP Ledger. The latter is open-source and is not based on blockchain but preferably on the aforementioned distributed ledger database. Finally, the cryptocurrency itself is called XRP that runs on the RippleNet.

Even though the Ripple payment platform's premise was first formulated in 2004 by Ryan Fugger, Ripple did not begin to be built until Jed McCaleb, and Chris Larson took over the project in 2012 (also called OpenCoin, at that time). Ripple's purpose behind the XRP's creation is to be a speedy, less costly, and more scalable alternative to other digital assets and existing monetary payment platforms like SWIFT.

Since the generation of the cryptocurrency XRP is not based on a blockchain system, the operations rely on the RippleNet payment platform, a real-time gross settlement (RTGS) system. The objective is to enable instant monetary transactions globally thanks to The XRP Ledger that processes transactions roughly every 3-5 seconds. Unlike the proof-of-work mining assets for Bitcoin (BTC), the transactions can be executed whenever independent validator nodes reach a consensus on both the order and validity of XRP transactions.

7.2. Description of the standard's financial assets dataset

This Appendix provides a brief description of the six standard financial assets used in the research. Moreover, insights into their history are given. All this section is based on the website of (Investopedia, 2020). The Appendix is organized into six sections, one for each financial asset.

7.2.1. Gold²³

Gold constitutes the ultimate commodity, the one that has always captivated human societies. Since the beginning of recorded time, it has retained humanity's enchantment due to, amongst others, the fact that it does not get used, exhausted, or absorb, unlike other commodities such as oil or wheat. Once gold is mined, it stays in the world, relatively in the same physical state. Although gold may be transformed into jewelry or placed for various other uses, the precious metal is persistent. Its chemical composition cannot be used up like oil turned into gas and other products.

The consideration of gold has expanded, through time, to several aspects of the world economy. History has offered gold a power exceeding any other commodities on the planet, and that power has never really disappeared. First, this metal was and still is deemed as a commodity to have and to invest in. Empires and kingdoms were built and destroyed over gold as civilizations developed because it was globally recognized as a gratifying payment form.

Following this idea, a monetary system, called the gold standard, started to develop during the 18th century. As paper money's introduction caused some problems, communities began to use gold to support the money's value. Concretely, this monetary system lets the liberty to convert paper money into a fixed amount of gold. At the beginning of the 19th century, the gold standard became conventional and officially adopted by England in 1821. This increase the international trade and production of gold, leading most developed nations to be linked, by 1900, to the gold standard.

Nevertheless, during the 20th century, several events, such as World War I, generated an absence of confidence in the gold standard. Even though western governments worked very well together to make the system work, this monetary system had few drawbacks. Indeed, the gold supply became limited and mainly controlled by the U.S. authorities by regulating the gold price. It gave few flexibilities to other nations leading them to try several hazardous monetary actions such as raising the interest rates to protect their global stock and, by extension, their national economy.

²³The whole section is based on the online articles of (Lioudis, 2020), (Mitchell, 2020) and (Hayes, Why Gold Matters: Everything You Need To Know, 2020).

After major countries had suspended and others had dropped the monetary system of standard gold, the latter officially disappeared in 1976 with the dissociation of the U.S. Dollar and the gold prices. Nowadays, the price of gold is freely established by the demand for the metal. Under a free market system, gold may be deemed as a currency like the Euro, the British Sterling Pound or the U.S. Dollar. More particularly, it is viewed as a safe haven, in which the price increase is generally considered as a signal of underlying economic issues. Moreover, gold is utilized as a significant financial asset for countries and central banks.

7.2.2. The CAC40²⁴

The CAC 40 is an acronym for “*Cotation Assistée en Continu*” in French, translating into “continuous assisted trading” in English. The French stock market index is tracking the 40 most extensive French stocks based on the market capitalization of Euronext Paris. It represents a capitalization-weighted measure of the 40 most significant stocks amid the 100 highest market caps on the exchange. More specifically, it encompasses the 40 largest equities listed on the Euronext Paris assessed by market capitalization, trading activity, size of the balance sheet, and liquidity.

In December 1987, the CAC 40 started with a base value of 1,000 and pursued to perform on a system conditioned by the total market capitalization system until 2003. At this date, the system switched to a free float-adjusted market capitalization methodology. Being one of the leading national indices of the transnational European stock exchange, Euronext, the CAC 40, is a benchmark index for funds investing in the French stock market.

7.2.3. The S&P500 Index²⁵ (SP500)

²⁴ The whole section is based on the online article of (Hayes, CAC 40, 2020).

²⁵ The whole section is based on the online articles of (Kenton, S&P 500 Index – Standard & Poor's 500 Index, 2020) and (Investopedia, 2020).

The S&P 500 Index or, more precisely, the Standard & Poor's 500 Index is a stock market index tracking 500 of the most prominent publicly traded companies in the U.S.A. It represents a market-capitalization-weighted index of the top 500 U.S. companies. More precisely, it uses a float-weighted system resulting in the company market capitalizations adjustment by the number of shares available for public trading.

Introduced in 1957 by Standard & Poor's, a leading index provider and data source of independent credit ratings, the S&P 500 was designed to portray the overall composition of the U.S. economy with corporations listed on the New York Stock Exchange (NYSE) and the NASDAQ Composite. Nowadays, the S&P 500 is a benchmark vastly perceived as the best barometer of large-cap U.S. equities.

7.2.4. The MSCI World Index (MSCIWORLD)²⁶

The MSCI World Index stands for Morgan Stanley Capital International (MSCI) World Index, a global stock index provided by the same name's investment research firm. The index is constituted by more than 1,600 large- and mid-cap companies in developed markets in the United States and Canada, 16 countries in Europe and the Middle East, and five countries in the Asia-Pacific region. It is interesting to mention that around two-thirds of the index comprises U.S. corporations, and an excessively vast proportion of the index is represented by technology, health care, and financial companies.

Regarding the investment research firm Morgan Stanley Capital International (MSCI), it is the association of investment firm Morgan Stanley that bought the licensing rights to Capital International data in 1986. Prior to this, Capital International was, in 1969, pioneered in providing global stock market indexes for markets outside the United States. Nowadays, the MSCI is somewhat known for its worldwide stock indexes such as the MSCI Emerging Market Index, MSCI Frontier Markets Index, MSCI All Country World Index (ACWI), or the MSCI EAFE Index. These stock indexes' purpose is to focus on diverse geographic areas and stock types such as small-caps, mid-caps, and large-caps.

²⁶The whole section is based on the online articles of (Kenton, MSCI, 2019) and (Reiff, 2020)

7.2.5. 10-Years U.S. Treasury Bonds (TBOND10US)²⁷

First of all, U.S. treasury bonds (T-bonds) designate fixed-rate government debt securities issued by the U.S. Federal government. With a maturity range between 10 and 30 years, T-bonds pay semiannual interest payments until maturity, where the bond's face value is paid to the titleholder. They are considered virtually risk-free government-issued securities, but they tend to provide lower returns than equities and corporate bonds.

Alongside Treasury bills, Treasury notes, and Treasury Inflation-Protected Securities (TIPS), U.S. treasury bonds constitute the sorts of debt issued by the U.S. Department of the Treasury to finance the U.S. government's expenditure activities. All four are deemed the safest in the world because the government backs them by taxing its citizens. Furthermore, the U.S. Treasuries are nearly as risk-free as an investment in the international scene relative to other national treasury bonds. Market participants and analysts use the 10-year Treasury bond as a benchmark and guidance for lending products' interest rates.

7.2.6. The Currency Pair EUR/USD(EURUSD)²⁸

The currency pair EUR/USD, shortened term for the euro against the U.S. dollar pair, represents the exchange rate between the European Union (EU) and the United States (USD). It denotes the number of U.S. dollars (the quote currency required to buy a single euro(the base currency)). Concretely, the value of the EUR/USD pair is outlined as 1 euro per x U.S. dollars meaning that if the pair is trading at 3.50, it takes 3.5 U.S. dollars to buy 1 euro. It is essential to know that the pair's base currency is fixed and always corresponds to one unit.

²⁷The whole section is based on the online article of(Chen, Treasury Bond (T-Bond), 2020)

²⁸The whole section is based on the online article of (Chen, Currency Pair: EUR/USD (Euro/U.S. Dollar), 2019)

As the EUR/USD pair embodies two of the world's biggest economies, it has changed into the international scene's most widely traded pair. Since the Euro's introduction as an accounting currency in 1999 and the official approval on Jan. 1, 2002, it integrated and represented a substantial European economy group like the European Union's circulating currency. Therefore, the euro enhanced the most heavily traded currencies in the forex market, second only to the U.S. dollar.

However, the EUR/USD pair's value is influenced by government policies and the economics of demand and supply in currency markets for the respective country. The EUR/USD rate can rise due to the increasing value of the euro or the decreasing value of the U.S. dollar. The rate (price) would have an upward movement in either situation, leading to a corresponding upward movement in a price chart.

7.3. Plots and density histograms of cryptocurrencies

In this Appendix, I provide density histograms of the five cryptocurrencies datasets used in my research, covering the period from January 19, 2018, to July 29, 2020. Besides, a plot (graphic) represents the evolution of each cryptocurrency's return during the same period. These were computed and extracted via the software RStudio based on the datasets. The Appendix is organized into five sections, one for each cryptocurrency.

7.3.1. Bitcoin (BTC)

Figure 51: Plot of Bitcoin Return

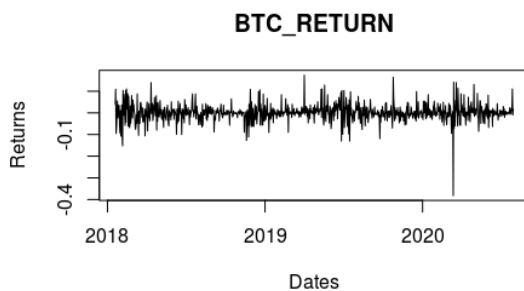
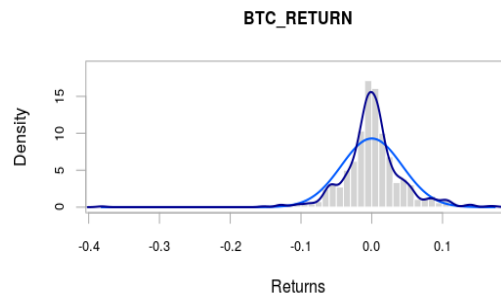


Figure 50: Density histogram of Bitcoin Return



7.3.2. Ethereum (ETH)

Figure 53: Plot of Ethereum Return

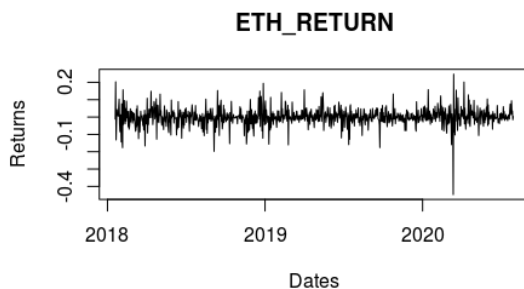
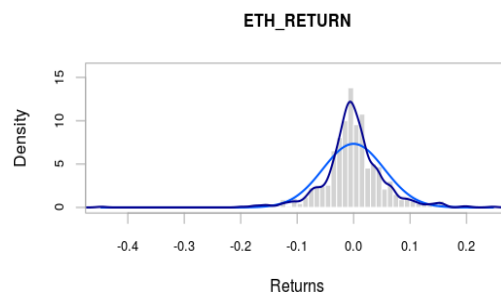


Figure 52: Density histogram of Ethereum Return



7.3.3. Litecoin (LTC)

Figure 54: Plot of Litecoin Return

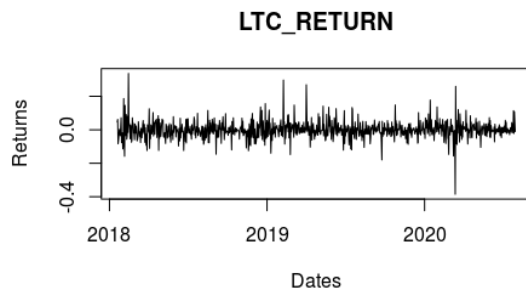
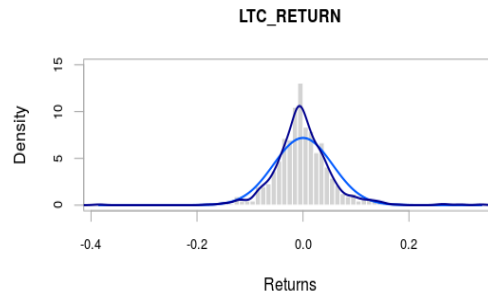


Figure 55: Density histogram of Litecoin Return



7.3.4. Ethereum Classic (ETC)

Figure 57: Plot of Ethereum Classic Return

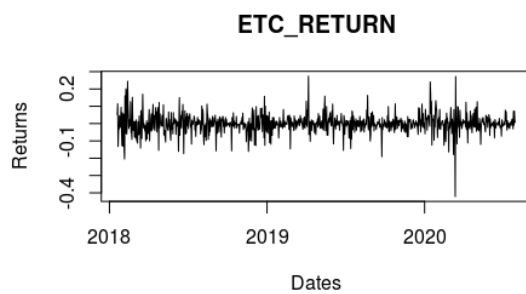
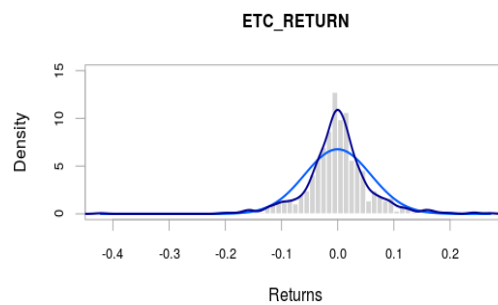


Figure 56: Density histogram of Ethereum Classic Return



7.3.5. Ripple (XRP)

Figure 59: Plot of Ripple Return

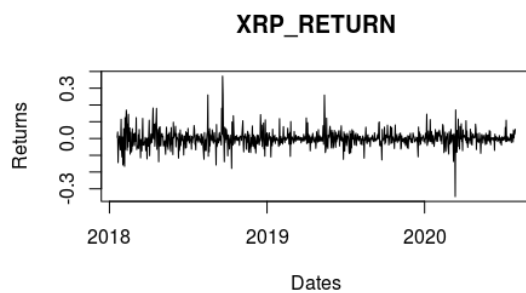
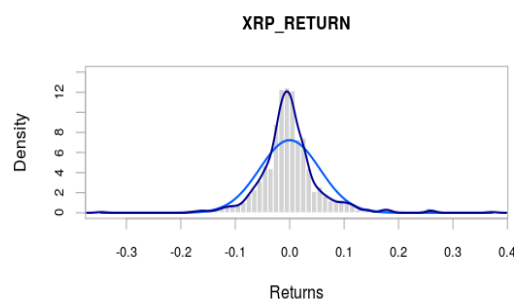


Figure 58: Density histogram of Ripple Return



7.4. Plots and density histograms of standard financial assets

This Appendix provides density histograms of the six standard financial assets datasets used in my research, covering the period from January 19, 2018, to July 29, 2020. Besides, a plot (graphic) represents the evolution of each standard's financial asset's return during the same period. These were computed and extracted via the software RStudio based on the datasets. The Appendix is organized into five sections, one for each standard's financial asset.

7.4.1. Gold

Figure 61: Plot of Gold Return

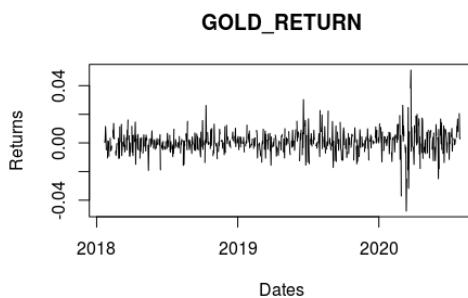
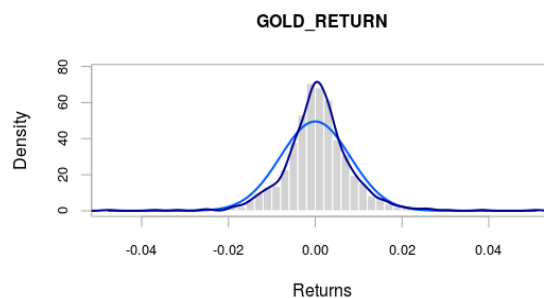


Figure 60: Density histogram of Gold Return



7.4.2. CAC40

Figure 63: Plot of CAC40 Return

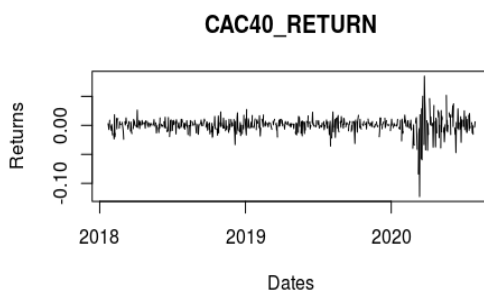
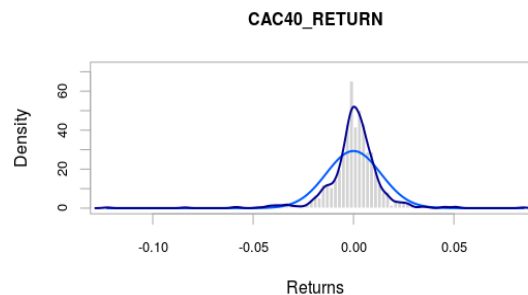


Figure 62: Descriptive Statistics of CAC40 Return



7.4.3. SP500

Figure 65: Plot of SP500 Return

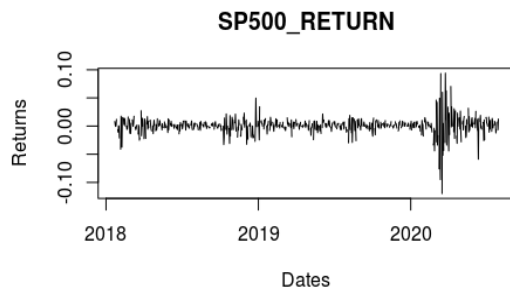
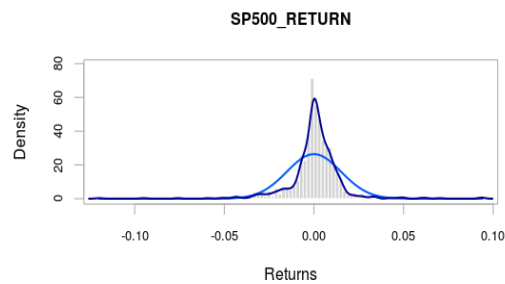


Figure 64: Density histogram of SP500 Return



7.4.4. MSCIWORLD

Figure 66: Plot of MSCIWORLD Return

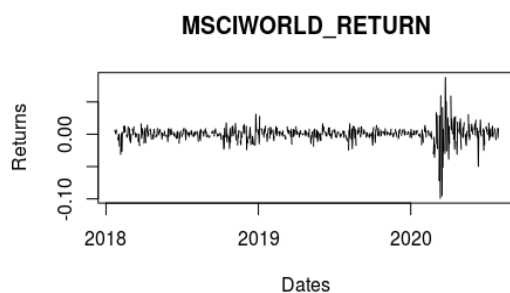
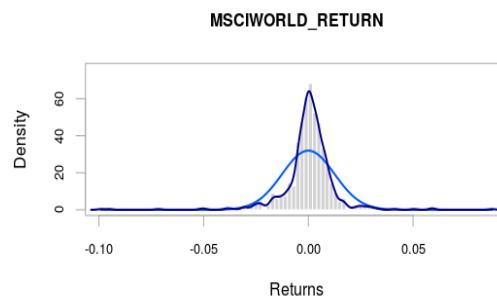


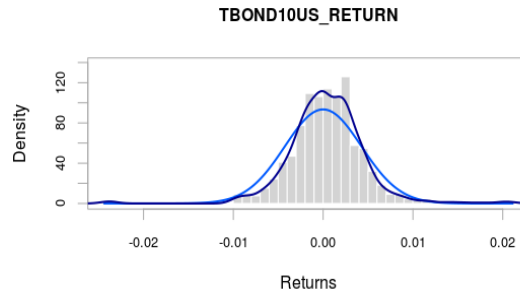
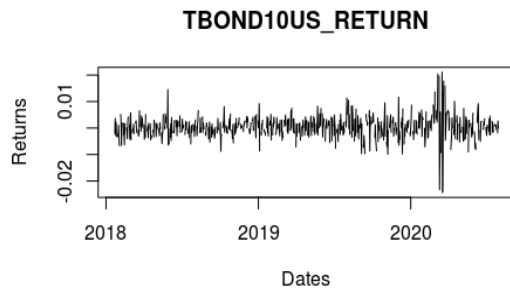
Figure 67: Density histogram of MSCIWORLD Return



7.4.5. TBOND10US

Figure 68: Plot of TBOND10US Return

Figure 69: Descriptive Statistics of TBOND10US Return



7.4.6. EURUSD

Figure 71: Plot of EURUSD Return

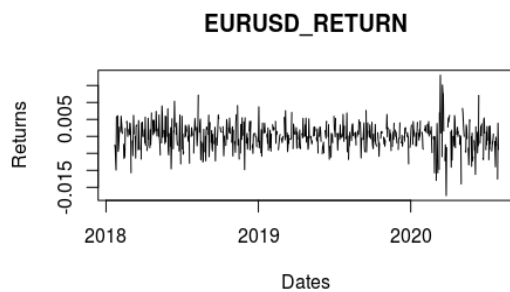
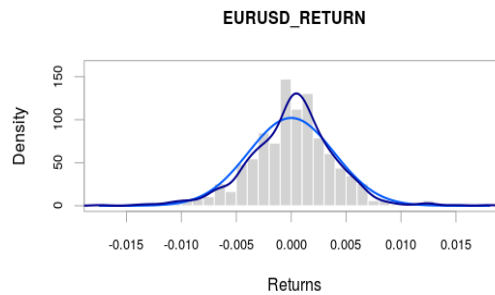


Figure 70: Density histogram of EURUSD Return



7.5. Boxplots: The weekdays and weekend prices for cryptocurrency data

In this appendix, I expose the boxplots comparing the weekdays and weekend prices for cryptocurrency datasets. These boxplots were extracted on RStudio for each cryptocurrency regarding the variable *weekend dummy* to visualize the data by group.

Figure 73: Boxplot of Bitcoin

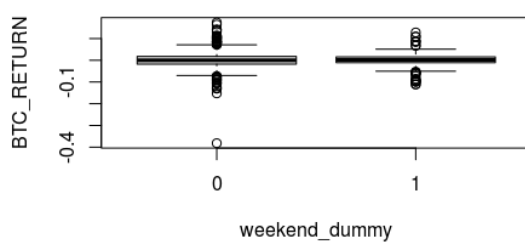


Figure 72: Boxplot of Ethereum

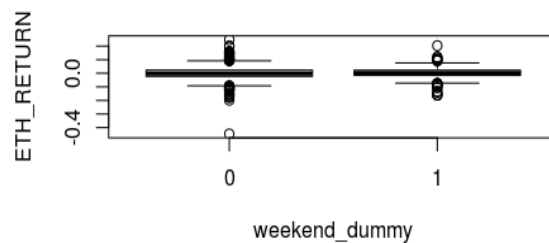


Figure 74: Boxplot of Litecoin

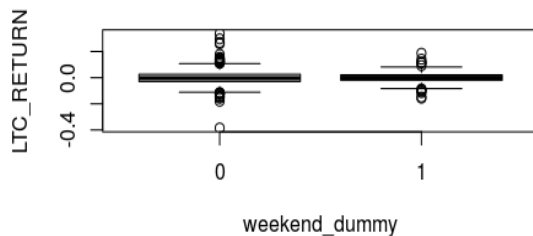


Figure 75: Boxplot of Ethereum Classic

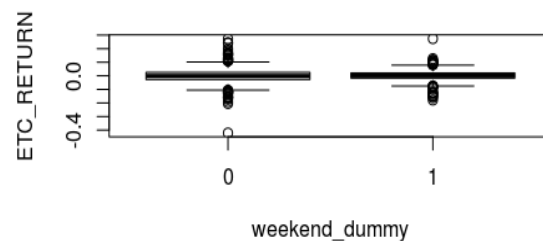
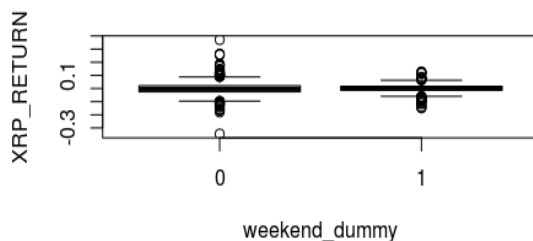


Figure 76: Boxplot of Ripple



7.6. Jarque-Bera Normality Test

In this appendix, I provide the Jarque-Bera test results in order to verify the distribution normality of cryptocurrency and traditional asset returns. This test specifies whether or not sample data present skewness and kurtosis that corresponds to a normal distribution. More precisely, the null hypothesis of normality consists of a kurtosis value of three associated with a skewness value of zero. These were computed and extracted via the software RStudio based on the datasets.

Table 14: Jarque-Bera results of the cryptocurrency returns distribution

Jarque-Bera Test	Bitcoin	Ethereum	Litecoin	Ethereum Classic	Ripple
X-Squared value	3215.0092	2022.024	1727.9939	967.87991	1707.6439
P-value	2.2204E-16	2.2204E-16	2.2204E-16	2.2204E-16	2.2204E-16

Table 15: Jarque-Bera results of the traditional asset returns distribution

Jarque-Bera Test	GOLD	CAC40	SP500	MSCIWORLD	TBOND10US	EURUSD
X-Squared value	975.40371	7160.7673	6290.5917	9209.6989	1181.7414	112.97274
P-value	2.2204E-16	2.2204E-16	2.2204E-16	2.2204E-16	2.2204E-16	2.2204E-16

7.7. DCC-GARCH Estimations Results

This Appendix provides results of the DCC-GARCH correlation estimations for the four series of pairs, including GOLD, CAC40, SP500, and MSCIWORLD. The datasets used in my research cover the period from January 19, 2018, to July 29, 2020. These were computed and extracted via the software EViews based on the datasets. The Appendix is organized into four sections, one for each series of pairs, including the standard's financial assets.

7.7.1. Correlation GOLD-

Table 16: DCC-GARCH Correlation
Estimation GOLD-BTC

System: GOLD BTC
 Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
 Covariance specification: Constant Conditional Correlation
 Date: 08/05/21 Time: 01:29
 Sample: 1/22/2018 7/29/2020
 Included observations: 658
 Total system (balanced) observations 1316
 Presample covariance: backcast (parameter =0.7)
 Convergence achieved after 31 iterations
 Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.		Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000379	0.000271	1.397582	0.1622	C(1)	0.000368	0.000272	1.349422	0.1772
C(2)	-0.006700	0.046807	-0.143136	0.8862	C(2)	-0.005672	0.046570	-0.121804	0.9031
C(3)	0.003654	0.006921	0.527996	0.5975	C(3)	0.003742	0.005041	0.742255	0.4579
C(4)	0.000817	0.001740	0.469639	0.6386	C(4)	-0.001061	0.002246	-0.472331	0.6367
C(5)	-0.044452	0.044656	-0.995414	0.3195	C(5)	-0.011027	0.040196	-0.274322	0.7838
C(6)	-0.022481	0.224409	-0.100178	0.9202	C(6)	-0.049933	0.282378	-0.176831	0.8596
Variance Equation Coefficients					Variance Equation Coefficients				
C(7)	2.95E-06	1.18E-06	2.496902	0.0125	C(7)	2.82E-06	1.12E-06	2.527332	0.0115
C(8)	0.087256	0.019283	4.524938	0.0000	C(8)	0.089742	0.019878	4.514542	0.0000
C(9)	0.863416	0.035429	24.37046	0.0000	C(9)	0.863928	0.034544	25.00923	0.0000
C(10)	0.000144	7.52E-05	1.920123	0.0548	C(10)	0.000287	8.11E-05	3.536148	0.0004
C(11)	0.023526	0.012090	1.945901	0.0517	C(11)	0.045632	0.013289	3.433766	0.0006
C(12)	0.894600	0.051910	17.23356	0.0000	C(12)	0.857220	0.033773	25.38163	0.0000
C(13)	0.152411	0.035561	4.285877	0.0000	C(13)	0.115869	0.032727	3.540524	0.0004
Log likelihood	3464.078	Schwarz criterion	-10.40091	Log likelihood	3306.228	Schwarz criterion	-9.921119		
Avg. log likelihood	2.632278	Hannan-Quinn criter.	-10.45522	Avg. log likelihood	2.512331	Hannan-Quinn criter.	-9.975430		
Akaike info criterion	-10.48960			Akaike info criterion	-10.00981				

Equation: GOLD RETURN = C(1)+C(2)*GOLD RETURN(-1)+C(3) *BTC RETURN(-1)				Equation: GOLD RETURN = C(1)+C(2)*GOLD RETURN(-1)+C(3) *ETC RETURN(-1)			
R-squared	0.000905	Mean dependent var	0.000614	R-squared	0.000562	Mean dependent var	0.000614
Adjusted R-squared	-0.002145	S.D. dependent var	0.008061	Adjusted R-squared	-0.002490	S.D. dependent var	0.008061
S.E. of regression	0.008069	Sum squared resid	0.042650	S.E. of regression	0.008071	Sum squared resid	0.042665
Durbin-Watson stat	1.890452			Durbin-Watson stat	1.892660		
Equation: BTC RETURN = C(4)+C(5)*BTC RETURN(-1)+C(6) *GOLD RETURN(-1)				Equation: ETH RETURN = C(4)+C(5)*ETC RETURN(-1)+C(6) *GOLD RETURN(-1)			
R-squared	0.004564	Mean dependent var	0.001031	R-squared	0.002069	Mean dependent var	-0.000501
Adjusted R-squared	0.001524	S.D. dependent var	0.042933	Adjusted R-squared	-0.000978	S.D. dependent var	0.054392
S.E. of regression	0.042900	Sum squared resid	1.205491	S.E. of regression	0.054419	Sum squared resid	1.939710
Durbin-Watson stat	2.036862			Durbin-Watson stat	2.200659		

Covariance specification: Constant Conditional Correlation GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1) COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))					Covariance specification: Constant Conditional Correlation GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1) COV(i,j) = R(i,j)*@SORT(GARCH(i)*GARCH(j))				
Transformed Variance Coefficients					Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.		Coefficient	Std. Error	z-Statistic	Prob.
M(1)	2.95E-06	1.18E-06	2.496902	0.0125	M(1)	2.82E-06	1.12E-06	2.527332	0.0115
A1(1)	0.087256	0.019283	4.524938	0.0000	A1(1)	0.089742	0.019878	4.514542	0.0000
B1(1)	0.863416	0.035429	24.37046	0.0000	B1(1)	0.863928	0.034544	25.00923	0.0000
M(2)	0.000144	7.52E-05	1.920123	0.0548	M(2)	0.000287	8.11E-05	3.536148	0.0004
A1(2)	0.023526	0.012090	1.945901	0.0517	A1(2)	0.045632	0.013289	3.433766	0.0006
B1(2)	0.894600	0.051910	17.23356	0.0000	B1(2)	0.857220	0.033773	25.38163	0.0000
R(1,2)	0.152411	0.035561	4.285877	0.0000	R(1,2)	0.115869	0.032727	3.540524	0.0004

**Table 19: DCC-GARCH Correlation
Estimation GOLD-LTC**

System: GOLD LTC
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:27
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 31 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000373	0.000273	1.366284	0.1718
C(2)	-0.007449	0.046788	-0.159205	0.8735
C(3)	0.004128	0.005737	0.719589	0.4718
C(4)	-0.000740	0.002344	-0.315778	0.7522
C(5)	-0.031815	0.047761	-0.666140	0.5053
C(6)	-0.196097	0.286028	-0.685587	0.4930

Variance Equation Coefficients				
C(7)	2.71E-06	1.03E-06	2.623778	0.0087
C(8)	0.086819	0.018569	4.675440	0.0000
C(9)	0.868543	0.031747	27.35806	0.0000
C(10)	0.003624	0.000996	3.638211	0.0003
C(11)	0.071877	0.034432	2.087504	0.0368
C(12)	-0.266541	0.323411	-0.824157	0.4099
C(13)	0.125060	0.032702	3.824238	0.0001

Log likelihood	3289.481	Schwarz criterion	-9.870217
Avg. log likelihood	2.499606	Hannan-Quinn criter.	-9.924527
Akaike info criterion	-9.958909		

Equation: GOLD RETURN = C(1)+C(2)*GOLD RETURN(-1)+C(3)*LTC RETURN(-1)

R-squared	0.000863	Mean dependent var	0.000614
Adjusted R-squared	-0.002188	S.D. dependent var	0.008061
S.E. of regression	0.008070	Sum squared resid	0.042652
Durbin-Watson stat	1.890355		

Equation: LTC RETURN = C(4)+C(5)*LTC RETURN(-1)+C(6)*GOLD RETURN(-1)

R-squared	0.005483	Mean dependent var	-0.000917
Adjusted R-squared	0.002446	S.D. dependent var	0.055551
S.E. of regression	0.055483	Sum squared resid	2.016362
Durbin-Watson stat	2.056240		

Covariance specification: Constant Conditional Correlation
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	2.71E-06	1.03E-06	2.623778	0.0087
A1(1)	0.086819	0.018569	4.675440	0.0000
B1(1)	0.868543	0.031747	27.35806	0.0000
M(2)	0.003624	0.000996	3.638211	0.0003
A1(2)	0.071877	0.034432	2.087504	0.0368
B1(2)	-0.266541	0.323411	-0.824157	0.4099
R(1,2)	0.125060	0.032702	3.824238	0.0001

**Table 18: DCC-GARCH Correlation
Estimation GOLD-ETC**

System: GOLD ETC
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:28
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 45 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000355	0.000272	1.306591	0.1914
C(2)	-0.004867	0.046652	-0.104320	0.9169
C(3)	0.003640	0.005015	0.725803	0.4680
C(4)	-0.001503	0.002310	-0.650739	0.5152
C(5)	-0.006177	0.045729	-0.135076	0.8926
C(6)	0.019244	0.277960	0.069233	0.9448

Variance Equation Coefficients				
C(7)	2.71E-06	1.07E-06	2.528913	0.0114
C(8)	0.088242	0.019234	4.587822	0.0000
C(9)	0.867391	0.033313	26.03733	0.0000
C(10)	0.000261	7.98E-05	3.264481	0.0011
C(11)	0.088561	0.019526	4.535477	0.0000
C(12)	0.836123	0.036338	23.00984	0.0000
C(13)	0.074043	0.036281	2.040809	0.0413

Log likelihood	3273.488	Schwarz criterion	-9.821604
Avg. log likelihood	2.487453	Hannan-Quinn criter.	-9.875914
Akaike info criterion	-9.910297		

Equation: GOLD RETURN = C(1)+C(2)*GOLD RETURN(-1)+C(3)*ETC RETURN(-1)

R-squared	0.000513	Mean dependent var	0.000614
Adjusted R-squared	-0.002538	S.D. dependent var	0.008061
S.E. of regression	0.008071	Sum squared resid	0.042667
Durbin-Watson stat	1.893950		

Equation: ETC RETURN = C(4)+C(5)*ETC RETURN(-1)+C(6)*GOLD RETURN(-1)

R-squared	-0.000421	Mean dependent var	-0.000230
Adjusted R-squared	-0.003476	S.D. dependent var	0.058999
S.E. of regression	0.059102	Sum squared resid	2.287933
Durbin-Watson stat	2.040088		

Covariance specification: Constant Conditional Correlation
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	2.71E-06	1.07E-06	2.528913	0.0114
A1(1)	0.088242	0.019234	4.587822	0.0000
B1(1)	0.867391	0.033313	26.03733	0.0000
M(2)	0.000261	7.98E-05	3.264481	0.0011
A1(2)	0.088561	0.019526	4.535477	0.0000
B1(2)	0.836123	0.036338	23.00984	0.0000
R(1,2)	0.074043	0.036281	2.040809	0.0413

**Table 20: DCC-GARCH Correlation
Estimation GOLD-XRP**

System: GOLD XRP

Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)

Covariance specification: Constant Conditional Correlation

Date: 08/05/21 Time: 01:26

Sample: 1/22/2018 7/29/2020

Included observations: 658

Total system (balanced) observations 1316

Presample covariance: backcast (parameter =0.7)

Convergence achieved after 43 iterations

Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000356	0.000272	1.307961	0.1909
C(2)	-0.007043	0.046950	-0.150019	0.8807
C(3)	0.001955	0.005454	0.358432	0.7200
C(4)	-0.002549	0.002290	-1.113141	0.2656
C(5)	-0.003119	0.057942	-0.053831	0.9571
C(6)	-0.059706	0.280277	-0.213027	0.8313

Variance Equation Coefficients				
C(7)	2.72E-06	1.08E-06	2.506338	0.0122
C(8)	0.088697	0.019448	4.560807	0.0000
C(9)	0.866855	0.033672	25.74420	0.0000
C(10)	0.001081	0.000203	5.320992	0.0000
C(11)	0.206406	0.049440	4.174853	0.0000
C(12)	0.445538	0.099253	4.488904	0.0000
C(13)	0.090428	0.032518	2.780869	0.0054

Log likelihood	3316.097	Schwarz criterion	-9.951116
Avg. log likelihood	2.519831	Hannan-Quinn criter.	-10.00543
Akaike info criterion	-10.03981		

Equation: GOLD RETURN = C(1)+C(2)*GOLD RETURN(-1)+C(3)
*XRP RETURN(-1)

R-squared	-0.000945	Mean dependent var	0.000614
Adjusted R-squared	-0.004001	S.D. dependent var	0.008061
S.E. of regression	0.008077	Sum squared resid	0.042729
Durbin-Watson stat	1.883376		

Equation: XRP RETURN = C(4)+C(5)*XRP RETURN(-1)+C(6)
*GOLD RETURN(-1)

R-squared	-0.001228	Mean dependent var	-0.000565
Adjusted R-squared	-0.004285	S.D. dependent var	0.055262
S.E. of regression	0.055381	Sum squared resid	2.008904
Durbin-Watson stat	1.988399		

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i)(-1)$
 $COV(i,i) = R(i,i)*@SQRT(GARCH(i)*GARCH(i))$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	2.72E-06	1.08E-06	2.506338	0.0122
A1(1)	0.088697	0.019448	4.560807	0.0000
B1(1)	0.866855	0.033672	25.74420	0.0000
M(2)	0.001081	0.000203	5.320992	0.0000
A1(2)	0.206406	0.049440	4.174853	0.0000
B1(2)	0.445538	0.099253	4.488904	0.0000
R(1,2)	0.090428	0.032518	2.780869	0.0054

7.7.2. Correlation CAC40-

Table 22: DCC-GARCH Correlation
Estimation CAC40-BTC

System: CAC40 BTC
 Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
 Covariance specification: Constant Conditional Correlation
 Date: 08/05/21 Time: 01:36
 Sample: 1/22/2018 7/29/2020
 Included observations: 658
 Total system (balanced) observations 1316
 Presample covariance: backcast (parameter =0.7)
 Convergence achieved after 32 iterations
 Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000882	0.000365	2.416227	0.0157
C(2)	0.025733	0.048233	0.533520	0.5937
C(3)	0.005739	0.008241	0.696401	0.4862
C(4)	0.001586	0.001777	0.892154	0.3723
C(5)	-0.033433	0.045355	-0.737130	0.4610
C(6)	-0.262074	0.136134	-1.925117	0.0542
Variance Equation Coefficients				
C(7)	6.11E-06	1.27E-06	4.810955	0.0000
C(8)	0.207023	0.029970	6.907671	0.0000
C(9)	0.760662	0.029756	25.56373	0.0000
C(10)	0.000143	7.83E-05	1.828777	0.0674
C(11)	0.024318	0.013480	1.803946	0.0712
C(12)	0.894181	0.055127	16.22035	0.0000
C(13)	0.127757	0.040584	3.147956	0.0016
Log likelihood	3252.744	Schwarz criterion	-9.758553	
Avg. log likelihood	2.471690	Hannan-Quinn criter.	-9.812863	
Akaike info criterion	-9.847246			

Equation: CAC40 RETURN = C(1)+C(2)*CAC40 RETURN(-1)+C(3)*BTC RETURN(-1)
 R-squared -0.004072 Mean dependent var 5.63E-05
 Adjusted R-squared -0.007137 S.D. dependent var 0.013616
 S.E. of regression 0.013665 Sum squared resid 0.122301
 Durbin-Watson stat 2.075110

Equation: BTC RETURN = C(4)+C(5)*BTC RETURN(-1)+C(6)*CAC40 RETURN(-1)
 R-squared 0.012720 Mean dependent var 0.001031
 Adjusted R-squared 0.009706 S.D. dependent var 0.042933
 S.E. of regression 0.042724 Sum squared resid 1.195614
 Durbin-Watson stat 2.011667

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i)(-1)$
 $COV(i,i) = R(i,i)*@SQRT(GARCH(i)*GARCH(i))$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	6.11E-06	1.27E-06	4.810955	0.0000
A1(1)	0.207023	0.029970	6.907671	0.0000
B1(1)	0.760662	0.029756	25.56373	0.0000
M(2)	0.000143	7.83E-05	1.828777	0.0674
A1(2)	0.024318	0.013480	1.803946	0.0712
B1(2)	0.894181	0.055127	16.22035	0.0000
R(1,2)	0.127757	0.040584	3.147956	0.0016

Table 21: DCC-GARCH Correlation
Estimation CAC40-ETH

System: CAC40 ETH
 Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
 Covariance specification: Constant Conditional Correlation
 Date: 08/05/21 Time: 01:35
 Sample: 1/22/2018 7/29/2020
 Included observations: 658
 Total system (balanced) observations 1316
 Presample covariance: backcast (parameter =0.7)
 Convergence achieved after 29 iterations
 Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000884	0.000367	2.409188	0.0160
C(2)	0.019729	0.048292	0.408534	0.6829
C(3)	0.007888	0.007145	1.103873	0.2696
C(4)	-0.000149	0.002299	-0.065040	0.9481
C(5)	-0.054579	0.044477	-1.227125	0.2198
C(6)	-0.162056	0.190525	-0.850575	0.3950
Variance Equation Coefficients				
C(7)	5.95E-06	1.26E-06	4.741654	0.0000
C(8)	0.200595	0.029180	6.874288	0.0000
C(9)	0.767040	0.029613	25.90218	0.0000
C(10)	0.000268	8.15E-05	3.285479	0.0010
C(11)	0.041080	0.013038	3.150823	0.0016
C(12)	0.867604	0.033562	25.85071	0.0000
C(13)	0.147730	0.038665	3.820765	0.0001
Log likelihood	3099.855	Schwarz criterion	-9.293846	
Avg. log likelihood	2.355513	Hannan-Quinn criter.	-9.348156	
Akaike info criterion	-9.382538			

Equation: CAC40 RETURN = C(1)+C(2)*CAC40 RETURN(-1)+C(3)*ETH RETURN(-1)
 R-squared -0.003565 Mean dependent var 5.63E-05
 Adjusted R-squared -0.006630 S.D. dependent var 0.013616
 S.E. of regression 0.013661 Sum squared resid 0.122240
 Durbin-Watson stat 2.070383

Equation: ETH RETURN = C(4)+C(5)*ETH RETURN(-1)+C(6)*CAC40 RETURN(-1)
 R-squared 0.014226 Mean dependent var -0.000501
 Adjusted R-squared 0.011216 S.D. dependent var 0.054392
 S.E. of regression 0.054086 Sum squared resid 1.916080
 Durbin-Watson stat 2.079031

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i)(-1)$
 $COV(i,i) = R(i,i)*@SQRT(GARCH(i)*GARCH(i))$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	5.95E-06	1.26E-06	4.741654	0.0000
A1(1)	0.200595	0.029180	6.874288	0.0000
B1(1)	0.767040	0.029613	25.90218	0.0000
M(2)	0.000268	8.15E-05	3.285479	0.0010
A1(2)	0.041080	0.013038	3.150823	0.0016
B1(2)	0.867604	0.033562	25.85071	0.0000
R(1,2)	0.147730	0.038665	3.820765	0.0001

**Table 24: DCC-GARCH Correlation
Estimation CAC40-LTC**

System: CAC40 LTC
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:35
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 29 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000896	0.000365	2.456226	0.0140
C(2)	0.025199	0.048454	0.520051	0.6030
C(3)	0.004660	0.006226	0.748496	0.4542
C(4)	-0.000102	0.002418	-0.042114	0.9664
C(5)	-0.030110	0.047598	-0.632594	0.5270
C(6)	-0.218129	0.166202	-1.312432	0.1894

Variance Equation Coefficients				
C(7)	6.12E-06	1.28E-06	4.775248	0.0000
C(8)	0.208544	0.030042	6.941836	0.0000
C(9)	0.759630	0.030200	25.15348	0.0000
C(10)	0.003513	0.001050	3.347362	0.0008
C(11)	0.068536	0.035670	1.921386	0.0547
C(12)	-0.230414	0.343739	-0.670317	0.5027
C(13)	0.134722	0.037269	3.614866	0.0003

Log likelihood	3080.267	Schwarz criterion	-9.234309
Avg. log likelihood	2.340629	Hannan-Quinn criter.	-9.288619
Akaike info criterion	-9.323001		

Equation: CAC40 RETURN = C(1)+C(2)*CAC40 RETURN(-1)+C(3)*LTC RETURN(-1)

R-squared	-0.003578	Mean dependent var	5.63E-05
Adjusted R-squared	-0.006642	S.D. dependent var	0.013616
S.E. of regression	0.013661	Sum squared resid	0.122241
Durbin-Watson stat	2.074132		

Equation: LTC RETURN = C(4)+C(5)*LTC RETURN(-1)+C(6)*CAC40 RETURN(-1)

R-squared	0.010006	Mean dependent var	-0.000917
Adjusted R-squared	0.006983	S.D. dependent var	0.055551
S.E. of regression	0.055357	Sum squared resid	2.007191
Durbin-Watson stat	2.035345		

Covariance specification: Constant Conditional Correlation
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,i) = R(i,i)*@SQRT(GARCH(i)*GARCH(i))

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	6.12E-06	1.28E-06	4.775248	0.0000
A1(1)	0.208544	0.030042	6.941836	0.0000
B1(1)	0.759630	0.030200	25.15348	0.0000
M(2)	0.003513	0.001050	3.347362	0.0008
A1(2)	0.068536	0.035670	1.921386	0.0547
B1(2)	-0.230414	0.343739	-0.670317	0.5027
R(1,2)	0.134722	0.037269	3.614866	0.0003

**Table 23: DCC-GARCH Correlation
Estimation CAC40-ETC**

System: CAC40 ETC
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:37
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 30 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000877	0.000363	2.416864	0.0157
C(2)	0.025540	0.049690	0.513989	0.6073
C(3)	0.005165	0.005739	0.899991	0.3681
C(4)	-0.000739	0.002354	-0.313894	0.7536
C(5)	-0.004154	0.046341	-0.089642	0.9286
C(6)	-0.079031	0.198133	-0.398880	0.6900

Variance Equation Coefficients				
C(7)	6.00E-06	1.26E-06	4.775500	0.0000
C(8)	0.209562	0.030237	6.930606	0.0000
C(9)	0.760078	0.029880	25.43770	0.0000
C(10)	0.000233	6.67E-05	3.483958	0.0005
C(11)	0.085058	0.018623	4.567327	0.0000
C(12)	0.848089	0.031683	26.76789	0.0000
C(13)	0.111881	0.035894	3.116953	0.0018

Log likelihood	3065.342	Schwarz criterion	-9.188942
Avg. log likelihood	2.329287	Hannan-Quinn criter.	-9.243252
Akaike info criterion	-9.277635		

Equation: CAC40 RETURN = C(1)+C(2)*CAC40 RETURN(-1)+C(3)*ETC RETURN(-1)

R-squared	-0.004291	Mean dependent var	5.63E-05
Adjusted R-squared	-0.007358	S.D. dependent var	0.013616
S.E. of regression	0.013666	Sum squared resid	0.122328
Durbin-Watson stat	2.076199		

Equation: ETC RETURN = C(4)+C(5)*ETC RETURN(-1)+C(6)*CAC40 RETURN(-1)

R-squared	0.002655	Mean dependent var	-0.000230
Adjusted R-squared	-0.000390	S.D. dependent var	0.058999
S.E. of regression	0.059011	Sum squared resid	2.280897
Durbin-Watson stat	2.036812		

Covariance specification: Constant Conditional Correlation
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,i) = R(i,i)*@SQRT(GARCH(i)*GARCH(i))

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	6.00E-06	1.26E-06	4.775500	0.0000
A1(1)	0.209562	0.030237	6.930606	0.0000
B1(1)	0.760078	0.029880	25.43770	0.0000
M(2)	0.000233	6.67E-05	3.483958	0.0005
A1(2)	0.085058	0.018623	4.567327	0.0000
B1(2)	0.848089	0.031683	26.76789	0.0000
R(1,2)	0.111881	0.035894	3.116953	0.0018

**Table 26: DCC-GARCH Correlation
Estimation CAC40-XRP**

System: CAC40 XRP
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:33
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000867	0.000367	2.364493	0.0181
C(2)	0.023573	0.048267	0.488393	0.6253
C(3)	0.011325	0.007235	1.565237	0.1175
C(4)	-0.002013	0.002367	-0.850379	0.3951
C(5)	-0.006700	0.056150	-0.119323	0.9050
C(6)	0.088505	0.161742	0.547196	0.5842
Variance Equation Coefficients				
C(7)	5.90E-06	1.25E-06	4.707030	0.0000
C(8)	0.203624	0.029714	6.852912	0.0000
C(9)	0.765240	0.030042	25.47209	0.0000
C(10)	0.001062	0.000200	5.310247	0.0000
C(11)	0.210552	0.050479	4.171090	0.0000
C(12)	0.449206	0.100571	4.466544	0.0000
C(13)	0.143027	0.041145	3.476165	0.0005
Log likelihood	3111.524	Schwarz criterion	-9.329313	
Avg. log likelihood	2.364380	Hannan-Quinn criter.	-9.383623	
Akaike info criterion	-9.418005			

Equation: CAC40 RETURN = C(1)+C(2)*CAC40 RETURN(-1)+C(3)*XRP RETURN(-1)

R-squared	-0.002263	Mean dependent var	5.63E-05
Adjusted R-squared	-0.005323	S.D. dependent var	0.013616
S.E. of regression	0.013652	Sum squared resid	0.122081
Durbin-Watson stat	2.085176		

Equation: XRP RETURN = C(4)+C(5)*XRP RETURN(-1)+C(6)*CAC40 RETURN(-1)

R-squared	-0.003435	Mean dependent var	-0.000565
Adjusted R-squared	-0.006499	S.D. dependent var	0.055262
S.E. of regression	0.055442	Sum squared resid	2.013331
Durbin-Watson stat	1.995155		

Covariance specification: Constant Conditional Correlation
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	5.90E-06	1.25E-06	4.707030	0.0000
A1(1)	0.203624	0.029714	6.852912	0.0000
B1(1)	0.765240	0.030042	25.47209	0.0000
M(2)	0.001062	0.000200	5.310247	0.0000
A1(2)	0.210552	0.050479	4.171090	0.0000
B1(2)	0.449206	0.100571	4.466544	0.0000
R(1,2)	0.143027	0.041145	3.476165	0.0005

**Table 25: DCC-GARCH Correlation
Estimation CAC40-GOLD**

System: CAC40 GOLD
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:32
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 41 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000929	0.000351	2.645593	0.0082
C(2)	0.022777	0.049297	0.462042	0.6441
C(3)	-0.057875	0.048872	-1.184204	0.2363
C(4)	0.000314	0.000274	1.143142	0.2530
C(5)	-0.017497	0.047306	-0.369876	0.7115
C(6)	-0.056184	0.023928	-2.347992	0.0189
Variance Equation Coefficients				
C(7)	5.70E-06	1.21E-06	4.701217	0.0000
C(8)	0.220010	0.030784	7.146913	0.0000
C(9)	0.756190	0.029772	25.39950	0.0000
C(10)	2.87E-06	9.67E-07	2.964473	0.0030
C(11)	0.096855	0.020700	4.679050	0.0000
C(12)	0.856449	0.032563	26.30138	0.0000
C(13)	-0.139627	0.032027	-4.359636	0.0000
Log likelihood	4410.341	Schwarz criterion	-13.27709	
Avg. log likelihood	3.351323	Hannan-Quinn criter.	-13.33140	
Akaike info criterion	-13.36578			

Equation: CAC40 RETURN = C(1)+C(2)*CAC40 RETURN(-1)+C(3)*GOLD RETURN(-1)

R-squared	-0.005565	Mean dependent var	5.63E-05
Adjusted R-squared	-0.008636	S.D. dependent var	0.013616
S.E. of regression	0.013675	Sum squared resid	0.122483
Durbin-Watson stat	2.043391		

Equation: GOLD RETURN = C(4)+C(5)*GOLD RETURN(-1)+C(6)*CAC40 RETURN(-1)

R-squared	-0.012153	Mean dependent var	0.000614
Adjusted R-squared	-0.015244	S.D. dependent var	0.008061
S.E. of regression	0.008122	Sum squared resid	0.043207
Durbin-Watson stat	1.817700		

Covariance specification: Constant Conditional Correlation
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	5.70E-06	1.21E-06	4.701217	0.0000
A1(1)	0.220010	0.030784	7.146913	0.0000
B1(1)	0.756190	0.029772	25.39950	0.0000
M(2)	2.87E-06	9.67E-07	2.964473	0.0030
A1(2)	0.096855	0.020700	4.679050	0.0000
B1(2)	0.856449	0.032563	26.30138	0.0000
R(1,2)	-0.139627	0.032027	-4.359636	0.0000

7.7.3. Correlation SP500-

Table 28: DCC-GARCH Correlation Estimation SP500-BTC

System: SP500 BTC
 Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
 Covariance specification: Constant Conditional Correlation
 Date: 08/05/21 Time: 01:20
 Sample: 1/22/2018 7/29/2020
 Included observations: 658
 Total system (balanced) observations 1316
 Presample covariance: backcast (parameter =0.7)
 Convergence achieved after 24 iterations
 Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.001336	0.000288	4.641216	0.0000
C(2)	-0.070071	0.048374	-1.448527	0.1475
C(3)	0.015522	0.007823	1.984147	0.0472
C(4)	0.001466	0.001791	0.818531	0.4131
C(5)	-0.035786	0.044319	-0.807460	0.4194
C(6)	-0.105733	0.148996	-0.709633	0.4779

Variance Equation Coefficients				
C(7)	3.75E-06	8.85E-07	4.241807	0.0000
C(8)	0.277851	0.037349	7.439292	0.0000
C(9)	0.734438	0.030453	24.11748	0.0000
C(10)	0.000141	8.04E-05	1.747680	0.0805
C(11)	0.021497	0.012545	1.713595	0.0866
C(12)	0.898511	0.055627	16.15243	0.0000
C(13)	0.096858	0.039220	2.469616	0.0135

Log likelihood	3269.978	Schwarz criterion	-9.810935
Avg. log likelihood	2.484785	Hannan-Quinn criter.	-9.865245
Akaike info criterion	-9.899628		

Equation: SP500 RETURN = C(1)+C(2)*SP500 RETURN(-1)+C(3)*BTC RETURN(-1)

R-squared	0.018947	Mean dependent var	0.000416
Adjusted R-squared	0.015951	S.D. dependent var	0.015129
S.E. of regression	0.015008	Sum squared resid	0.147525
Durbin-Watson stat	2.402231		

Equation: BTC RETURN = C(4)+C(5)*BTC RETURN(-1)+C(6)*SP500 RETURN(-1)

R-squared	0.008563	Mean dependent var	0.001031
Adjusted R-squared	0.005536	S.D. dependent var	0.042933
S.E. of regression	0.042814	Sum squared resid	1.200648
Durbin-Watson stat	2.040310		

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i)(-1)$
 $COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	3.75E-06	8.85E-07	4.241807	0.0000
A1(1)	0.277851	0.037349	7.439292	0.0000
B1(1)	0.734438	0.030453	24.11748	0.0000
M(2)	0.000141	8.04E-05	1.747680	0.0805
A1(2)	0.021497	0.012545	1.713595	0.0866
B1(2)	0.898511	0.055627	16.15243	0.0000
R(1,2)	0.096858	0.039220	2.469616	0.0135

Table 27: DCC-GARCH Correlation Estimation SP500-ETH

System: SP500 ETH
 Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
 Covariance specification: Constant Conditional Correlation
 Date: 08/04/21 Time: 23:37
 Sample: 1/22/2018 7/29/2020
 Included observations: 658
 Total system (balanced) observations 1316
 Presample covariance: backcast (parameter =0.7)
 Convergence achieved after 33 iterations
 Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.001370	0.000293	4.684677	0.0000
C(2)	-0.073588	0.047901	-1.536239	0.1245
C(3)	0.009880	0.006458	1.530010	0.1260
C(4)	-4.39E-05	0.002320	-0.018940	0.9849
C(5)	-0.053370	0.042684	-1.250348	0.2112
C(6)	-0.077291	0.146986	-0.525842	0.5990

Variance Equation Coefficients				
C(7)	3.73E-06	9.05E-07	4.122296	0.0000
C(8)	0.270288	0.037578	7.192763	0.0000
C(9)	0.739685	0.031156	23.74165	0.0000
C(10)	0.000249	8.33E-05	2.988083	0.0028
C(11)	0.037002	0.012841	2.881553	0.0040
C(12)	0.877879	0.034886	25.16409	0.0000
C(13)	0.152058	0.043206	3.519397	0.0004

Log likelihood	3119.486	Schwarz criterion	-9.353515
Avg. log likelihood	2.370430	Hannan-Quinn criter.	-9.407825
Akaike info criterion	-9.442207		

Equation: SP500 RETURN = C(1)+C(2)*SP500 RETURN(-1)+C(3)*ETH RETURN(-1)

R-squared	0.021689	Mean dependent var	0.000416
Adjusted R-squared	0.018702	S.D. dependent var	0.015129
S.E. of regression	0.014987	Sum squared resid	0.147113
Durbin-Watson stat	2.391476		

Equation: ETH RETURN = C(4)+C(5)*ETH RETURN(-1)+C(6)*SP500 RETURN(-1)

R-squared	0.012989	Mean dependent var	-0.000501
Adjusted R-squared	0.009975	S.D. dependent var	0.054392
S.E. of regression	0.054120	Sum squared resid	1.918485
Durbin-Watson stat	2.094194		

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i)(-1)$
 $COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	3.73E-06	9.05E-07	4.122296	0.0000
A1(1)	0.270288	0.037578	7.192763	0.0000
B1(1)	0.739685	0.031156	23.74165	0.0000
M(2)	0.000249	8.33E-05	2.988083	0.0028
A1(2)	0.037002	0.012841	2.881553	0.0040
B1(2)	0.877879	0.034886	25.16409	0.0000
R(1,2)	0.152058	0.043206	3.519397	0.0004

**Table 29: DCC-GARCH Correlation
Estimation SP500-LTC**

System: SP500 LTC
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/04/21 Time: 23:34
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 29 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.001335	0.000295	4.527771	0.0000
C(2)	-0.064814	0.048442	-1.337953	0.1809
C(3)	0.006054	0.005459	1.108920	0.2675
C(4)	-4.50E-05	0.002445	-0.018408	0.9853
C(5)	-0.028996	0.047330	-0.612630	0.5401
C(6)	-0.136630	0.125158	-1.091661	0.2750

Variance Equation Coefficients				
C(7)	3.91E-06	9.01E-07	4.333128	0.0000
C(8)	0.269441	0.038100	7.072013	0.0000
C(9)	0.738235	0.031501	23.43530	0.0000
C(10)	0.003761	0.001190	3.159714	0.0016
C(11)	0.058306	0.032692	1.783523	0.0745
C(12)	-0.302633	0.387710	-0.780565	0.4351
C(13)	0.119990	0.045702	2.625499	0.0087

Log likelihood	3097.539	Schwarz criterion	-9.286805
Avg. log likelihood	2.353753	Hannan-Quinn criter.	-9.341115
Akaike info criterion	-9.375498		

Equation: SP500 RETURN = C(1)+C(2)*SP500 RETURN(-1)+C(3)*LTC RETURN(-1)

R-squared	0.023203	Mean dependent var	0.000416
Adjusted R-squared	0.020220	S.D. dependent var	0.015129
S.E. of regression	0.014975	Sum squared resid	0.146885
Durbin-Watson stat	2.400990		

Equation: LTC RETURN = C(4)+C(5)*LTC RETURN(-1)+C(6)*SP500 RETURN(-1)

R-squared	0.007797	Mean dependent var	-0.000917
Adjusted R-squared	0.004767	S.D. dependent var	0.055551
S.E. of regression	0.055419	Sum squared resid	2.011670
Durbin-Watson stat	2.049878		

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i-1)$
 $COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	3.91E-06	9.01E-07	4.333128	0.0000
A1(1)	0.269441	0.038100	7.072013	0.0000
B1(1)	0.738235	0.031501	23.43530	0.0000
M(2)	0.003761	0.001190	3.159714	0.0016
A1(2)	0.058306	0.032692	1.783523	0.0745
B1(2)	-0.302633	0.387710	-0.780565	0.4351
R(1,2)	0.119990	0.045702	2.625499	0.0087

**Table 30: DCC-GARCH Correlation
Estimation SP500-ETC**

System: SP500 ETC
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:16
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 34 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.001343	0.000293	4.587608	0.0000
C(2)	-0.069989	0.048419	-1.445500	0.1483
C(3)	0.009304	0.005096	1.825667	0.0679
C(4)	-0.000482	0.002314	-0.208297	0.8350
C(5)	-0.001166	0.045594	-0.025570	0.9796
C(6)	-0.075715	0.176764	-0.428337	0.6684

Variance Equation Coefficients				
C(7)	3.77E-06	8.93E-07	4.215965	0.0000
C(8)	0.275172	0.037893	7.261873	0.0000
C(9)	0.736147	0.030957	23.77949	0.0000
C(10)	0.000200	5.69E-05	3.504381	0.0005
C(11)	0.079571	0.017531	4.538747	0.0000
C(12)	0.863241	0.028335	30.46511	0.0000
C(13)	0.117060	0.037776	3.098798	0.0019

Log likelihood	3085.496	Schwarz criterion	-9.250201
Avg. log likelihood	2.344602	Hannan-Quinn criter.	-9.304512
Akaike info criterion	-9.338894		

Equation: SP500 RETURN = C(1)+C(2)*SP500 RETURN(-1)+C(3)*ETC RETURN(-1)

R-squared	0.023468	Mean dependent var	0.000416
Adjusted R-squared	0.020486	S.D. dependent var	0.015129
S.E. of regression	0.014973	Sum squared resid	0.146845
Durbin-Watson stat	2.395885		

Equation: ETC RETURN = C(4)+C(5)*ETC RETURN(-1)+C(6)*SP500 RETURN(-1)

R-squared	0.002780	Mean dependent var	-0.000230
Adjusted R-squared	-0.000265	S.D. dependent var	0.058999
S.E. of regression	0.059007	Sum squared resid	2.280613
Durbin-Watson stat	2.043713		

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i-1)$
 $COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	3.77E-06	8.93E-07	4.215965	0.0000
A1(1)	0.275172	0.037893	7.261873	0.0000
B1(1)	0.736147	0.030957	23.77949	0.0000
M(2)	0.000200	5.69E-05	3.504381	0.0005
A1(2)	0.079571	0.017531	4.538747	0.0000
B1(2)	0.863241	0.028335	30.46511	0.0000
R(1,2)	0.117060	0.037776	3.098798	0.0019

**Table 31: DCC-GARCH Correlation
Estimation SP500-XRP**

System: SP500 XRP
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/04/21 Time: 23:32
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.001303	0.000295	4.416524	0.0000
C(2)	-0.060056	0.048411	-1.240562	0.2148
C(3)	0.006201	0.006054	1.024262	0.3057
C(4)	-0.001938	0.002288	-0.847025	0.3970
C(5)	-0.012524	0.057745	-0.216875	0.8283
C(6)	0.168020	0.072780	2.308590	0.0210
Variance Equation Coefficients				
C(7)	3.76E-06	9.14E-07	4.115468	0.0000
C(8)	0.265074	0.037033	7.157854	0.0000
C(9)	0.742882	0.030942	24.00899	0.0000
C(10)	0.001062	0.000177	5.999099	0.0000
C(11)	0.229590	0.053880	4.261139	0.0000
C(12)	0.435932	0.093158	4.679513	0.0000
C(13)	0.132783	0.043510	3.051789	0.0023
Log likelihood	3128.262	Schwarz criterion	-9.380188	
Avg. log likelihood	2.377099	Hannan-Quinn criter.	-9.434498	
Akaike info criterion	-9.468880			

Equation: SP500 RETURN = C(1)+C(2)*SP500 RETURN(-1)+C(3)*XRP RETURN(-1)
R-squared 0.022389 Mean dependent var 0.000416
Adjusted R-squared 0.019404 S.D. dependent var 0.015129
S.E. of regression 0.014981 Sum squared resid 0.147008
Durbin-Watson stat 2.411481

Equation: XRP RETURN = C(4)+C(5)*XRP RETURN(-1)+C(6)*SP500 RETURN(-1)
R-squared -0.010459 Mean dependent var -0.000565
Adjusted R-squared -0.013544 S.D. dependent var 0.005262
S.E. of regression 0.055635 Sum squared resid 2.027425
Durbin-Watson stat 1.996748

Covariance specification: Constant Conditional Correlation
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))

	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	3.76E-06	9.14E-07	4.115468	0.0000
A1(1)	0.265074	0.037033	7.157854	0.0000
B1(1)	0.742882	0.030942	24.00899	0.0000
M(2)	0.001062	0.000177	5.999099	0.0000
A1(2)	0.229590	0.053880	4.261139	0.0000
B1(2)	0.435932	0.093158	4.679513	0.0000
R(1,2)	0.132783	0.043510	3.051789	0.0023

**Table 32: DCC-GARCH Correlation
Estimation SP500-GOLD**

System: SP500 GOLD
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:19
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.001320	0.000297	4.446621	0.0000
C(2)	-0.059461	0.049475	-1.201841	0.2294
C(3)	0.005445	0.040774	0.133550	0.8938
C(4)	0.000303	0.000273	1.108854	0.2675
C(5)	-0.007190	0.046240	-0.155492	0.8764
C(6)	-0.003633	0.023058	-0.157547	0.8748
Variance Equation Coefficients				
C(7)	3.77E-06	9.15E-07	4.115881	0.0000
C(8)	0.275958	0.038004	7.261343	0.0000
C(9)	0.736156	0.031176	23.61281	0.0000
C(10)	2.46E-06	8.29E-07	2.964258	0.0030
C(11)	0.085750	0.017764	4.827285	0.0000
C(12)	0.874367	0.027772	31.48344	0.0000
C(13)	-0.079862	0.036233	-2.204119	0.0275
Log likelihood	4422.234	Schwarz criterion	-13.31323	
Avg. log likelihood	3.360360	Hannan-Quinn criter.	-13.36754	
Akaike info criterion	-13.40193			

Equation: SP500 RETURN = C(1)+C(2)*SP500 RETURN(-1)+C(3)*GOLD RETURN(-1)
R-squared 0.024833 Mean dependent var 0.000416
Adjusted R-squared 0.021855 S.D. dependent var 0.015129
S.E. of regression 0.014963 Sum squared resid 0.146640
Durbin-Watson stat 2.400145

Equation: GOLD RETURN = C(4)+C(5)*GOLD RETURN(-1)+C(6)*SP500 RETURN(-1)
R-squared -0.002133 Mean dependent var 0.000614
Adjusted R-squared -0.005193 S.D. dependent var 0.008061
S.E. of regression 0.008082 Sum squared resid 0.042780
Durbin-Watson stat 1.877088

Covariance specification: Constant Conditional Correlation
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))

	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	3.77E-06	9.15E-07	4.115881	0.0000
A1(1)	0.275958	0.038004	7.261343	0.0000
B1(1)	0.736156	0.031176	23.61281	0.0000
M(2)	2.46E-06	8.29E-07	2.964258	0.0030
A1(2)	0.085750	0.017764	4.827285	0.0000
B1(2)	0.874367	0.027772	31.48344	0.0000
R(1,2)	-0.079862	0.036233	-2.204119	0.0275

7.7.4. Correlation MSCIWORLD-

Table 34: DCC-GARCH Correlation Estimation MSCIWORLD-BTC

System: MSCIWORLD BTC
 Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
 Covariance specification: Constant Conditional Correlation
 Date: 08/05/21 Time: 01:25
 Sample: 1/22/2018 7/29/2020
 Included observations: 658
 Total system (balanced) observations 1316
 Presample covariance: backcast (parameter =0.7)
 Convergence achieved after 27 iterations
 Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000867	0.000254	3.410366	0.0006
C(2)	0.087537	0.047816	1.830691	0.0671
C(3)	0.009816	0.006562	1.495804	0.1347
C(4)	0.001457	0.001791	0.813350	0.4160
C(5)	-0.036574	0.044425	-0.823270	0.4104
C(6)	-0.137332	0.182439	-0.752756	0.4516
Variance Equation Coefficients				
C(7)	2.90E-06	6.31E-07	4.600869	0.0000
C(8)	0.261437	0.041423	6.311385	0.0000
C(9)	0.736766	0.033921	21.72013	0.0000
C(10)	0.000140	8.05E-05	1.734824	0.0828
C(11)	0.021283	0.012645	1.683178	0.0923
C(12)	0.899185	0.055856	16.09833	0.0000
C(13)	0.105520	0.039287	2.685860	0.0072
Log likelihood	3397.041	Schwarz criterion	-10.19715	
Avg. log likelihood	2.581338	Hannan-Quinn criter.	-10.25146	
Akaike info criterion	-10.28584			

Equation: MSCIWORLD_RETURN = C(1)+C(2)*MSCIWORLD_RETURN(-1)+C(3)*BTC_RETURN(-1)
 R-squared -0.039498 Mean dependent var 0.000250
 Adjusted R-squared -0.042672 S.D. dependent var 0.012491
 S.E. of regression 0.012755 Sum squared resid 0.106555
 Durbin-Watson stat 2.471206

Equation: BTC_RETURN = C(4)+C(5)*BTC_RETURN(-1)+C(6)*MSCIWORLD_RETURN(-1)
 R-squared 0.009186 Mean dependent var 0.001031
 Adjusted R-squared 0.006161 S.D. dependent var 0.042933
 S.E. of regression 0.042801 Sum squared resid 1.199894
 Durbin-Watson stat 2.035246

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i)(-1)$
 $COV(i,j) = R(i,j)*SQRT(GARCH(i)*GARCH(j))$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	2.90E-06	6.31E-07	4.600869	0.0000
A1(1)	0.261437	0.041423	6.311385	0.0000
B1(1)	0.736766	0.033921	21.72013	0.0000
M(2)	0.000140	8.05E-05	1.734824	0.0828
A1(2)	0.021283	0.012645	1.683178	0.0923
B1(2)	0.899185	0.055856	16.09833	0.0000
R(1,2)	0.105520	0.039287	2.685860	0.0072

Table 33: DCC-GARCH Correlation Estimation MSCIWORLD-ETH

System: MSCIWORLD ETH
 Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
 Covariance specification: Constant Conditional Correlation
 Date: 08/05/21 Time: 01:24
 Sample: 1/22/2018 7/29/2020
 Included observations: 658
 Total system (balanced) observations 1316
 Presample covariance: backcast (parameter =0.7)
 Convergence achieved after 30 iterations
 Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000884	0.000256	3.448375	0.0006
C(2)	0.084118	0.046947	1.791752	0.0732
C(3)	0.006408	0.005422	1.181844	0.2373
C(4)	-0.000162	0.002317	-0.069825	0.9443
C(5)	-0.056185	0.042891	-1.309964	0.1902
C(6)	-0.051404	0.186356	-0.275839	0.7827
Variance Equation Coefficients				
C(7)	2.86E-06	6.39E-07	4.478324	0.0000
C(8)	0.254325	0.041587	6.115549	0.0000
C(9)	0.742303	0.034732	21.37245	0.0000
C(10)	0.000254	8.22E-05	3.086837	0.0020
C(11)	0.038636	0.013066	2.956926	0.0031
C(12)	0.874722	0.034468	25.37790	0.0000
C(13)	0.156167	0.042461	3.677866	0.0002
Log likelihood	3246.728	Schwarz criterion	-9.740268	
Avg. log likelihood	2.467119	Hannan-Quinn criter.	-9.794578	
Akaike info criterion	-9.828961			

Equation: MSCIWORLD_RETURN = C(1)+C(2)*MSCIWORLD_RETURN(-1)+C(3)*ETH_RETURN(-1)
 R-squared -0.037404 Mean dependent var 0.000250
 Adjusted R-squared -0.040572 S.D. dependent var 0.012491
 S.E. of regression 0.012742 Sum squared resid 0.106341
 Durbin-Watson stat 2.461494

Equation: ETH_RETURN = C(4)+C(5)*ETH_RETURN(-1)+C(6)*MSCIWORLD_RETURN(-1)
 R-squared 0.011555 Mean dependent var -0.000501
 Adjusted R-squared 0.008537 S.D. dependent var 0.054392
 S.E. of regression 0.054159 Sum squared resid 1.921271
 Durbin-Watson stat 2.093672

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i)(-1)$
 $COV(i,j) = R(i,j)*SQRT(GARCH(i)*GARCH(j))$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	2.86E-06	6.39E-07	4.478324	0.0000
A1(1)	0.254325	0.041587	6.115549	0.0000
B1(1)	0.742303	0.034732	21.37245	0.0000
M(2)	0.000254	8.22E-05	3.086837	0.0020
A1(2)	0.038636	0.013066	2.956926	0.0031
B1(2)	0.874722	0.034468	25.37790	0.0000
R(1,2)	0.156167	0.042461	3.677866	0.0002

**Table 36: DCC-GARCH Correlation
Estimation MSCIWORLD-LTC**

System: MSCIWORLD LTC
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:22
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 31 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000872	0.000257	3.388390	0.0007
C(2)	0.090949	0.047141	1.929281	0.0537
C(3)	0.003361	0.004705	0.714355	0.4750
C(4)	-9.02E-05	0.002435	-0.037035	0.9705
C(5)	-0.030723	0.047348	-0.648875	0.5164
C(6)	-0.156344	0.157754	-0.991060	0.3217

Variance Equation Coefficients				
C(7)	2.92E-06	6.50E-07	4.496743	0.0000
C(8)	0.258413	0.041989	6.154256	0.0000
C(9)	0.738530	0.034571	21.36299	0.0000
C(10)	0.003731	0.001177	3.171100	0.0015
C(11)	0.059606	0.033330	1.788352	0.0737
C(12)	-0.293672	0.383595	-0.765580	0.4439
C(13)	0.128188	0.044435	2.884859	0.0039

Log likelihood	3225.306	Schwarz criterion	-9.675155
Avg. log likelihood	2.450840	Hannan-Quinn criter.	-9.729465
Akaike info criterion	-9.763847		

**Table 35: DCC-GARCH Correlation
Estimation MSCIWORLD-ETC**

System: MSCIWORLD ETC
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:24
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 33 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000863	0.000257	3.357098	0.0008
C(2)	0.088739	0.047530	1.867000	0.0619
C(3)	0.005685	0.004417	1.287148	0.1980
C(4)	-0.000539	0.002318	-0.232423	0.8162
C(5)	-0.001362	0.046011	-0.029606	0.9764
C(6)	-0.118201	0.223252	-0.529452	0.5965

Variance Equation Coefficients				
C(7)	2.90E-06	6.46E-07	4.492920	0.0000
C(8)	0.259137	0.041601	6.229057	0.0000
C(9)	0.738325	0.034518	21.38964	0.0000
C(10)	0.000199	5.68E-05	3.510228	0.0004
C(11)	0.079684	0.017441	4.568841	0.0000
C(12)	0.863248	0.028283	30.52231	0.0000
C(13)	0.115222	0.036745	3.135734	0.0017

Log likelihood	3212.055	Schwarz criterion	-9.634878
Avg. log likelihood	2.440771	Hannan-Quinn criter.	-9.689188
Akaike info criterion	-9.723571		

Equation: MSCIWORLD RETURN = C(1)+C(2)*MSCIWORLD RETURN(-1)+C(3)*LTC RETURN(-1)

R-squared	-0.036425	Mean dependent var	0.000250
Adjusted R-squared	-0.039590	S.D. dependent var	0.012491
S.E. of regression	0.012736	Sum squared resid	0.106240
Durbin-Watson stat	2.466580		

Equation: LTC RETURN = C(4)+C(5)*LTC RETURN(-1)+C(6)*MSCIWORLD RETURN(-1)

R-squared	0.007927	Mean dependent var	-0.000917
Adjusted R-squared	0.004897	S.D. dependent var	0.055551
S.E. of regression	0.055415	Sum squared resid	2.011408
Durbin-Watson stat	2.045912		

Equation: MSCIWORLD RETURN = C(1)+C(2)*MSCIWORLD RETURN(-1)+C(3)*ETC RETURN(-1)

R-squared	-0.037120	Mean dependent var	0.000250
Adjusted R-squared	-0.040286	S.D. dependent var	0.012491
S.E. of regression	0.012740	Sum squared resid	0.106312
Durbin-Watson stat	2.467875		

Equation: ETC RETURN = C(4)+C(5)*ETC RETURN(-1)+C(6)*MSCIWORLD RETURN(-1)

R-squared	0.003814	Mean dependent var	-0.000230
Adjusted R-squared	0.000772	S.D. dependent var	0.058999
S.E. of regression	0.058977	Sum squared resid	2.278248
Durbin-Watson stat	2.040546		

Covariance specification: Constant Conditional Correlation
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	2.92E-06	6.50E-07	4.496743	0.0000
A1(1)	0.258413	0.041989	6.154256	0.0000
B1(1)	0.738530	0.034571	21.36299	0.0000
M(2)	0.003731	0.001177	3.171100	0.0015
A1(2)	0.059606	0.033330	1.788352	0.0737
B1(2)	-0.293672	0.383595	-0.765580	0.4439
R(1,2)	0.128188	0.044435	2.884859	0.0039

Covariance specification: Constant Conditional Correlation
GARCH(i) = M(i) + A1(i)*RESID(i)(-1)^2 + B1(i)*GARCH(i)(-1)
COV(i,j) = R(i,j)*@SQRT(GARCH(i)*GARCH(j))

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	2.90E-06	6.46E-07	4.492920	0.0000
A1(1)	0.259137	0.041601	6.229057	0.0000
B1(1)	0.738325	0.034518	21.38964	0.0000
M(2)	0.000199	5.68E-05	3.510228	0.0004
A1(2)	0.079684	0.017441	4.568841	0.0000
B1(2)	0.863248	0.028283	30.52231	0.0000
R(1,2)	0.115222	0.036745	3.135734	0.0017

**Table 38: DCC-GARCH Correlation
Estimation MSCIWORLD-XRP**

System: MSCIWORLD XRP
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:21
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000846	0.000256	3.307188	0.0009
C(2)	0.096375	0.046784	2.060011	0.0394
C(3)	0.004291	0.005157	0.832105	0.4053
C(4)	-0.002127	0.002266	-0.938591	0.3479
C(5)	-0.017005	0.057290	-0.296814	0.7666
C(6)	0.261422	0.091282	2.863899	0.0042

Variance Equation Coefficients				
C(7)	2.83E-06	6.31E-07	4.492343	0.0000
C(8)	0.252431	0.040591	6.218866	0.0000
C(9)	0.744240	0.033950	21.92135	0.0000
C(10)	0.001048	0.000171	6.119238	0.0000
C(11)	0.237368	0.054461	4.358525	0.0000
C(12)	0.435733	0.091324	4.771269	0.0000
C(13)	0.143501	0.042417	3.383085	0.0007

Log likelihood	3256.657	Schwarz criterion	-9.770448
Avg. log likelihood	2.474663	Hannan-Quinn criter.	-9.824758
Akaike info criterion	-9.859140		

Equation: MSCIWORLD RETURN = C(1)+C(2)*MSCIWORLD RETURN(-1)+C(3)*XRP RETURN(-1)			
R-squared	-0.038583	Mean dependent var	0.000250
Adjusted R-squared	-0.041754	S.D. dependent var	0.012491
S.E. of regression	0.012749	Sum squared resid	0.106461
Durbin-Watson stat	2.480792		

Equation: XRP RETURN = C(4)+C(5)*XRP RETURN(-1)+C(6)*MSCIWORLD RETURN(-1)			
R-squared	-0.013221	Mean dependent var	-0.000565
Adjusted R-squared	-0.016315	S.D. dependent var	0.055262
S.E. of regression	0.055711	Sum squared resid	2.032967
Durbin-Watson stat	1.995332		

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i)(-1)$
 $COV(i,j) = R(i,j)*\sqrt{GARCH(i)*GARCH(j)}$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	2.83E-06	6.31E-07	4.492343	0.0000
A1(1)	0.252431	0.040591	6.218866	0.0000
B1(1)	0.744240	0.033950	21.92135	0.0000
M(2)	0.001048	0.000171	6.119238	0.0000
A1(2)	0.237368	0.054461	4.358525	0.0000
B1(2)	0.435733	0.091324	4.771269	0.0000
R(1,2)	0.143501	0.042417	3.383085	0.0007

**Table 37: DCC-GARCH Correlation
Estimation MSCIWORLD-GOLD**

System: MSCIWORLD GOLD
Estimation Method: ARCH Maximum Likelihood (BFGS / Marquardt steps)
Covariance specification: Constant Conditional Correlation
Date: 08/05/21 Time: 01:23
Sample: 1/22/2018 7/29/2020
Included observations: 658
Total system (balanced) observations 1316
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000864	0.000251	3.446302	0.0006
C(2)	0.094580	0.047871	1.975712	0.0482
C(3)	0.023379	0.034003	0.687560	0.4917
C(4)	0.000338	0.000274	1.233677	0.2173
C(5)	-0.006329	0.046567	-0.135904	0.8919
C(6)	-0.020343	0.029304	-0.694230	0.4875

Variance Equation Coefficients				
C(7)	2.74E-06	6.31E-07	4.344090	0.0000
C(8)	0.273365	0.043286	6.315339	0.0000
C(9)	0.732300	0.034175	21.42775	0.0000
C(10)	2.56E-06	8.59E-07	2.984383	0.0028
C(11)	0.087742	0.018313	4.791309	0.0000
C(12)	0.870571	0.028695	30.33870	0.0000
C(13)	-0.042624	0.034410	-1.238715	0.2155

Log likelihood	4548.547	Schwarz criterion	-13.69716
Avg. log likelihood	3.456343	Hannan-Quinn criter.	-13.75147
Akaike info criterion	-13.78586		

Equation: MSCIWORLD RETURN = C(1)+C(2)*MSCIWORLD RETURN(-1)+C(3)*GOLD RETURN(-1)			
R-squared	-0.035987	Mean dependent var	0.000250
Adjusted R-squared	-0.039150	S.D. dependent var	0.012491
S.E. of regression	0.012733	Sum squared resid	0.106195
Durbin-Watson stat	2.474570		

Equation: GOLD RETURN = C(4)+C(5)*GOLD RETURN(-1)+C(6)*MSCIWORLD RETURN(-1)			
R-squared	-0.002126	Mean dependent var	0.000614
Adjusted R-squared	-0.005186	S.D. dependent var	0.008061
S.E. of regression	0.008082	Sum squared resid	0.042779
Durbin-Watson stat	1.868497		

Covariance specification: Constant Conditional Correlation
 $GARCH(i) = M(i) + A1(i)*RESID(i)^2 + B1(i)*GARCH(i)(-1)$
 $COV(i,j) = R(i,j)*\sqrt{GARCH(i)*GARCH(j)}$

Transformed Variance Coefficients				
	Coefficient	Std. Error	z-Statistic	Prob.
M(1)	2.74E-06	6.31E-07	4.344090	0.0000
A1(1)	0.273365	0.043286	6.315339	0.0000
B1(1)	0.732300	0.034175	21.42775	0.0000
M(2)	2.56E-06	8.59E-07	2.984383	0.0028
A1(2)	0.087742	0.018313	4.791309	0.0000
B1(2)	0.870571	0.028695	30.33870	0.0000
R(1,2)	-0.042624	0.034410	-1.238715	0.2155

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