UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Cryptocurrency Spillover Effect on Non-Fungible Token Pricing

An empirical study on the connection between the cryptocurrency and NFT markets

Bachelor Thesis, Financial Economics

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Abstract

The thesis is designated to understand if the pricing of Non-Fungible Tokens (NFTs) is affected by the volatility present in the cryptocurrency market. NFTs are digital assets such as art, music, videos, and virtual property, that are encoded with blockchain-traded rights and have in the recent one a half year seen a large increase in prices and popularity amongst investors. Since NFTs are closely related to the cryptocurrency market it is of interest to research how they might affect each other. Using a Vector Autoregressive model to derive a Spillover Index, an EGARCH model, a DCC-GARCH model and a Wavelet Coherence Model our conclusion is that volatility is present in both markets but that the volatility in the cryptocurrency market is of low or no importance in the pricing of NFTs.

Keywords: NFT, Cryptocurrency, Bitcoin, Ether, Spillover Index, Wavelet, GARCH

"När det går bra då äter man nudlar.
Men om det går sämre,
då blir det Kobe biff."
-Ibra Kadabra, 2020

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1. Introduction

1.1 Background

As a result of the 2008 economic crisis and the reveal of a broken economic system, blockchain technology[1] was developed. This new technology enabled a decentralized monetary system that would be more transparent allowing for a power shift from entities to users. Building on blockchain technology Bitcoin, a cryptocurrency, became its first major innovation. Bitcoin was the first global currency and can be traded on platforms such as Coinbase, Robinhood, or Metamask. Ether is the second largest cryptocurrency built on blockchain technology but was implemented with an additional "feature" allowing for the use of "smart contracts" by developers. Each smart contract holds a code that ensures that each digital asset is unique, verifiable, and traceable (Silver, 2021).

Non-fungible tokens[2] (NFTs) are digital assets such as art, music, videos, virtual property, that are encoded with blockchain-traded rights (Dowling, 2022). NFTs are traded in cryptocurrency, typically Ether, meaning that each NFT holds a smart contract via the Ethereum blockchain that protects it from being copied, but also verifies its uniqueness and traceability as mentioned above (Conti and Schmidt, 2022). Even though NFTs have been around since 2014, their popularity did not start rising until the beginning of 2021 (Howcroft, 2022). The NFT market's first peak was a sale amounting up to $69.3 million on March 11th, 2021, by an artist known as Beeple, rendering the digital artwork the third most expensive artwork sold by a living artist (Brown, 2021).

As NFT's have become more popular researchers have begun to dedicate their time to understand them. A study by Michael Dowling (2022) first assesed the relationship between NFTs and cryptocurrencies. Dowling's focus was to evaluate whether the prevalent volatility in the cryptocurrency market might spill over onto the NFT market. A similar study was published around the same time by Özdemir (2022), but he instead only looked at the volatility spillover effect between cryptocurrencies and how these aspects might have come to affect investors during the COVID-19 pandemic. Even though the two studies had different aims their combination of models will together function as the basis of this thesis in order to answer our

[1] See Definition 1 in Appendix 1 for exact definition.
[2] Will hereinafter be referred to as NFT or NFTs.

main research question: Is there a cryptocurrency volatility spillover effect on the pricing of NFTs?

1.2 Problem Definition

Cryptocurrencies are known to be volatile due to their speculative nature with nothing intrinsically valuable to reinforce their value (Lapin, 2021). Cryptocurrencies, as their name describes, are designed as currencies with only some asset-like properties (Baur et al., 2017). NFTs on the other hand can be described as pure assets which is prevalent in their name Non-Fungible Tokens. Fungible, meaning interchangeable, can be applied to currencies, whilst non-fungible, meaning that something that is not interchangeable, is a key characteristic to NFTs (Dowling, 2022).

NFTs are typically traded using Ether which in turn means that they are tied to the Ethereum blockchain. As mentioned above, Cryptocurrencies are subject to volatility meaning that NFTs might be exposed to some level of volatility from the cryptocurrency market. Reasoning behind this statement can be found in the soaring prices of NFTs. An example can be shown using data regarding the first transaction sales of the digital art NFT collection, CryptoPunk. Between November 2017 and March 2022, the average price of CryptoPunk increased by 310,884.1 %[3]. Looking at this large increase and knowing the NFT connection to the cryptocurrency market one might intuitively think it is caused by the volatility in the cryptocurrency market, but when comparing the increase to how the price of Ether and Bitcoin changed during the same time period, 822.4 %[4] and 537.4 %[5] respectively, CryptoPunk is considerably higher. Since there is a discrepancy between the intuitive mind and this superficial reasoning it becomes of interest to understand the connection between the two markets.

As of 2022, few studies have been conducted into understanding the economics of NFTs, let alone the combined economics of the NFT and cryptocurrency market. The available literature is therefore scarce and offer only a cursory economic analysis[6]. To begin to comprehend the market interaction, this thesis focuses on extending the superficial reasoning presented above,

[3] See Table 1.11.
[4] See Table 1.11.
[5] See Table 1.11.
[6] See Literature Review.

whether the volatility of the cryptocurrency market effect the pricing of NFTs, through a robust empirical study.

1.3 Purpose of Thesis

The purpose of this thesis is to study the two largest cryptocurrencies, Bitcoin and Ether, and the two largest digital art NFT's on the Ethereum blockchain with regards to market cap, CrytpoPunk and Bored Ape Yacht Club[7] (CoinMarketCap, 2022). The purpose of analyzing these two markets is to understand if there is a volatility spillover effect from cryptocurrencies onto NFTs, as well as understanding how in turn the spillover might affect the pricing NFTs.
In this thesis we therefore inquire to answer the following questions:

1. How volatile are the cryptocurrency and NFT markets?
2. How much does the volatility present in the respective market spillover onto the other?
3. How much is the pricing of NFTs affected by the volatility from the cryptocurrency market?

As we present in the Data section of this thesis, we are using two datasets. Having the two datasets will allow for a short and long run comparison, since the datasets are over two periods. It will also allow for deeper understanding into how certain aspects of the interaction between the two markets might have altered as a result of the peaking interest into the NFT market in the beginning of 2021.

1.4 Economic Theory

Spillover effect is a positive or negative impact because of a seemingly unrelated occurrence. This theory can be applied within economics, politics and sociology and can therefore be used to interpret the causes of both micro and macro related events. The spillover effect also introduces the theory that larger markets might spillover into smaller connected markets (CFI, 2022).

In this thesis we are using the spillover effect specifically related to volatility to measure how much of the volatility in one large market, the cryptocurrency market, spills over to a second

[7] Will hereinafter be referred to as BAYC.

smaller and related market, the NFT market, and what that might say about certain aspects of that second smaller market.

1.5 Thesis Structure

In the next chapter we introduce a review of the literature within related research fields. The purpose is to explain as to why the literature acts as a basis to this thesis from a constructive perspective discussing aspects such as missing elements and insufficient information. The following chapter presents the data and methodology we use to answer our research question. Chapter four is designated to our empirical results of the used methods, which is later be discussed in chapter five. The last chapter summarizes and concludes our thesis.

2. Literature Review

As NFTs are a relatively new phenomenon with a peak in popularity in 2021 (Google Trend, 2022), presented economic research on the topic is scarce. As a result, research papers specifically related to NFTs, and cryptocurrency spill-over effects are limited and non-exhaustive. We have been able to find one research paper addressing our exact topic by Michael Dowling (2022)[8]. Dowling's article explores if NFT pricing is related to cryptocurrency pricing through a wavelet coherence analysis and a spillover matrix based on a VAR model analysis.

The data used in this thesis are two cryptocurrencies, Bitcoin and Ether, along with three NFTs, Decentraland LAND tokens, CryptoPunk images, and Axie Infinity game characters. All data were collected between March 2019 and March 2021, which we define as the first gap in Dowlings study. All the variables considered are available before the set time span. Therefore, it can be questioned why more data was not sourced to provide a more nuanced result.

As presented, the thesis is based on five variables chosen for different reasons. Bitcoin is chosen since it is the largest cryptocurrency and therefore has the largest volatility transmissions to other cryptocurrencies. Ether is used due to it being the primary blockchain upon which NFTs are traded. The premise upon which the three NFT markets were chosen is what we conclude to be the second gap presented in the research.

Dowling (2022) presents all three NFTs as individual markets to make them comparable for analysis, but the level of complexity of the three NFTs makes comparability questionable. CryptoPunk is a NFT collection of avatars that can be purchased on the Ethereum blockchain (Rees, 2021), whilst Axie Infinity is an NFT video game on the Ethereum blockchain that has its own in-game cryptocurrency, Axie Infinity Shard (AXS), that is needed to buy Axies, Axie Infinity game characters (Gonzales, 2021). Decentraland is a virtual world where users can use the in-world cryptocurrency called MANA, Decentraland LAND token, to buy LAND or exchange products and services with other players (Decentraland, 2022). As both Axies and MANA are, unlike CryptoPunk, not first-level transactions on the Ethereum blockchain they offer an added layer of complexity in measuring volatility transmissions and price correlation

[8] Ph.D. and Full Professor of Finance at DCU Business School, Ireland.

to Ether and Bitcoin. Therefore, we conclude that the three NFTs are not comparable nor able to offer the same reliability in the presented results.

The result of the study is based on an analysis using a Wavelet Coherence model and a spillover index through a VAR model. Through the spillover index, Dowling (2022) concludes that there are limited volatility transmission effects between cryptocurrencies and NFTs suggesting that NFTs can potentially be considered as a low-correlation asset class and therefore distinct from cryptocurrencies. But the wavelet coherence analysis indicates co-movement between the two sets of markets suggesting that cryptocurrency pricing behaviors might be of some benefit in understanding NFT pricing patterns. As the two models present two separate conclusions, we have confirmed a third gap in the literature that might benefit from adding two GARCH models: EGARCH and DCC-GARCH.

The second piece of literature relevant to our thesis is by Özdemir (2022)[9] who investigates volatility spillovers across eight major cryptocurrency returns, namely Bitcoin, Ethereum, Stellar, Ripple, Tether, Cardano, Litecoin, and Eos from November 17, 2019, to January 25, 2021. The purpose of report is to analyze the financial behavior of investors during the COVID-19 pandemic. Özdemir uses EGARCH, DCC-GARCH, and wavelet models to understand if cryptocurrencies have been exposed to volatility. The research concludes that the overall results show that the cryptocurrency markets are highly volatile and mutually dependent over the sample period. This result means that any kind of shock in one market leads investors to act in the same way in the other market and thus indirectly causes volatility spillovers in those markets.

Since Özdemirs (2022) research is not directly tied to our research question, we have instead used this paper as an outline in adding a broader perspective to the article presented earlier by Dowling (2022). Özdemir uses the two GARCH models to measure volatility between cryptocurrencies which is a method that we can apply to in our thesis to fill the third presented gap in Dowlings (2022) study.

[9] Ph.D. and Associate Professor at the Department of International Trade and Finance, Istanbul Gelisim University, Istanbul, Turkey.

3. Data and Methodology

3.1 Data

The data used in this thesis are the two largest cryptocurrencies, Bitcoin and Ether, along with the two largest NFTs in terms of estimated market cap on the Ethereum blockchain, CryptoPunk and Bored Ape Yacht Club (BAYC). The cryptocurrency data for Bitcoin and Ether is raw data obtained from coinmarketcap.com. Bitcoin is chosen to be included in this thesis since it is the largest cryptocurrency and therefore has the largest volatility transmissions onto other cryptocurrencies. Ether on the other hand is included in this thesis due to its strong connection to the NFT market. A majority of NFTs are on the Ethereum blockchain, where Ether is the connected cryptocurrency (Conti and Schmidt, 2022).

The daily average price data for CryptoPunk and BAYC is secondary data sourced from cryptoslam.io. As stated earlier each NFT was chosen due to the estimated market cap on the Ethereum blockchain where CryptoPunk is the largest and BAYC is the second largest. Another criterion for choosing these two NFTs is based on them being comparable allowing us to fill the second presented gap of the study conducted by Dowling (2022)[10]. Both are NFT collections of avatars that can be classified as digital art. The art is the product and can therefore be defined as a level-one transaction. In the NFT market, there are several types of products and services classified as NFTs that can be defined as level-two or three transactions since the consumer needs to exchange Ether into other cryptocurrencies to reach the end product.

As CryptoPunk was launched in June 2017 and BAYC was launched in April 2021 we have decided to create two datasets that will also allow for a benchmark comparison pre and post the hype of 2021. The use of two datasets also takes into consideration the short time frame in Dowling's (2022) study. The first dataset is from November 2017 to March 2022 and consists of the daily closing price of Ether and Bitcoin along with the daily average price of CryptoPunk. Since the daily average price for CryptoPunk was not available for every day within the period, we used linear interpolation[11] to fill in a total of 372 missing values The reason to the first dataset not starting from the launch date of CryptoPunk is due to data not being available for

[10] See Chapter 2, Literature Review.

[11] Linear Interpolation is a statistical method used to estimate unknown values using the known values within a sequence. The method has a disadvantage of not being exact and also not being differentiable at the point x_k. (Kenton, 2020).

all three included variables prior to November 2017. The second dataset is between April 2021 to March 2022. This dataset includes dataset 1 limited within the given time span with additional data regarding the daily average prices of BAYC.

For all of the models we will be transforming the daily price data into daily return and the observations will therefore for dataset 1 decrease with one day from 1604 observations to 1603 and for dataset 2 decrease with one day from 345 observations to 344. For the VAR model and Spillover Index along with the EGARCH and DCC-GARCH we have used the R program to build the models. To compute the Wavelet Coherence Analysis the programming platform Matlab has been used.

3.2 Methodology

3.2.1 Vector Autoregressive Model and Spillover Index

A vector autoregressive model, VAR, is a stochastic process model that allows for the analysis of a multivariate time series. The model's purpose is to analyze the bi-directional relationship between two or more variables as they change over time. The VARs bi-directional aspect is specifically what makes it different from other autoregressive models such ARMA (Autoregressive Moving Average Model) and ARIMA (Autoregressive Integrated Moving Average Model) that are one-directional models (Prabhakaran, 2019). In this thesis we will be using two datasets. Dataset 1 consists of three variables, Bitcoin, Ether and CryptoPunk, whilst dataset 2 consists of four variables, Bitcoin, Ether, CryptoPunk and BYAC.

Since the purpose of this thesis is to understand the relationship between the cryptocurrency and NFT market specifically related to volatility spillover, we will be using the VAR model as the building block for creating a spillover index (Diebold and Yilmaz, 2012).

Before building a VAR model three tests need to be performed testing the VAR models appropriateness to our time series'. Depending on the results of these tests it can be decided whether the VAR is the correct model. The three essential tests are: Augmented Dickey-Fuller Test, Granger Causality Test, and Cointegration Test. (Prabhakaran, 2019).

1. Augmented Dickey-Fuller Test

Since the aim of a VAR model is forecasting a time series the first test relevant is a stationarity test. A time series that is stationary is characterized by a mean and variance that does not change

over time. There are several stationarity tests that can be implemented, but for the purpose of this thesis we will be using the Augmented Dickey-Fuller Test (ADF Test). The null and alternative hypotheses are as follows:

$$H_0 = X\ is\ not\ stationary$$
$$H_A = X\ is\ stationary$$

For a VAR model to perform well the alternative hypothesis of the series being stationary is desired. This is where the p-value is smaller than the significance level of 0.05.

2. Granger Causality Test

A Granger Causality test is used to understand the bi-directional relationship between the variables. The test is bivariate and can therefore only measure causality between two variables at once. The test can also only measure causality in one direction, therefore, the test also needs to be performed in reverse. The null and alternative hypotheses are as follows:

$$H_0 = Time\ series\ X\ does\ not\ Granger - cause\ time\ series\ Y$$
$$H_A = Time\ series\ X\ does\ Granger - cause\ time\ series\ Y$$

In the case of a VAR model, the desired outcome is to be able to reject the null hypothesis and therefore ascertain that time series X does Granger-cause time series Y. Since the VAR model requires a bi-directional outcome, the test performed in reverse desires an outcome to reject the null hypothesis of that time series Y does not Granger-cause time series X. To be able to reject the null hypothesis in both cases above the test requires that the p-value is smaller than the significance level of 0.05.

3. Johansen and Engle-Granger Cointegration Test

A cointegration test has the purpose of understanding if there is a statistically significant connection between the variables. The null and alternative hypotheses for both the Johansen and Engle-Granger tests are as follows:

$$H_0 = No\ cointegration\ betwen\ X\ and\ Y$$
$$H_A = Cointegration\ between\ X\ and\ Y$$

The desired outcome for a VAR model is that the cointegration test does not reject the null hypothesis rendering that there is no cointegration between the variables. If the Johansen test statistic is larger than the significance level of 0.05 and the Engle-Granger p-value is smaller than the significance level of 0.05 the assumption is that there is cointegration between variables.

Building a VAR model requires choosing a correct lag length. To determine the appropriate lag length, we will be using the information criterion. The information criterion that we will run will give us three different possibilities: Akaike (AIC), Hannan-Quinn (HQ), and Schwartz (SW). The general idea when choosing which information criterion to follow seems to be the lower the better even though there is risk of under fitting. Even so, in this thesis we will apply the lower of the three information criterions (Stock and Watson, 2015).

Having decided on a lag length the VAR can be modeled. Since it is a linear combination of past values both of the other variables in the system but also itself, the system will model one equation per variable. For a two variable VAR, X_t and Y_t, the equations are as follows (Stock and Watson, 2015):

$$Y_t = \beta_{10} + \beta_{11}Y_{t-1} + \cdots + \beta_{1p}Y_{t-p} + \gamma_{11}X_{t-1} + \gamma_{1p}X_{t-p} + u_{1t}$$
$$X_t = \beta_{20} + \beta_{21}Y_{t-1} + \cdots + \beta_{2p}Y_{t-p} + \gamma_{21}X_{t-1} + \gamma_{2p}X_{t-p} + u_{2t}$$

Once the model has been created there are two goodness-of-fit tests necessary: Autocorrelation Test and Residual Normality Test.

1. Autocorrelation Test

Autocorrelation tests are used to measure the correlation between the residuals in the model. The autocorrelation test applied is the Portmanteau Test which has the following null and alternative hypotheses:

$$H_0 = No\ autocorrelation\ in\ the\ residuals$$
$$H_A = Autocorrelation\ in\ the\ residuals$$

In a VAR model the desired result is to not reject the null hypothesis and therefore getting a p-value larger than 0.05. Autocorrelation being present results in the MSE underestimating the true variance of the errors or that the standard error of the model coefficients may underestimate the true standard deviation of the estimated coefficients. This suggests that the chosen model is not suited for the time series (PSU, 2022).

2. Residual Normality Test

To test if the residuals are normally distributed the multivariate Jacque-Bera test will be applied. The multivariate Jacque-Bera test computes standardized residuals using a Choleski decomposition of the variance and covariance matrix for the centered residuals (Rdocumentation.org, 2022). The null and alternative hypotheses are as follows:

$$H_0 = Residuals\ are\ normally\ distributed$$

$$H_A = Residuals\ are\ not\ normally\ distributed$$

When modelling VAR the goal is that the residuals are normally distributed since it indicates that the dataset is not random and that the model explains the trends in the dataset. If the test were to reject the null hypothesis with a p-value smaller than the significance level 0.05, it would indicate the opposite.

As presented earlier the purpose of the VAR model in this thesis is to derive a spillover index. To do so the Forecast Error Variance Decomposition will be used to measure how chocks in one variable affect the other variables in the model. The spillover Index was developed by Diebold and Yilmaz (2012) and will be applied to understand how volatility spillover effects from the cryptocurrency market affect the pricing of NFTs.

3.2.2 General Autoregressive Conditionally Heteroscedastic Model

The second model applied to measure spillover across the selected variables is the generalized autoregressive conditionally heteroscedastic (GARCH) set of models. The exponential GARCH model is conducted to estimate the conditional volatility of each asset. Subsequently the Dynamic conditional correlation (DCC) GARCH model is applied to measure the co-movement between the analyzed assets. This section provides a walkthrough regarding the assumptions of GARCH such as heteroskedasticity, volatility clustering and conditional volatility. After the assumptions have been established the building blocks of the GARCH model will be explained, those being, 1) the mean model, i.e., the Autoregressive Moving Average (ARMA) model and 2) the variance model, i.e., the Autoregressive Conditional Heteroscedastic (ARCH) model.

First and foremost, the GARCH set of models work on the assumption of heteroscedasticity, meaning that the variance of each residual is not constant, but that it changes over time. The assumption of Heteroscedasticity differs from the assumption of homoscedasticity in the Ordinary Least Squares (OLS) models. As can be observed in Figure 1.14. when it comes to volatility in the cryptocurrency and NFT market, volatility changes over time. GARCH models take the notion of heteroskedastic disturbance terms and treat them as their own data set to be modeled. Another important feature of a time series that provides motivation for the GARCH set of models is what is known as “Volatility Clustering” or “Volatility Pooling”. In essence it describes the tendency of how the volatility in an asset is correlated with its level of volatility in the immediately preceding periods. In simple terms it means that a large change in an assets

price, either up or down is followed by a large change, up or down, the following period. The conditional volatility refers to the fact that the volatility of today is conditioned on past values of the volatility (Brooks, 2019).

The building blocks of the GARCH include two parts, an ARMA model and an ARCH model. The ARMA model is derived by combining autoregressive terms and moving average terms to create a model to measure volatility. The autoregressive model specifies that the output variable depends linearly on its own previous values and on a random term while the moving average model is a statistic that captures the average change in a data series over time. Depending on how many autoregressive and moving average terms the model encompasses it can be written differently, as for example an ARMA(1,1), with one autoregressive term and one moving average term:

$$Y_t = c + t + \varphi_1 Y_t + \theta 1_t - 1$$

The Autoregressive Integrated Moving Average model (ARIMA) is an evolution of the ARMA model, ARIMA(p, d, q) has p autoregressive terms and q moving average terms, with d degree of differencing in the form:

$$Y_t^d = c + \sum_{i=1}^{p} \phi_i Y_{t-1} + \sum_{j=1}^{q} \theta_i \varepsilon_{t-j}$$

In contrast to ARMA and ARIMA, ARCH treats the weights as parameters to be estimated. This provides a more realistic approach to estimating volatility because it is presumed that recent observations are more likely to be relevant in estimating future volatility. The GARCH model was developed by Bollerslev (1986) and Taylor (1986) and is an evolution of the ARCH model as it allows the conditional variance to be dependent upon previous own lags, so that the conditional variance equation can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2$$

The equation above is an example a GARCH(1,1) model were σ2 is known as the conditional variance since the model is estimating variance one-period ahead based on past information.

The main model of GARCH used in this thesis is the Exponential GARCH (EGARCH) model introduced by Nelson (1991). The model is designed to capture the asymmetry in volatility distribution of each asset. Given a time series:

$$y_t = E_{t-1}(y_t) + \varepsilon_t, \varepsilon_t \; I_{t-1} \; N(0, H_t)$$

Where $E_{t-1}(y_t)$ is the conditional expectation of y_t at time series $t-1$. The variance of the error term estimated by univariate EGARCH (1,1) model can be defined as:

$$h_t = \ln(\sigma_t^2) = \omega_t + \sum_{j=1}^{k} \alpha_t f(z_{j,t-1}) + \beta h_t - 1 \quad (1)$$

$$f(z_{j,t-1}) = [|z_{t-1}| - E(|z_{t-1}|] + \gamma z_{t-1} \quad (2)$$

The conditional variance σ_t^2 of the residual factors given in (1) is an exponential function of the GARCH effect measured by β and past standardized innovations $z_t = \frac{\varepsilon_t}{\sigma_t}$ as given by (2) is a zero-mean, i.i.d. random sequence. A significant GARCH effect (β) implies that past volatility is a valid predictor for future volatility. The asymmetry effect of the EGARCH model is measured by γ. A significant negative γ indicates a leverage effect meaning that bad news has a larger impact on the volatility of a market than good news. The ARCH effect is measured by α, a significant positive α implies the existence of volatility clustering. In conjunction with the EGARCH model, residual diagnostics are conducted, those being the weighted ljung-box test on standardized residuals, Weighted Ljung-Box Test on Standardized Squared Residuals as well as the Weighted ARCH-LM Test and Adjusted Pearson Goodness-of-Fit.

To establish the dynamic co-movement between the cryptocurrencies and selected NFTs over time a Dynamic Conditional Correlation (DCC) GARCH model was constructed. Correlation coefficients in essence are static and are unable to show how correlation between two variables change over time, the DCC model on the other hand uses the conditional variance calculated by the EGARCH model and gives a dynamic correlation over the selected time interval. Being that the DCC GARCH model is univariate, it combines the computed coefficients of each variable and therefore decreases complexity compared to other multivariate GARCH models (Engle, 2002). According to Engle, the DCC-GARCH can be presented as follows:

$$H_t = D_t R_t D_t$$

Where H_t represents the conditional covariance matrix and R_t the conditional correlation matrix. D_t is in general viewed as univariate GARCH models but not restricted to only being univariate GARCH models.

$$D_t = diag\{\sqrt{h_{i,t}}\}$$

The elements of D_t are written as univariate EGARCH model:

$$h_{i,t} = \omega_{it} + \sum_{j=1}^{k} \alpha_{it} f(z_{j,it-1}) + \beta h_{it} - 1$$

R_t can be derived from:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

where

$$Q_t = \left(1 - \sum_{m-1}^{M} \alpha_m - \sum_{n-1}^{N} \beta_n\right) Q^{hat} + \sum_{m-1}^{M} \alpha_m (\varepsilon_{t-m}\ \varepsilon'_{t-m}) + \sum_{n-1}^{N} \beta_n\ Q_{t-n}$$

and

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & 0 \\ 0 & \sqrt{q_{22}} & 0 \\ 0 & 0 & \sqrt{q_{33}} \end{bmatrix}$$

and Q^{hat} is the unconditional covariance of standardized residuals from the first stage of estimation.

3.2.3 Wavelet Coherence Model

The last empirical model conducted to analyze the spillover effects between cryptocurrencies and from cryptocurrencies to NFTs is a wavelet coherence analysis. Wavelet coherence allows for estimating the extent of the co-movement between two series across different frequencies and time, which gives a quantity between 0 and 1 for the different values within the time and frequency axis. Wavelet also allows for determining the direction of influence, which variable is leading the other. Simply put the wavelet coherence shows where in the time frequency space that two time series co-vary. The wavelet coherence between two-time series $x(t)$ and $y(t)$ can be denoted as follows:

$$R_{x,y}^2(\tau, s) = \frac{\left|S(s^{-1} W_{x_I x_j}((\tau, s))\right|^2}{S\left(s^{-1}\left[W_{x_i}(\tau, s)\right]^2\right) * S\left(s^{-1}\left[W_{x_j}(\tau, s)\right]^2\right)}$$

Where $R^2 \epsilon [0,1]$. S is the smooth operator, τ is the location parameter, s is the scale parameter $W_{x_I x_j}$ is the wavelet cross spectrum between x and y, and W_{x_i} and W_{x_j} are the wavelet transformations of x and y (Özdemir, 2022). The smooth operator, S, is determined as follows:

$$S_{time}(W)\Big| = \left(W_n(s) * c_1^{\frac{-t^2}{2s2}}\right)\Big|,$$

$$S_{time}(W)| = (W_n(s) * c_2 \Pi(0.6s))|$$

In the equations above c1 and c2 are normalization constants and Π is the rectangle function. The number 0.6 is an empirically determined scale factor of decorrelation length in the Morlet wavelet. The Morlet wavelet is an analytical wavelet within the Continuous Wavelet Transform, CWT, family. A CWT is one of two types of wavelets and is specified for time series analysis.

To derive the wavelet coherence the MIT licensed "Cross Wavelet and Wavelet Coherence Toolbox" developed for Matlab by Aslak Grinsted (2014) is used. The toolbox provides the user with code to be able to create a scalogram with the frequency and time parameters stated above. The toolbox also offers a Monte Carlo Significance test in order to determine the significance level of the presented result in the scalogram. To be able to interpret the outcome of the Wavelet Coherence Scalogram one needs to become familiar with the term Cone of Influence, COI. The COI shows areas in the scalogram that may be influenced by the end points of the length signals. The area within the COI consists of information that accurately represent the time-period data. (MathWorks, 2022).

Four more aspects important in understanding how to interpret the scalogram is the color, the direction of the arrows, the areas contoured with a black line, and the indication that the y-axis gives us. A wavelet coherence scalogram is presented in different colors to show the level of correlation between the two-time series. The hotter colors represent high correlations whilst the cool blue colors represent low correlations. The arrows present go in four different directions: up, down, left, and right. The arrows pointing right indicate positive correlation. The arrows pointing up to the right as well as down to the left indicate that X leads Y and arrows pointing up to the left and down to the right indicate that Y leads X. The areas that are contoured with a black line are the areas within Monte Carlo significance level. The scalogram also gives us information regarding how co-movement and correlation develops over time by looking at the Y-axis of period in days (Dowling, 2022).

4. Result

4.1 Descriptive Statistics

Table 1.11 presents the descriptive statistics for dataset 1, which consists of the cryptocurrencies Ether and Bitcoin as well as the NFT CryptoPunk for the period 10th of November 2017 until the 31st of March 2022. Table 1.21 represents the cryptocurrencies Ether and Bitcoin as well as the NFTs CryptoPunk and BAYC for the period from 2nd of May 2021 until 31st of March 2022. The descriptive statistics encompass both the prices of the cryptocurrencies and NFTs as well as the returns, as the return data will later be used in the models to capture the volatility spillover. The minimum and maximum values for the selected assets show the instability of prices across time, with the NFTs showing highest total return relative to the cryptocurrencies returns during the same periods, with CryptoPunk showing the highest total return of 312 987% in the four years observed from dataset 1.

TABLE 1.11 ***DESCRIPTIVE STATISTICS DATASET 1***

	BITCOIN		**ETHER**		**CRYPTOPUNK**	
	Price	**Return**	**Price**	**Return**	**Price**	**Return**
MEAN	$19460	.00200	$1036	.00278	$60957	.2473169
MEDIAN	$9786	.00170	$387	.00157	$211	.0001374
STANDARD DEVIATION	17830	.04099	1237	.05127	138529	2.3181
VARIANCE	3.18e+08	.00168	1530023	.00263	1.92e+10	5.3738
MAXIMUM	$67567	.25247	$4812	.26458	$1171325	71.695
MINIMUM	$3237	-.37169	$84.3	-.42347	$4.66	-.98457
TOTAL RETURN	537,40%		922,40%		312 987%	
SKEWNESS	1.1132	-.11553	1.3718	-.2539	2.924	22.266
KURTOSIS	2.706	10.149	3.552	8.516	13.277	621.007
JARQUE–BERA	337.07	3414.45	523.7	2074.2	9434.79	26326410
ADF TEST (P)	0.4993	0.0000	0.6567	0.0000	0.5009	0.0000
OBSERVATIONS	1604	1603	1604	1603	1604	1603

Dataset 2 shows negative returns for cryptocurrencies but positive returns for the NFTs in the selected period. CryptoPunk increased by 177% while BAYC increased by 126 228%. The selected cryptocurrencies Bitcoin and Ether decreased 21% and 18% respectively, this shows that NFTs and Cryptocurrencies to not behave similarly, in terms of returns, on all time scales. The kurtosis values for all returns are above 3, which means that the data is not normally distributed (Balanda and MacGillivray 1988). This is also verified from the Jaque-Bera normality test that shows that the null hypothesis of normality is rejected at the 1% significance level for all variables. The skewness of the cryptocurrency returns is negative for both datasets

while the skewness for the NFTs in both datasets are positive, implying large outlier returns in NFTs compared to cryptocurrencies.

TABLE 1.21 ***DESCRIPTIVE STATISTICS DATASET 2***

	BITCOIN		ETHER		CRYPTOPUNK		BAYC	
	Price	**Return**	**Price**	**Return**	**Price**	**Return**	**Price**	**Return**
MEAN	$45481	.00004	$3196	.00166	$273971	.05484	$160351	.04173
MEDIAN	$43962	.00126	$3157	.00294	$242700	.00800	$165207	.01026
STANDARD DEVIATION	8815	.03890	737.86	.05145	183255.2	.37176	119606	.24188
VARIANCE	7.77E+07	.00151	544439.3	.00264	3.36E+10	.13820	1.43e+10	.05851
MAXIMUM	$67567	.14540	$4812	.25308	$1171325	2.1042	$418657	1.7384
MINIMUM	$29807	-.13766	$1788	-.27189	$29908	-.78802	$967	-.58461
TOTAL RETURN	−21.1%		-18.4%		176.7%		126 228%	
SKEWNESS	.5419	-.01771	.17825	-.10529	1.1241	2.6499	.05683	2.551
KURTOSIS	2.4732	4.6306	2.1530	6.9174	5.6123	14.719	1.7863	17.79
JARQUE–BERA	20.12	37.76	11.83	211.67	166.4	2319.81	20.94	3416.73
ADF TEST (P)	0.4298	0.0000	0.5221	0.0000	0.6149	0.0000	0.1160	0.0000
OBSERVATIONS	335	334	335	334	335	334	335	334

Figure 1.13: Daily Price Dataset 1

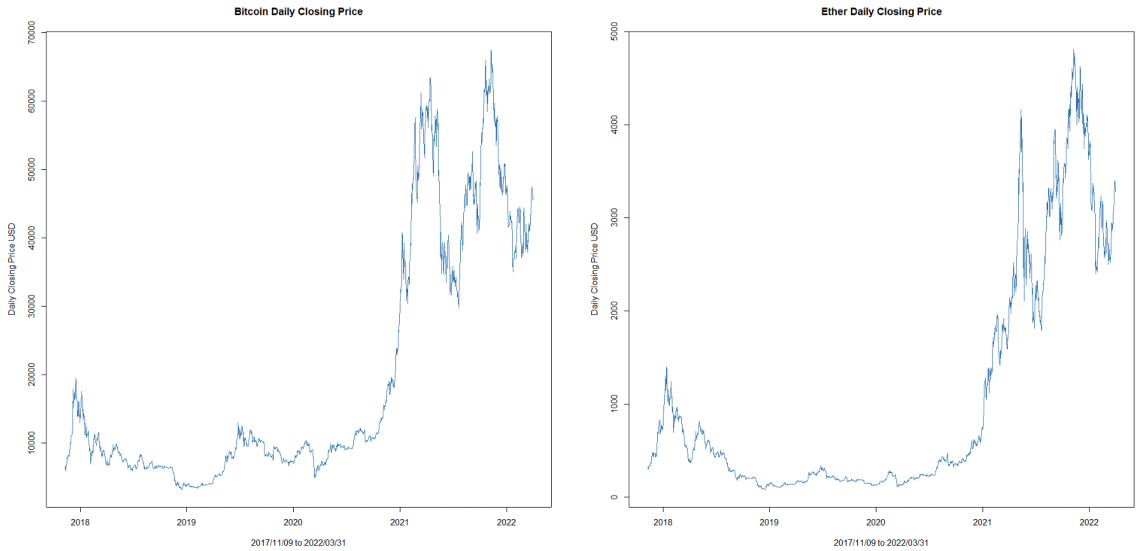


Figure 1.13: Daily Price Dataset 1

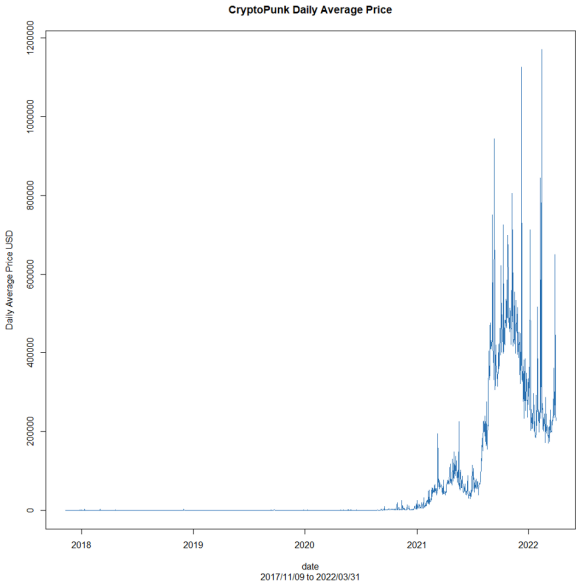
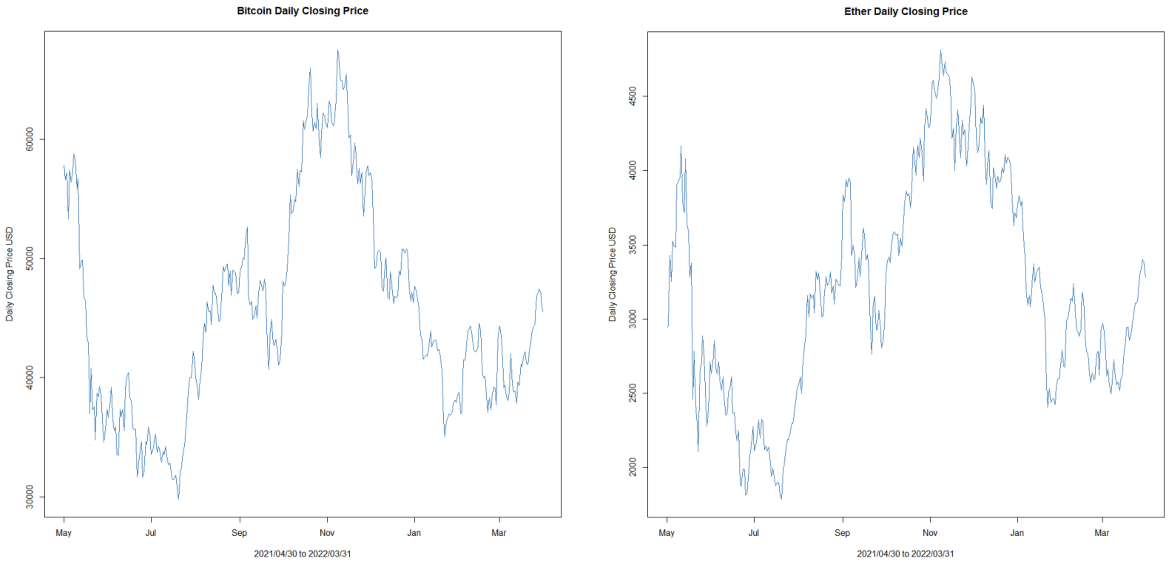


Figure 1.13 shows the daily price for the variables Bitcoin, Ether, and CryptoPunk of Dataset 1. The graph shows an upwards swing in daily price during the beginning of 2021, not only for the selected cryptocurrencies but also for the NFT CryptoPunk. Bitcoin closing prices increased rapidly in January 2021, while Ethers prices increased to similar levels first in March 2021. CryptoPunk on the other hand saw another upwards swing during August and September 2021, with several large outliers, when the price drastically increased and then decreased.

Figure 1.23: Daily Price Dataset 2



For dataset 2 (Figure 1.23) it is again possible to see very similar price developments in Bitcoin and Ether but not as similar of developments when comparing the NFTs with each other and with the cryptocurrencies. Again, outliers in price were observed in the NFTs, one explanation for this could be sporadic purchases for large amounts.

Figure 1.23: Daily Price Dataset 2

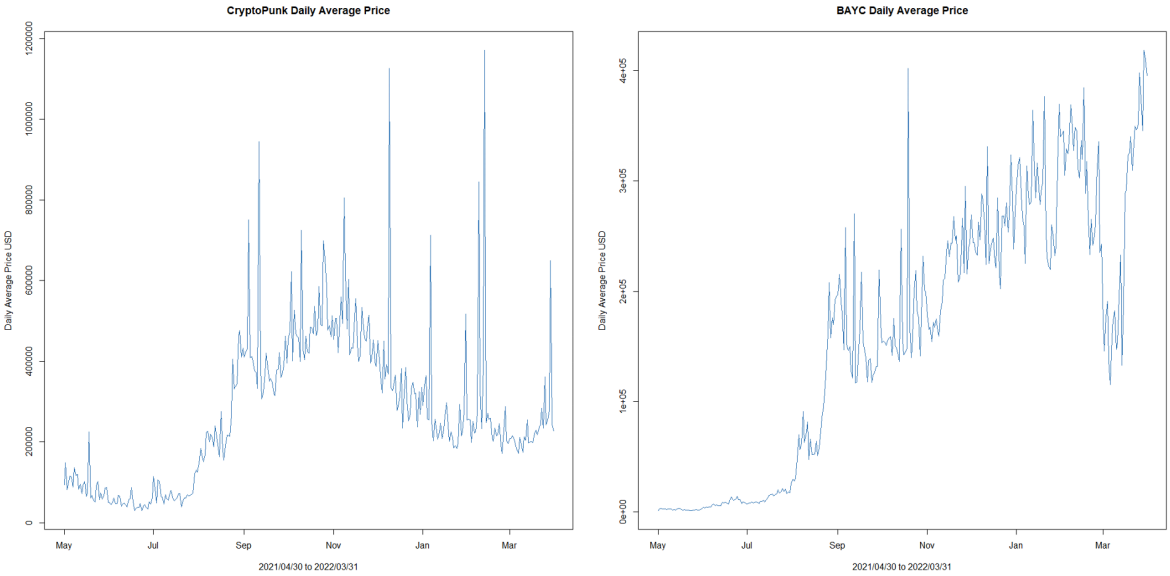


Figure 1.14 shows the daily return data for Bitcoin, Ether, and CryptoPunk of Dataset 1. Both Bitcoin and Ether show similar volatility graphs, and both witnessed large drawdowns after the outbreak of COVID-19, Bitcoin saw drawdowns of -37% and Ether -42% during that time frame.

Figure 1.14: Daily Return Dataset 1

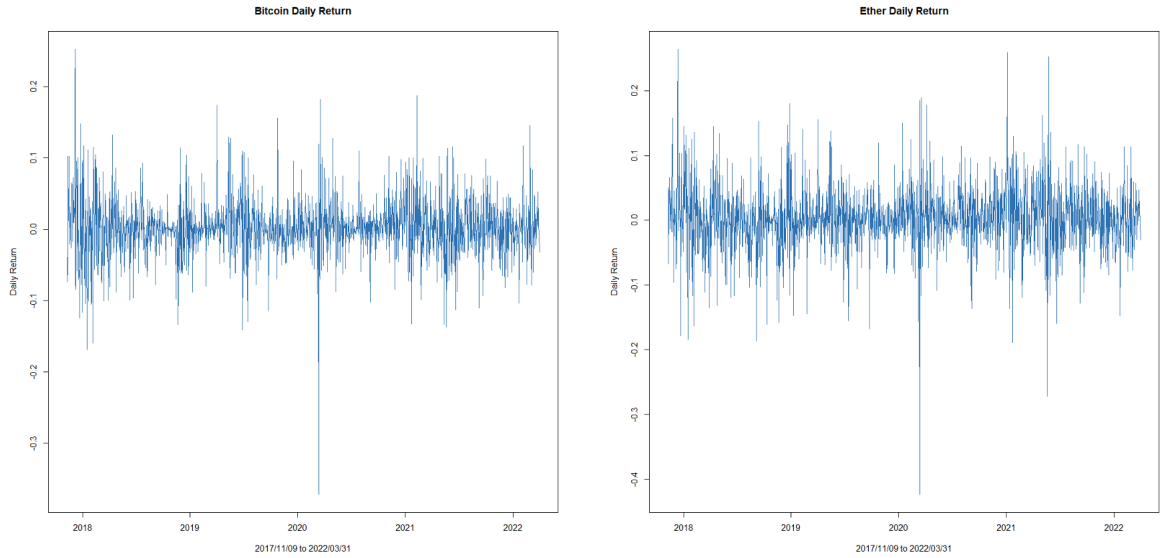
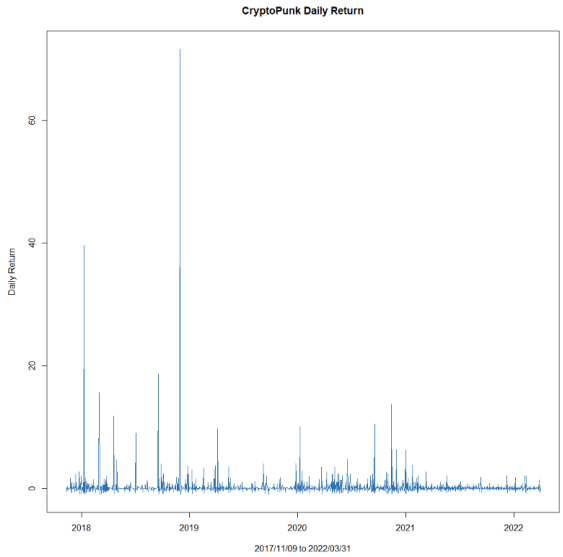


Figure 1.14: Daily Return Dataset 1



From the Figure 1.14 it is also shows signs of heteroscedasticity and volatility clustering, where there are times of higher volatility followed by higher volatility and periods of lower volatility followed by lower volatility. CryptoPunk witnessed large volatility spikes during some periods and on the 10th of January 2018 CryptoPunk spiked 4 000% after six transactions totaling 15 680 USD, and a witnessed drawdown of 40% the day after. The outliers of daily return in CryptoPunk were lower in Dataset 2 (Figure 1.24) with spikes of around 200% on several occasions, BAYC also saw a spike in daily return of 200% during its introduction.

Figure 1.24: Daily Return Dataset 2

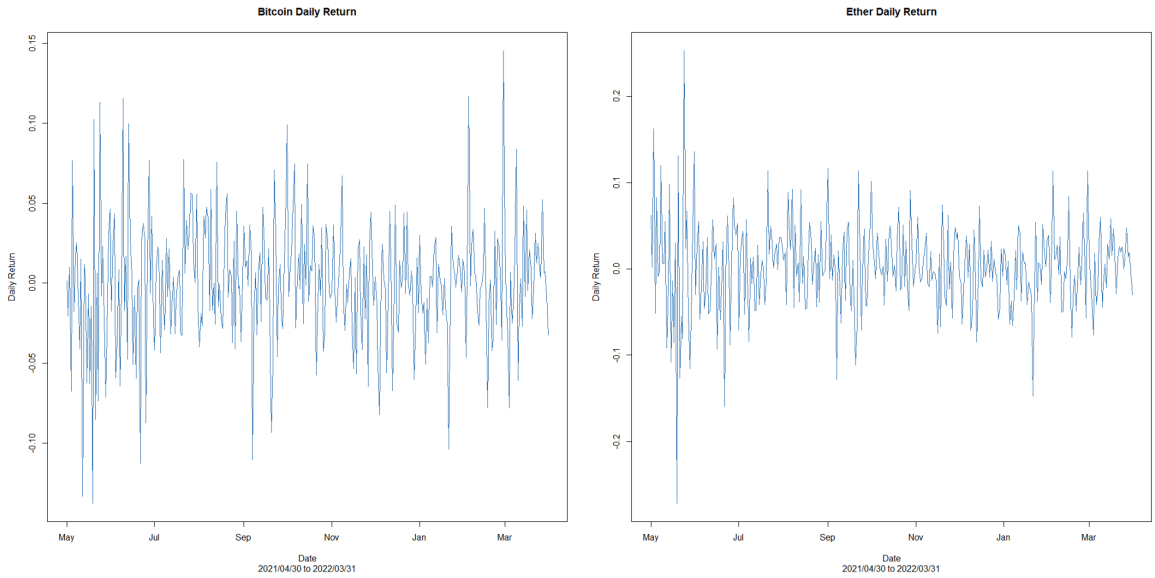


Figure 1.24: Daily Return Dataset 2

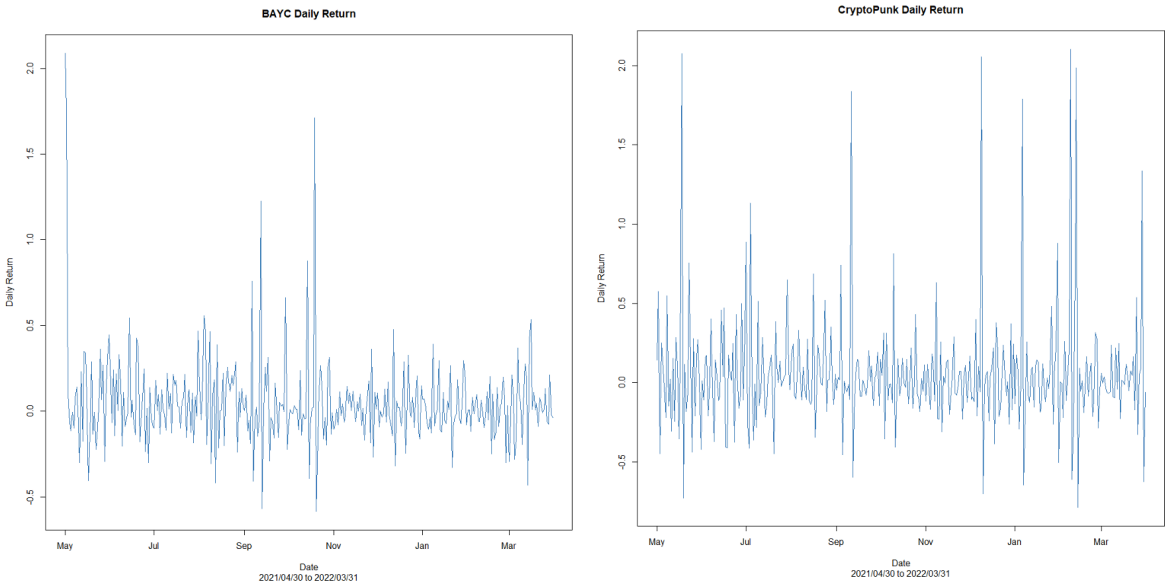


Table 1.12 and 1.23 presents the findings of the correlation matrix with the prices of the selected cryptocurrencies NFTs. Dataset 1 shows only positive values with significant correlation between Bitcoin and Ether as well as for Ether and CryptoPunk, implying that they correlated highly during this period, but as correlation is static, it does not conclude anything about the dynamic correlation during the period, something that will be examined further with the DCC-GARCH. Dataset 2 only shows positive values as well, but compared to dataset 1, witnessed a decrease in correlation between Ether and Bitcoin as well as with Ether and CryptoPunk, implying that the co-movement was lower during that period. BAYCs correlation with other digital assets was the lowest compared to the other assets measured.

TABLE 1.12: PEARSON'S PRODUCT-MOMENT CORRELATION ON PRICES DATASET 1

	BITCOIN	ETHER	CRYPTOPUNK
BITCOIN	1.000000		
ETHER	0.9255274	1.000000	
CRYPTOPUNK	0.7383914	0.8498129	1.000000

TABLE 1.23: PEARSON'S PRODUCT-MOMENT CORRELATION ON PRICES DATASET 2

	BITCOIN	ETHER	CRYPTOPUNK	BAYC
BITCOIN	1.000000			
ETHER	0.9157572	1.000000		
CRYPTOPUNK	0.6596019	0.6795784	1.000000	
BAYC	0.2775006	0.4285095	0.5271300	1.00000

4.2 VAR and Spillover Index

The purpose of the VAR model is to derive a spillover index using Forecast Error Variance Decomposition, FEVD, to measure how chocks in one of the three variables affect the other two. The Spillover Index is shown in Tables 1.21 and 2.21 and show us how much of the forecast error variance in the markets comes from volatility spillovers. The table provides an approximate decomposition of ''input–output'' of the total volatility spillover index (Diebold and Yilmaz, 2012).

TABLE 2.11: VOLATILITY SPILLOVER INDEX FOR DATASET 1

ALL VALUES ARE IN PERCENTAGES	**BITCOIN**	**ETHER**	**CRYPTOPUNK**	**DIRECTIONAL FROM OTHERS**
BITCOIN	21.04901	12.27762	0.00670	12.28432
ETHER	12.21118	21.11593	0.00621	12.21739
CRYPTOPUNK	0.00797	0.04174	33.28362	0.04972
DIRECTIONAL TO OTHERS[12]	12.21915	12.31936	0.01291	
DIRECTIONAL INCLUDING OWN	33.26817	33.43529	33.29653	

First, we consider the interpretation of Tables 2.11 and 2.21 for dataset 1 and 2 respectively. The row "directional to others" gives information regarding the gross directional volatility spillover to others. What can be noted in both tables and therefore in both dataset is that there is only a slight difference between Ether and Bitcoin with a gross volatility spillover to others between 12.2 % to 12.3 % in dataset 1 and from 10.4 % to 11.4 % in dataset 2. The difference in result between the dataset tells that the volatility spillover is higher during a longer period of time. CryptoPunk has a gross volatility spillover of only 0.013% in dataset 1 and of 0.32% in dataset 2. Although the volatility spillover is higher in dataset 2 both datasets provide a result meaning that CryptoPunk has a low spillover effect onto Bitcoin and Ether. BAYC, which is the added variable in dataset 2 only has a gross volatility spillover of 0.01 %, indicating a similar conclusion as with CryptoPunk.

The "directional from others" column shows that Bitcoin and Ether are again similar with spillovers from others between 12.2 % and 12.3 % in dataset 1 and between 10.4 % to 10.6 %

[12] The total of the variables above excluding own.

in dataset 2, whilst volatility spillover only explains 0.049 % of CryptoPunk forecast error variance in dataset 1 and 0.14 % dataset 2. BAYC has a forecast error variance of 1.89 % in this column indicating it receives volatility spillover more than it gives. To further explain the dataset, we can interpret that Ether and Bitcoin affect each other greater than they affect CryptoPunk. This is also clear when looking at the degree of which Bitcoins directional spillover explains the forecast error variance of Ether, 12.22 % and 9.81 %, and the degree of which Ethers directional spillover explains the forecast error variance of Bitcoin, 12.28 % and 10.11 % (numbers that are almost the same as the information presented in the "direction to others row" in both datasets). The index also presents that the forecast error variance of CryptoPunk and BAYC cannot be explained by any spillover from either each other, Ether, or Bitcoin.

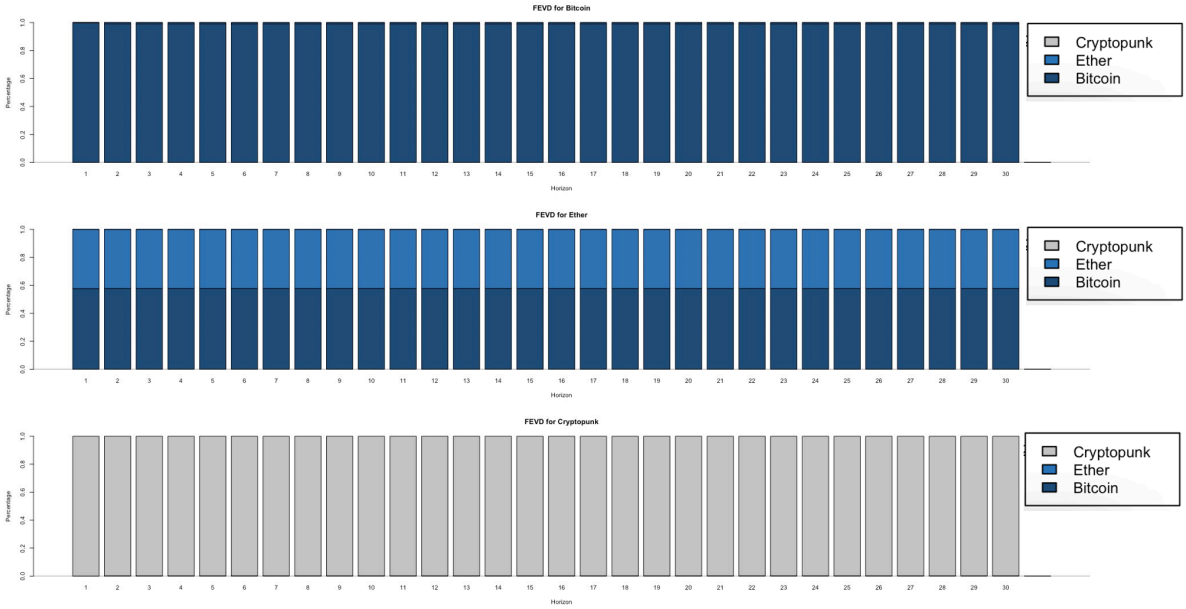
TABLE 2.21: VOLATILITY SPILLOVER INDEX FOR DATASET 2

ALL VALUES ARE IN PERCENTAGES	**BITCOIN**	**ETHER**	**CRYPTOPUNK**	**BAYC**	**DIRECTIONAL FROM OTHERS**
BITCOIN	14.59007	10.10661	0.07479	0.22852	10.40992
ETHER	9.81437	14.45907	0.14259	0.58396	10.54093
CRYPTOPUNK	0.02866	0.01099	24.86158	0.09877	0.13842
BAYC	0.58397	1.20899	0.10596	23.10107	1.89892
DIRECTIONAL TO OTHERS	10.42701	11.32660	0.32334955	0.91124	
DIRECTIONAL INCLUDING OWN	25.0170	25.785	25.18492	24.01231	

The total spillover to others is about 24.5 in dataset 1 and 23 in dataset 2, which is mostly from Bitcoin and Ether. In dataset 1 we compare 24.5 to the total (non-directional) volatility spillover[13] of 100[14] and we can infer that across the entire sample, 24.5 %[15] of the volatility forecast error variance in the three variables are a result of spillovers. The same process can be applied to dataset 2 which gives us the result that 23% of the volatility forecast error variance in the three variables are a result of spillovers.

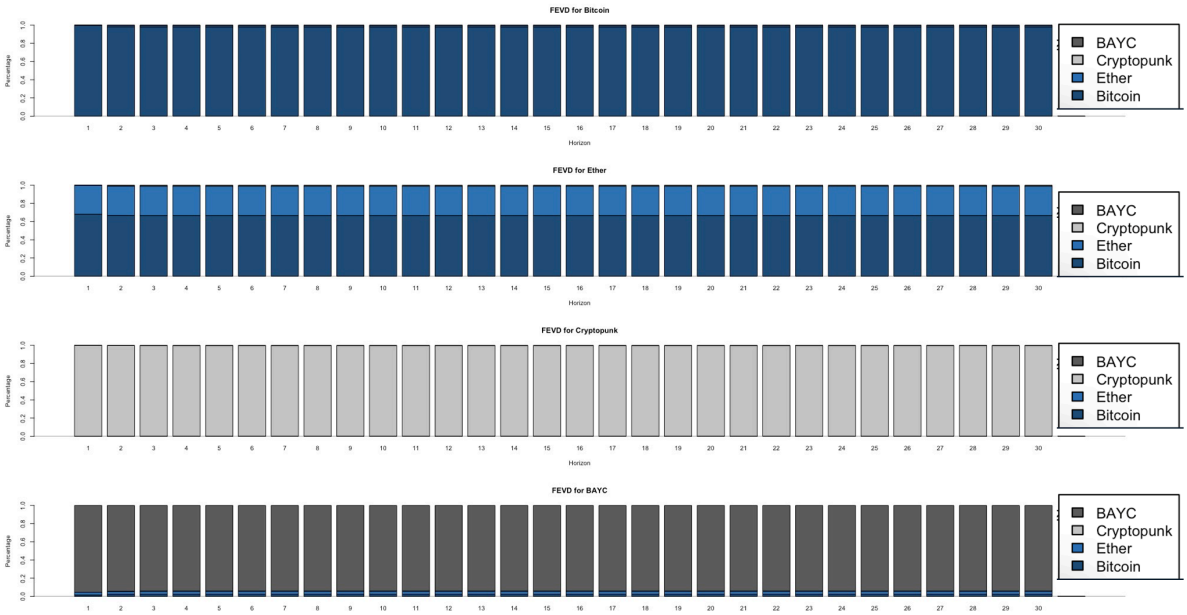
[13] A single index created through refining the three directional volatility spillovers.
[14] The total of the "directional including own" row.
[15] Total directional spillover to others/total directional including own.

Figure 2.11 - Dataset 1



Figures 2.11 and 2.21 gives us a visualization of the FEVD. The y-axis shows us the percentage, whilst the x-axis shows us the horizon in days over which the FEVD is measured. The horizon is set to 30 days since the cryptocurrency market is fast paced and shocks to Bitcoin affect other cryptocurrencies within a very short period of time. Therefore, the short run aspect for the FEVD is not more than a couple of days and the long run aspect is at the 20-to-30-day mark.

Figure 2.21 - Dataset 2



Looking at the FEVD for Bitcoin over the forecast period, it is clear that 100 % of the forecast error variance can be explained by itself in both datasets. This also means that Ether and CryptoPunk in dataset 1 have 0 % influence on Bitcoin which can also be said regarding dataset 2 with the addition of BAYC. The FEVD of Ether shows that it can be explained by Bitcoin by more than 50 % in dataset 1 and by more than 60% in dataset 2, the remaining being explained by itself below 50 %. This result demonstrates that Ether is heavily influenced by Bitcoin in both datasets, with no influence from CryptoPunk in dataset 1 or from CryptoPunk and BAYC in dataset 2. As both Bitcoin and Ether showed no influence from CryptoPunk in neither dataset, the result that they also do not influence CryptoPunk is not unpredictable. BAYC in dataset 2 has a similar result as that of CryptoPunk, but with some influence from Bitcoin and Ether. It can also be noted that for all the variables the amount of influence is stable over time, meaning that there is not difference between a short run and long run perspective.

As mentioned, the forecast error variance decomposition of the spillover index derives from the VAR model. Therefore, the validity of the interpretation above is based upon the fitness of the VAR model to the dataset. Prior to running the VAR model the Granger Causality test was applied to understand the bi-directional relationship between the variables. As presented in the methodology section of this thesis the desired outcome for a VAR model are Granger-Causal relationships from X to Y. Using dataset 1 the only two variables with a relationship was Bitcoin and Ether. The result also did not show a bi-directional relationship, but only that Ether Granger-causes Bitcoin[16]. Using dataset 2 the only variables with a relationship was Ether and BAYC as well as CryptoPunk and BAYC. The result also did not show a bi-directional relationship, but only that Ether and CryptoPunk Granger-causes BAYC. A Johansen and Engle-Granger Cointegration test was also conducted, and it also did not provide with the desired result. All variables in both datasets demonstrate cointegration[17].

The result of the VAR model, which can be seen in Tables 6.5 through 6.7 for dataset 1 and Tables 6.8 through 6.11 for dataset 2 in Appendix 1[18], were also not positive. The R^2, a number between 0 and 1, measures the fit of the model and indicated how much the variation in the dependent variable is explained by the independent variables. For all the estimated equations the R^2 is very small, indicating that the model is a "bad" fit since a low percentage of the

[16] See Table 6.1 in the Appendix 1.
[17] See Table 6.2 in Appendix 1.
[18] See Table 6.13 for information regarding results of lag-selection criterion.

variation in the variable is explained (Fernando, 2021). The Pr(>|t|), the p-value of the T-statistic, of the estimated equations are also on a majority not significant within a 0.05 significance level, meaning that the predictor variable does not have a statistically significant relationship with the response variable.

To further understand whether the VAR model was a good fit a normality [19] and autocorrelation[20] test was completed of the residuals on the two datasets. Both tests rejected the null hypothesis at a 5% significance level meaning that the residuals are autocorrelated and are not normally distributed. This is not a desired outcome of the VAR model since it can result in a number of issues regarding estimation accuracy due to their being autocorrelation as well as that the model does not describe all the trends in the dataset as a result of the residuals not being normally distributed.

As a result of the above tests a VECM model was considered since it allows for cointegration between variables. Unfortunately, the VECM model could not be conducted as it requires -1 lag from the result of the lag selection criterion, which for both datasets were 1 lag[21]. The decision was therefore made to proceed with the VAR model since it presented a new gap in Dowling's (2022) study allowing for a critical approach to his presented result[22].

4.3 EGARCH Model

The EGARCH estimation was conducted on each dataset separately, using the return data for the selected cryptocurrency and NFTs. As determined in the descriptive statistics (table 1.11 and table 1.21) all return data was stationary at level. First and foremost, autocorrelation and partial autocorrelation functions were conducted on the selected assets to determine optimal lag lengths for the autoregressive and moving average terms, this was done in conjunction with the Auto Arima function in R (Table 6.14 Appendix 1). The confidence interval for the selected autoregressive and moving average lag orders was determined according to the information criteria from AIC and BIC.

[19] See Table 6.3 in Appendix 1.
[20] See Table 6.4 in Appendix 1.
[21] See Table 6.13 in Appendix 1.
[22] See "Literature Review" for information regarding Dowling's (2022) use of the VAR model.

Because of the negative skewness in the return data of Bitcoin and Ether, an exponential GARCH (EGARCH) was chosen. The optimal lag model was determined to be an ARMA (1,1) EGARCH (1,1) model with a normal distribution. Although not optimal for all variables individually, it yielded the best results overall.

TABLE 3.11 ***THE ESTIMATION RESULTS OF EGARCH (1,1) MODEL DATASET 1***

PROBABILITIES ARE IN PARENTHESIS	**BITCOIN**	**ETHER**	**CRYPTOPUNK**
MEAN MODEL			
	0.0016 (0.0127)	0.0033 (0.7686)	0.0452 (0.0000)
ϕ (1)	0.3665 (0.0003)	0.9552 (0.0000)	0.0297 (0.0000)
θ (1)	-0.3969 (0.0001)	-0.9284 (0.0000)	-0.4718 (0.0000)
VARIANCE MODEL			
ω	-0.3092 (0.0000)	-0.4616 (0.4504)	-0.0056 (0.0000)
α (1)	-0.0747 (0.0003)	-0.1255 (0.1927)	-0.0767 (0.0000)
β (1)	0.9529 (0.0000)	0.9246 (0.0000)	0.9998 (0.0000)
γ	0.0160 (0.2806)	0.1665 (0.0215)	-0.0906 (0.0000)
INFORMATION CRITERIA			
AKAIKE	-3.6699	-3.1875	0.4287
HANNAN-QUINN	-3.6382	-3.1557	0.46047
RESIDUAL DIAGNOSTICS			
WEIGHTED-LJUNG-BOX STANDARDIZED RESIDUALS (LAG 9)	1.9133 (0.9879)	3.464 (0.8085)	10.636 (4.880e-03)
WEIGHTED LJUNG-BOX TEST ON STANDARDIZED SQUARED RESIDUALS (LAG 9)	4.850 (0.4518)	6.507 (0.2440)	2.2463 (0.8736)
WEIGHTED ARCH-LM TESTS (LAG 7)	4.107 (0.3314)	6.340 (0.1200)	2.419 (0.6290)
ADJUSTED PEARSON GOODNESS-OF-FIT (GROUP 20)	21.72 (0.2986)	26.37 (0.1201)	68.16 (1.852e-07)

As mentioned in the Method section, the EGARCH model includes a mean model where μ is a representation of the mean estimation, the autoregressive (ϕ) and moving average (θ) are for

one order of lag. α represents the ARCH effect, in essence to what extent that the magnitude of a shock to the variance affects future volatility in the returns of the asset. β on the other hand, is the GARCH term and it gives insight into the persistence of past volatility and how past volatility helps predict future volatility. The information criteria Akaike, Hanna-Quinn was used to determine the optimal GARCH model and residual diagnostics were conducted to test the validity of the model.

TABLE 3.21 ***THE ESTIMATION RESULTS OF EGARCH (1,1) MODEL DATASET 2***

	BITCOIN	**ETHER**	**CRYPTO PUNK**	**BAYC**
MEAN MODEL				
μ	0.0001 (0.9443)	0.0033 (0.7686)	0.0452 (0.0000)	0.0402 (0.0000)
ϕ (1)	0.3666 (0.0003)	0.9552 (0.0000)	0.0297 (0.0000)	0.0538 (0.0000)
θ (1)	-0.3969 (0.0001)	-0.9284 (0.0000)	-0.4718 (0.0000)	-0.4336 (0.0000)
VARIANCE MODEL				
ω	0.3092 (0.0000)	-0.4616 (0.4505)	-0.0056 (0.0000)	-0.1872 (0.0850)
α (1)	-0.0747 (0.0003)	-0.1255 (0.1927)	-0.0767 (0.0000)	-0.1096 (0.0669)
β (1)	0.9529 (0.0000)	0.9247 (0.0000)	0.9998 (0.0000)	0.9294 (0.0000)
γ	0.0160 (0.2805)	0.1665 (0.0215)	-0.0905 (0.0000)	0.4990 (0.0000)
INFORMATION CRITERIA				
AKAIKE	-3.6699	-3.1875	0.42870	-0.0597
HANNAN-QUINN	-3.6382	-3.1557	0.46047	-0.0279
RESIDUAL DIAGNOSTICS				
WEIGHTED LJUNG-BOX STANDARDIZED RESIDUALS (LAG 9)	1.91330 (0.9879)	3.464 (0.8085)	10.6356 (4.88e-03)	9.566 (0.0140)
WEIGHTED LJUNG-BOX TEST ON STANDARDIZED SQUARED RESIDUALS (LAG 9)	4.850 (0.4518)	6.507 (0.2440)	2.2463 (0.8736)	2.9934 (0.7601)
WEIGHTED ARCH-LM TESTS (LAG 7)	4.107 (0.3314)	6.3400 (0.1200)	2.4199 (0.6290)	2.9277 (0.5273)
ADJUSTED PEARSON GOODNESS-OF-FIT (GROUP 20)	21.72 (0.2986)	26.37 (0.1201)	68.16 (1.85e-07)	56.34 (1.444e-05)

As can be seen from Table 3.11 for dataset one in the mean model for the EGARCH (1,1) all coefficients in the mean equation show significant values except for the μ value for Bitcoin and Ether, the same applies for the values in dataset two (Table 3.21), suggesting that one order of

lag in the autoregressive as well as moving average term are significant in determining the volatility of the assets. With regards to the variance model, ω is insignificant for Ether in both datasets and insignificant for BAYC in dataset two. α is significant for all variables but not for Ether, suggesting that an EGARCH (0,1) model might be more suitable to study the volatility of Ether. β is significant for all studied assets for both datasets implying that past volatility is a valid predictor of future volatility. γ is negative and significant for CryptoPunk in both datasets implying an asymmetric volatility effect, meaning that a negative shock has influence on the future volatility of the assets return. γ is also significant and positive for Ether in both datasets as well as for BAYC, implying that a positive chock has influence on the future volatility of the asset return. Bitcoin on the other hand had an insignificant γ value for both datasets implying no asymmetric volatility effect.

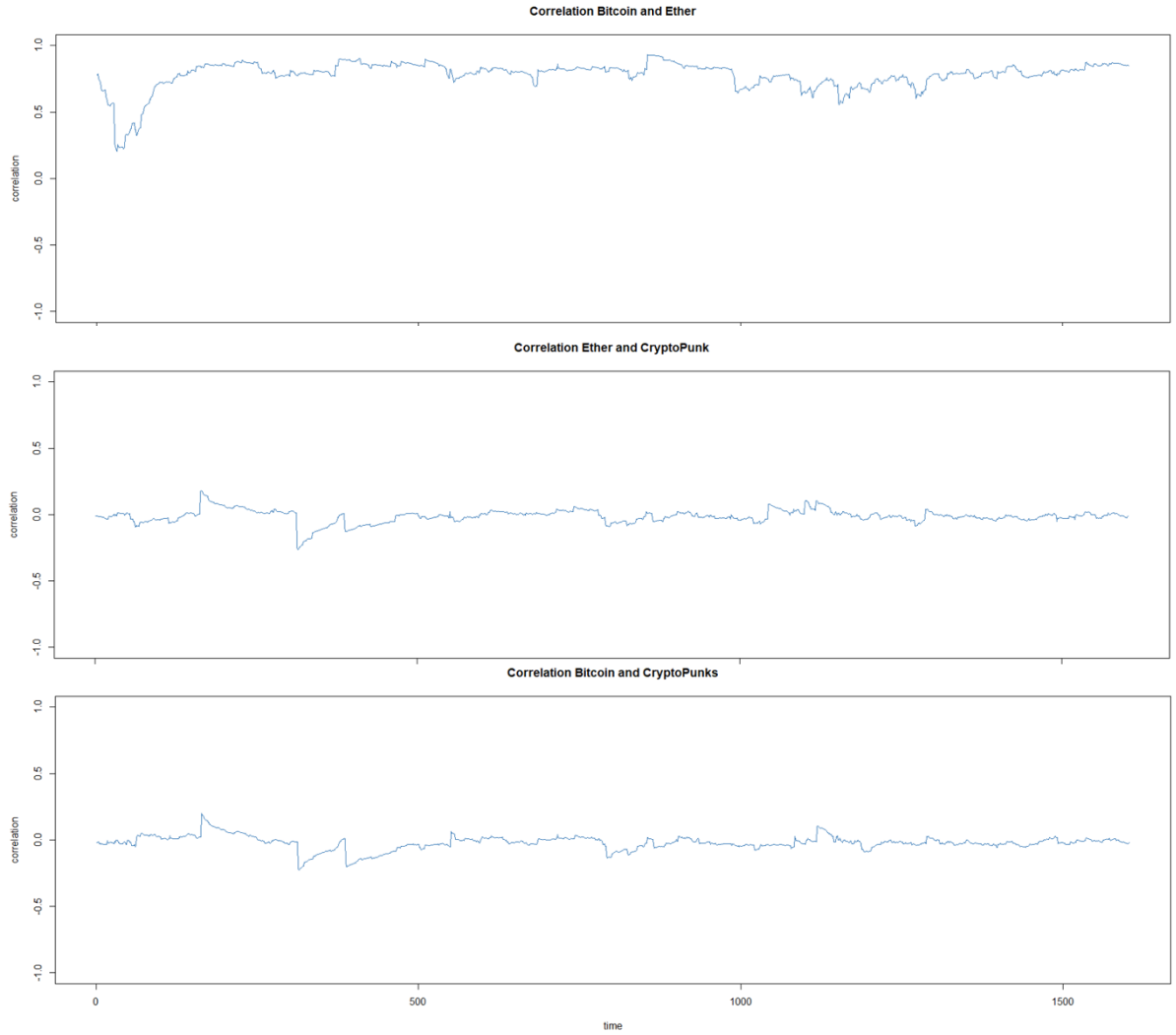
When evaluating the residual diagnostics, the Weighted Ljung-Box Test on Standardized Squared Residuals for a lag order of nine show a p-values>0.05 for all variables. The variables fail to reject the null hypothesis and there is no evidence of autocorrelation in the squared residuals. As a result, we can conclude that the squared residuals behave as white noise. The Weighted Ljung-Box Test on Standardized residuals with a lag order of nine show p-values<0.05 for CryptoPunk in both datasets and BAYC, rejecting the null hypothesis of no evidence of autocorrelation in the residuals. The p-values>0.05 for all variables in the weighted ARCH-LM test, fail to reject the null hypothesis and there is no ARCH effect. The residuals behave as a white noise process. the Adjusted Pearson Goodness-of-Fit test for Bitcoin and Ether show p-values>0.05, they fail to reject the null hypotheses which implies that the empirical and the theoretical distribution is identical, this is not the case for CryptoPunk and BAYC were the p-values<0.05, implying that the normality distribution selected is not adequate for the given dataset.

4.4 DCC-GARCH Model

The EGARCH model captures volatility as an estimate of previous volatility, but it is unable to capture the volatility spillovers across markets and unable to provide co-volatility. The assumption is that the current volatility of one asset is not only influenced by its own past volatility but also by the volatility of other assets. To capture the volatility spillovers across the selected cryptocurrency's and NFTs the DCC-GARCH model was constructed. The DCC-GARCH is based on the EGARCH (1,1) model constructed making it a DCC-EGARCH (1,1).

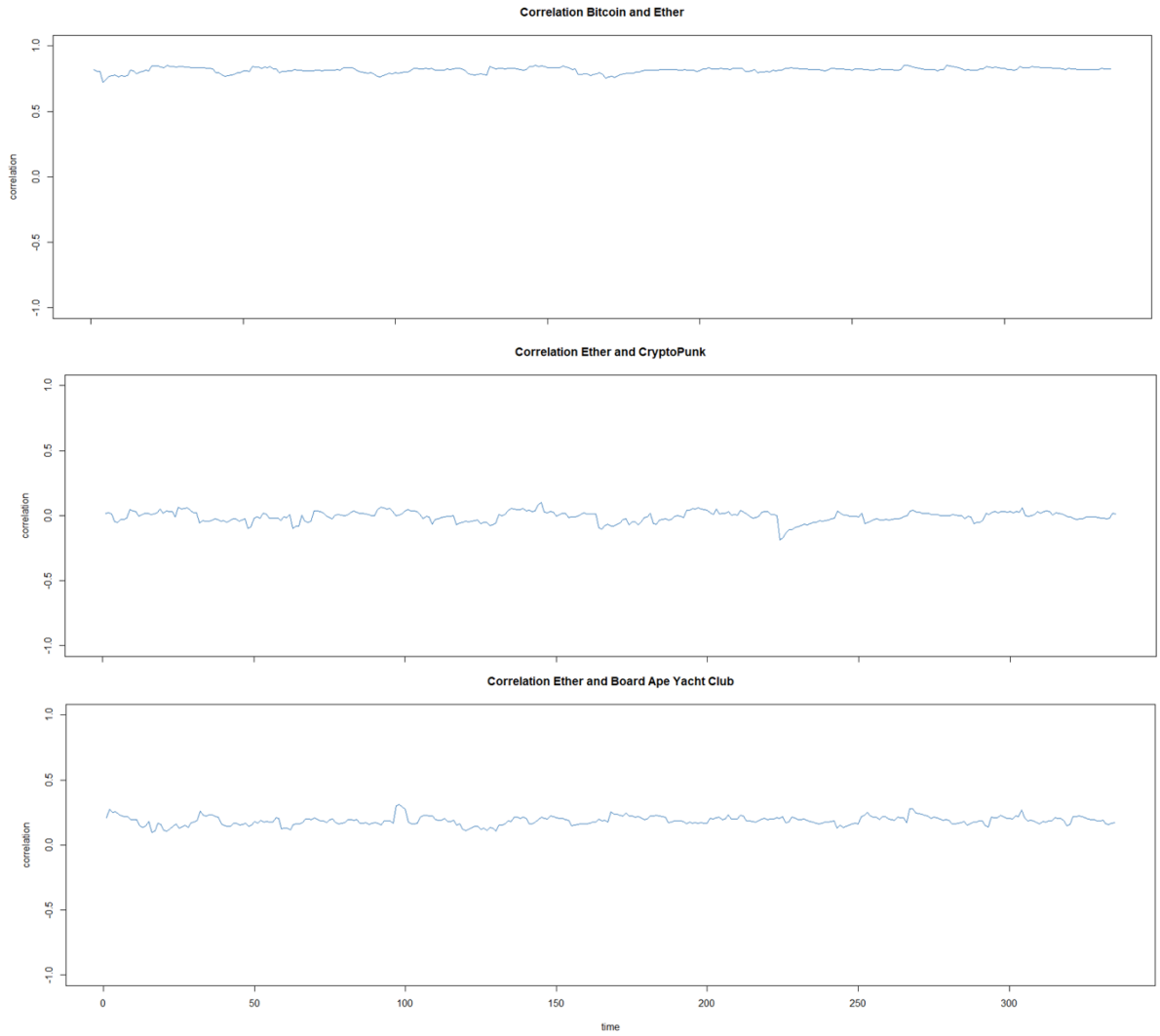
Figure 4.11 shows the conditional correlation between Bitcoin, Ether and CryptoPunk for dataset one. Bitcoin and Ether show significant correlation for most of the evaluated period, implying that their daily returns behave very similarly. From the plot it can be deducted that correlation between the return of Bitcoin and Ether was significantly lower during the end of November and early December 2017 compared to the other periods, coming down from a correlation of 0.8 to a correlation of 0.2. The correlation between Ether and CryptoPunk as well as the correlation of Bitcoin and CryptoPunk was insignificant between the selected assets for most of the period. Some spikes of higher as well as lower correlation can be witnessed, but most of the time there was no correlation between the cryptocurrencies and the NFT CryptoPunk. These spikes are a result of the outlier returns in CryptoPunk. The negative correlation in July 2018, was due to large spikes CryptoPunk daily volatility, increasing by 900% during the fifth of July compared to Bitcoin and Ether which decreased by 1% and 0,6% respectively.

Figure 4.11: Dynamic Conditional Correlation Dataset 1



Dataset two shows a more stable correlation during the observed period with less spikes in correlation. Figure 4.21 shows the conditional correlation between the selected cryptocurrencies Bitcoin and Ether as well as the conditional correlation between Ether and the selected NFTs CryptoPunk and BAYC. Bitcoin and Ether show significant correlation for the entire period. From the plot we are unable to determine significant changes in correlation over the period. The correlation between Ether and BAYC was low during most of the selected period, with a negative correlation during the middle of December 2021 of around -0.3. The correlation between Ether and CryptoPunk was low, with a smaller spike during the beginning of august 2021, were correlation increased to around 0.4.

Figure 4.21: Dynamic Conditional Correlation Dataset 2

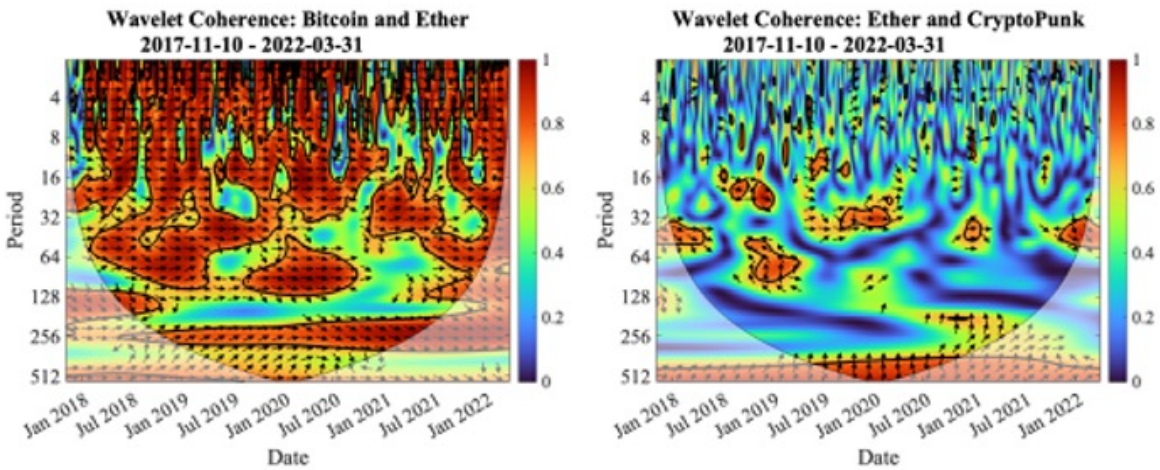


4.5 Wavelet Coherence Model

As mentioned in the Methodology section of this thesis, chapter 3.3.3, a wavelet coherence model can be described as a localized correlation coefficient, but in a time frequency space.

Figure 5.11 are the results of the wavelet coherence analysis for dataset 1 and consists of a co-movement analysis of daily returns between Bitcoin and Ether as well as Ether and CryptoPunk. As has been presented in the results of the DCC-GARCH, Bitcoin has a high conditional correlation with Ether, which is confirmed in the first scalogram in Figure 5.11. Within the COI, which gives us an accurate representation of the time series frequency, we have several parameters that align with the result from the DCC-GARCH. The areas that we are focusing on are those contoured in black since they are within the 5% Monte Carlo significance level.

Figure 5.11 – Dataset 1

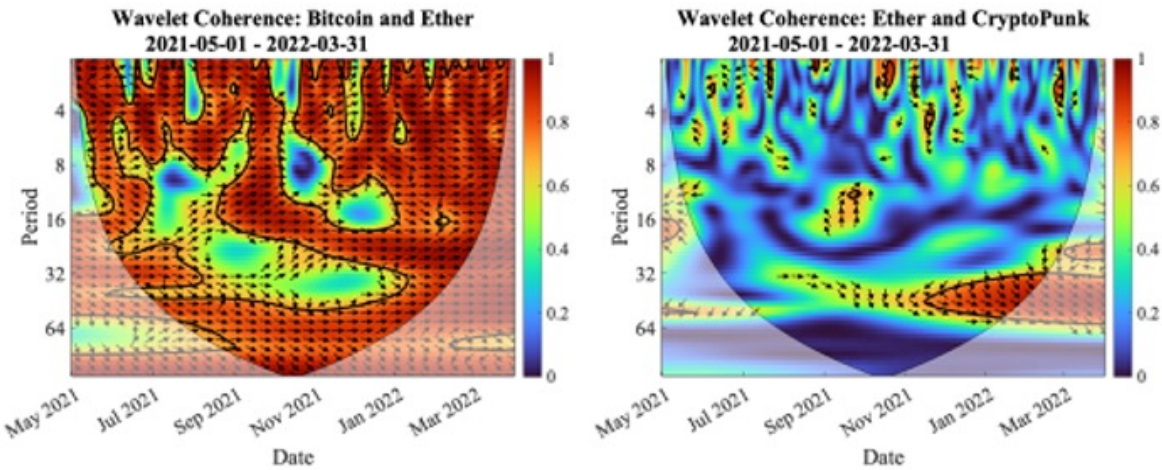


First, the direction of the arrows (↖ and ↘) that can be seen throughout the entire scalogram and more importantly within the significance level, indicates that Bitcoin is leading Ether. For the purpose of this thesis, it indicates that the daily return of Ether is strongly affected by the daily return of Bitcoin. Secondly, we can see that scalogram consists of a great amount of red which indicates high correlation between the two variables. The red is apparent within all periods of the scalogram but is even more concentrated between periods 1 and 8. This information tells us is that in the short term the two cryptocurrencies have a stronger correlation than that of the long term, but as the scalogram shows the correlation is strong throughout the whole time period of November 2017 and March 2022.

The second scalogram in Figure 5.11 shows us the co-movement and correlation between Ether and CryptoPunk. During the time period November 2017 and March 2022, we see low correlation between CryptoPunk and Ether. Within the significant areas, which in this case are very few, it can be said through looking at the arrows of ↖ and ↘ that Ether leads CryptoPunk. Even so, since these areas are so few and sporadic as well as being concentrated between periods 8 though 128, a period of three months, the affect Ether has on CryptoPunk is extremely low. Therefore, the conclusion can be made that volatility spillover from Ether to CryptoPunk is extremely low during this time period, which is in line with the results from DCC-GARCH.

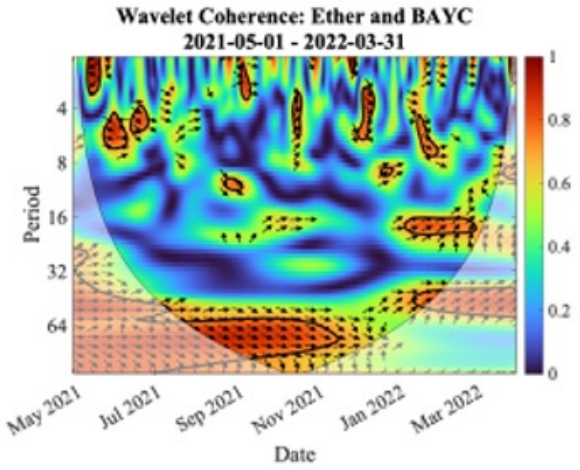
Figures 5.21 and 5.22 are the results of the wavelet coherence analysis for dataset 2 and they

Figure 5.21 – Dataset 2



consist of a co-movement analysis of daily returns between Bitcoin and Ether, Ether and CryptoPunk, and Ether and BAYC. The first scalogram in Figure 5.21 is the wavelet coherence between Bitcoin and Ether of the time period May 2021 to March 2022. The co-movement between Bitcoin and Ether in dataset 2 is similar to that of dataset 1, but even more concentrated. As the scalogram consists of mostly red there is a high correlation between the two variables. Dataset 2 also shows a greater area of significance in comparison to dataset 1, which can be a result of the shorter time frame. As with dataset 1 the arrows of ↖ and ↘ indicate that Bitcoin is leading Ether, meaning that the daily return of Ether is heavily influenced by the daily return of Bitcoin. This infers that the volatility spillover from Bitcoin to Ether is high, which in this dataset is also coherent with the result of the DCC-GARCH.

Figure 5.22 – Dataset 2



The second scalogram in Figure 5.21 is the wavelet coherence between Ether and CryptoPunk. As with dataset 1 the co-movement and correlation between Ether and CryptoPunk is low as can be seen with the amount of blue color present. The number of areas within the significance level are few and are mostly concentrated with periods 1 through 16. Within the areas of significance, the arrows of ↖ and ↘ indicate that Ether leads CryptoPunk, but due to the low overall correlation between the two variables that aspect is not of high implication.

The scalogram in Figure 5.22 shows the co-movement and correlation between Ether and BAYC. The correlation between Ether and BAYC is low, similar to that of the relationship between Ether and CryptoPunk. Although the two scalograms are not identical they are indicating a similar result. Within the majority of the significance areas the arrows of ↖ and ↘ indicate that Ether leads BAYC, but around January 2022 as well as when a longer period of time has passed by BAYC is leading Ether, which is a result not present in the wavelet coherence between Ether and CryptoPunk. This can be as a result of the BAYC having just being launched a short time prior and the hype of the collection still not having died down.

Since we know from the descriptive statistics, DCC-GARCH model, and the wavelet coherence analysis between Bitcoin and Ether that Ether is strongly affected by Bitcoin, an analysis between Bitcoin and CryptoPunk as well as Bitcoin and BAYC won't be conducted.

5. Discussion

The results from the EGARCH model indicate that both the cryptocurrency market and NFT market are volatile. The NFTs that were observed witnessed very high returns during the studied periods with standard deviations that were relatively higher than cryptocurrencies. Bitcoin and Ether correlate significantly, when observed dynamically, indicating that the existence of a spillover effect is prevalent between the cryptocurrencies. This can also be seen through the Spillover Index and FEVD for both datasets. From the Wavelet Coherence Analysis, it can be observed that Bitcoin leads Ether, meaning that daily price fluctuations in Bitcoin have a significant effect on the daily price movement of Ether. It can be concluded that even though cryptocurrencies and NFTs, both, have witnessed high returns in the last five years they behave quite differently from each other and that observed co-movement is low.

Although the price development of NFTs, especially CryptoPunk, correlate significantly with the cryptocurrencies Bitcoin and Ether in both datasets as can be seen in Figures 1.13 and 1.23, the return data shows no correlation when observed dynamically through the DCC-GARCH model and through the Wavelet Coherence analysis, indicating no volatility spillover between cryptocurrencies and NFTs. The volatility of the NFTs observed are determined by themselves or from other exogenous variables in the NFT sphere that have not been considered in this thesis. This is of interest due to the similarities between NFTs and cryptocurrencies; both originating as innovations of blockchain technology and NFTs are solely purchasable with cryptocurrencies. Intuitively one would assume that the chocks in a cryptocurrency would affect NFTs, but our models are presenting a different conclusion. The volatility present in the NFT market is rather attributed to the market becoming more popular since the beginning of 2021. Looking at Figure 1.13 in chapter 4.1 of CryptoPunks price development it is clear that its heights are reached post January 2021. It can also be seen in BAYC in Figure 1.23 that its price development from launch day at the end of April reached high numbers much quicker than CryptoPunk had during a much longer time period. The FEVD of both datasets also give the same conclusion since the volatility present in each variable is caused by itself and not Bitcoin or Ether.

Two datasets were used to conduct this thesis in order to capture a short and long run effect of co-movement. Because NFTs are still quite new, there is not much data available and the majority of NFTs have only existed in the last couple of years which makes it impossible to

measure a longer time interval as of now. Furthermore, only the largest NFTs by market capitalization, as of now, have been examined, making it unable to draw conclusions regarding the whole market from this thesis. As the daily trading volumes of these NFTs are low, other NFTs, that are traded more frequently might be more suitable to evaluate co-movement.

Although the VAR model and spillover index indicate similar results as the DCC-GARCH and Wavelet Analysis, the VAR model lacks reliability compared to the other models. The residual diagnostics show significant autocorrelation as well as a non-normal distribution in the residuals. The VAR model is thus inadequate for this type of dataset. This can also be said about the EGARCH model with regards to analyzing NFT data. As the EGARCH model is univariate, calculating the conditional variance for each asset independently, an all-encompassing model is difficult to construct, especially when data varies substantially from each other. The variables were not normally distributed, but they did not follow any other distributions either, which made it important to compromise on the best model. This could have an impact on the DCC-model that was later constructed. Lastly unconditional volatility was not modeled and instead captured through the Wavelet Coherence model, this could instead be modeled through an unconditional volatility matrix.

6. Conclusion

As mentioned previously in this thesis the research within the economics of NFTs as well as their connection to the cryptocurrency market is limited. Therefore, this thesis has contributed to the field by investing the relationship between the two markets through the application of not previously used models. The result of our analysis is clear in aspects of the volatility and volatility spillover effects between cryptocurrencies and gives us an understanding of the NFT markets independence of the cryptocurrency market with regards to volatility spillover on NFT pricing. Our result also offers a coherence conclusion with that of Dowling (2022) and Özdemir (2022) with reference to NFT pricing not seeing effects from the volatility of the cryptocurrency market and how volatility exists between the cryptocurrencies, respectively.

For further study within this field, we recommend an extended analysis of how spill-over effects of cryptocurrencies other than Bitcoin and Ethereum affect the pricing of NFTs. In this thesis, we limited our analysis to Bitcoin and Ethereum as well as NFTs on the Ethereum blockchain. Therefore, we see a possibility for a broader understanding through the analysis of cryptocurrencies such as MANA and how it affects the pricing of LAND in DecentraLand (Dowling, 2022). As we presented in our discussion the VAR model was not adequate for our chosen datasets as well as the EGARCH not necessarily being the best fit for NFT data. Therefore, we propose that the continued study of NFTs should apply models beyond this thesis.

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Appendix

Appendix 1

Definition 1 – Blockchain: Blockchain is a digital ledger that stores all data that is distributed on the blockchain. For example, a blockchain records cryptocurrency transactions and information regarding NFT ownership through smart contracts. Another unique aspect of a blockchain that differentiates it from databases is that is completely decentralized. This means that it is not upheld or maintained in on location by an administrator, such as an Excel spreadsheet or bank database, but rather that exact copies of the blockchain are stored on multiple computers across the network and are called nodes (Rodeck and Curry, 2022).

TABLE 6.1 – GRANGER CAUSALITY TEST

DATASET 1				
PR(>F)	**BITCOIN**	**ETHER**	**CRYPTOPUNK**	
BITCOIN	-	0.00135	0.9233	
ETHER	0.6035	-	0.7163	
CRYPTOPUNK	0.5239	0.07287	-	
DATASET 2				
PR(>F)	**BITCOIN**	**ETHER**	**CRYPTOPUNK**	**BAYC**
BITCOIN	-	0.277	0.3058	0.8247
ETHER	0.1727	-	0.1257	0.9765
CRYPTOPUNK	0.7209	0.9458	-	0.7839
BAYC	0.9382	0.01132	0.04887	-

TABLE 6.2 – COINTEGREATION TEST

DATASET 1 – ENGLE-GRANGER				
P-VALUE	**BITCOIN**	**ETHER**	**CRYPTOPUNK**	
BITCOIN	-	< 0.001	< 0.001	
ETHER	< 0.001	-	< 0.001	
CRYPTOPUNK	< 0.001	< 0.001	-	
DATASET 1 – JOHANSEN				
	TEST		***5 %***	
More than 2 variables cointegrate	583.27		9.24	
More than 1 variable cointegrate	634.82		15.67	
No variables cointegrate	700.06		22.00	
DATASET 2				
P-VALUE	**BITCOIN**	**ETHER**	**CRYPTOPUNK**	**BAYC**
BITCOIN	-	< 0.001	< 0.001	< 0.001
ETHER	< 0.001	-	< 0.001	< 0.001
CRYPTOPUNK	< 0.001	< 0.001	-	< 0.001
BAYC	< 0.001	< 0.001	< 0.001	-
DATASET 2 – JOHANSEN				
	TEST	***5 %***		
More than 3 variables cointegrate	111.51	9.24		

More than 2 variables cointegrate	260.77	19.96
More than 1 variable cointegrate	510.52	34.91
No variables cointegrate	782.33	53.12

TABLE 6.3 - NORMALITY PORTMANTEAU TEST

DATASET 1	
CHI-SQUARED	155.45
DF	99
P-VALUE	0.0002527
DATASET 2	
CHI-SQUARED	231.95
DF	176
P-VALUE	0.002991

TABLE 6.4 – AUTOCORRELATION TEST (MULTIVARIATE)

Jacque Bera Test		**Skewness Test**		**Kurtosis Test**	
DATASET 1					
Chi-Squared	25951332	**Chi-Squared**	133122	**Chi-Squared**	25818210
df	6	**df**	3	**df**	3
P-value	< 2.2e-16	**P-value**	< 2.2e-16	**P-value**	< 2.2e-16
DATASETt 2					
Chi-squared	6968.9	**Chi-squared**	950.83	**Chi-squared**	6018.1
df	8	**df**	4	**df**	4
P-VALUE	< 2.2E-16	**P-VALUE**	< 2.2E-16	**P-VALUE**	**< 2.2E-16**

TABLE 6.5: DATASET 1 - ESTIMATION RESULTS FOR EQUATION BITCOIN DAILY RETURN

	ESTIMATE	**STD.ERROR**	**T-VALUE**	**Pr(>|t|)**
BITCOIN DAILY RETURN	0.0825129	0.0380738	2.167	0.030368
ETHER DAILY RETURN	0.1156294	0.0304353	-3.799	0.000151
CRYPTOPUNK DAILY RETURN	0.0002181	0.0004398	0.496	0.620018
CONSTANT	0.0021557	0.0010268	2.099	0.035935
RESIDUAL STANDARD ERROR	0.0408			
ADJUSTED R-SQUARED	0.007985			
F-STATISTIC/P-VALUE	5.296	0.001238		

TABLE 6.6: DATASET 1 - ESTIMATION RESULTS FOR EQUATION ETHER DAILY RETURN

	ESTIMATE	**STD.ERROR**	**T-VALUE**	**Pr(>|t|)**
BITCOIN DAILY RETURN	-0.0518746	0.0478225	-1.085	0.2782
ETHER DAILY RETURN	-0.0092713	0.0382282	-0.243	0.8084
CRYPTOPUNK DAILY RETURN	0.0002282	0.0005524	0.413	0.6795
CONSTANT	0.0029078	0.0012897	2.255	0.0243

RESIDUAL STANDARD ERROR	0.05124	
ADJUSTED R-SQUARED	0.0006405	
F-STATISTIC/P-VALUE	1.342	0.2591

TABLE 6.7: DATASET 1 - ESTIMATION RESULTS FOR EQUATION CRYPTOPUNK DAILY RETURN

	ESTIMATE	**STD.ERROR**	**T-VALUE**	**Pr(>|t|)**
BITCOIN DAILY RETURN	-2.05530	2.16305	-0.950	0.342
ETHER DAILY RETURN	2.70973	1.72909	1.567	0.117
CRYPTOPUNK DAILY RETURN	-0.03419	0.02498	-1.368	0.171
CONSTANT	0.25243	0.05833	4.327	1.6e-05
RESIDUAL STANDARD ERROR	2.318			
ADJUSTED R-SQUARED	0.0009292			
F-STATISTIC/P-VALUE	1.496	0.2137		

TABLE 6.8: DATASET 2 - ESTIMATION RESULTS FOR EQUATION BITCOIN DAILY RETURN

	ESTIMATE	**STD.ERROR**	**T-VALUE**	**Pr(>|t|)**
BITCOIN DAILY RETURN	0.1201356	0.0978051	1.228	0.2202
ETHER DAILY RETURN	-0.1653761	0.0745485	-2.218	0.0272
CRYPTOPUNK DAILY RETURN	-0.0063813	0.0057148	-1.117	0.2650
BAYC DAILY RETURN	0.0055879	0.0089123	0.627	0.5311
CONSTANT	0.0004954	0.0021779	0.227	0.8202
RESIDUAL STANDARD ERROR	0.03874			
ADJUSTED R-SQUARED	0.01056			
F-STATISTIC/P-VALUE	1.886	0.1126		

TABLE 6.9: DATASET 2 - ESTIMATION RESULTS FOR EQUATION ETHER DAILY RETURN

	ESTIMATE	**STD.ERROR**	**T-VALUE**	**Pr(>|t|)**
BITCOIN DAILY RETURN	0.151138	0.129437	1.168	0.2438
ETHER DAILY RETURN	-0.183257	0.098659	-1.857	0.0641
CRYPTOPUNK DAILY RETURN	-0.012732	0.007563	-1.683	0.0932
BAYC DAILY RETURN	0.012267	0.011795	1.040	0.2991
CONSTANT	0.002145	0.002882	0.744	0.4574
RESIDUAL STANDARD ERROR	0.05127			
ADJUSTED R-SQUARED	0.01018			
F-STATISTIC/P-VALUE	1.854	0.1183		

TABLE 6.10: DATASET 2 - ESTIMATION RESULTS FOR EQUATION CRYPTOPUNK DAILY RETURN

	ESTIMATE	STD.ERROR	T-VALUE	Pr(>|t|)
BITCOIN DAILY RETURN	0.21303	0.90056	0.237	0.813154
ETHER DAILY RETURN	0.01468	0.68642	0.021	0.982951
CRYPTOPUNK DAILY RETURN	-0.28692	0.05262	-5.453	9.77e-08
BAYC DAILY RETURN	-0.10192	0.08206	-1.242	0.215142
CONSTANT	0.07333	0.02005	3.657	0.000297
RESIDUAL STANDARD ERROR	0.3567			
ADJUSTED R-SQUARED	0.07672			
F-STATISTIC/P-VALUE	7.896	4.359e-06		

TABLE 6.11: DATASET 2 - ESTIMATION RESULTS FOR EQUATION BAYC DAILY RETURN

	ESTIMATE	STD.ERROR	T-VALUE	Pr(>|t|)
BITCOIN DAILY RETURN	-0.07379	0.54657	-0.135	0.892683
ETHER DAILY RETURN	0.72639	0.41660	1.744	0.082166
CRYPTOPUNK DAILY RETURN	0.02371	0.03194	0.742	0.458405
BAYC DAILY RETURN	-0.22454	0.04981	-4.508	9.1e-06
CONSTANT	0.04349	0.01217	3.573	0.000405
RESIDUAL STANDARD ERROR	0.2165			
ADJUSTED R-SQUARED	0.06237			
F-STATISTIC/P-VALUE	6.521	4.64e-05		

Figure 6.12: Decomposition of returns in Bitcoin, Ether and CryptoPunks Dataset 1

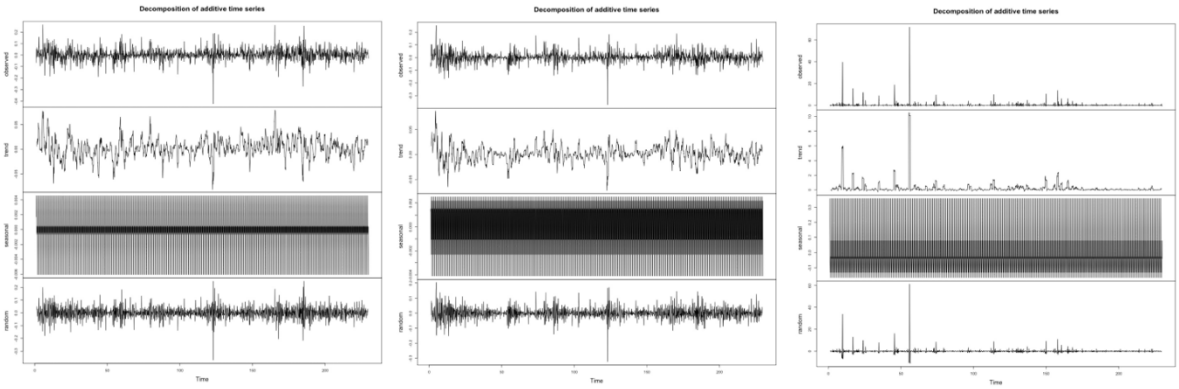

Figure 6.13: Decomposition of returns in Cryptopunks, Ether, Board Ape Yacht Club and Bitcoin Dataset 2

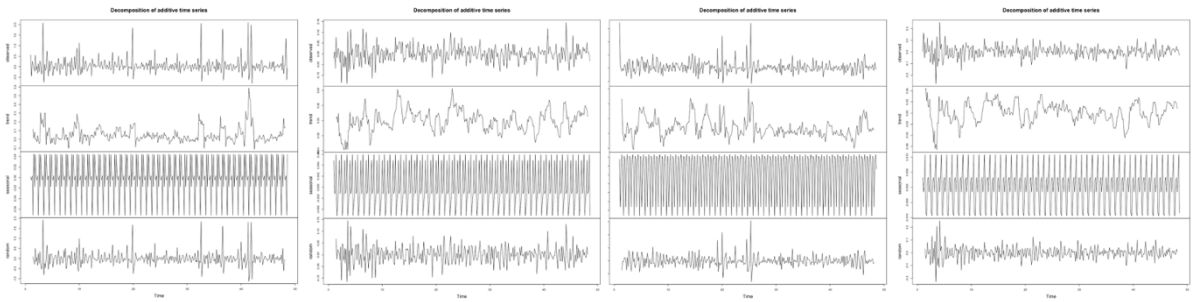

TABLE 6.13: LAG SELECTION CRITERION

	AKAIKE	HANNAN-QUINN	SCHWARTZ
DATASET 1	1	1	1
DATASET 2	1	1	1

TABLE 6.14: OPTIMAL ARIMA MODEL ACCORDING TO AIC AND BIC

	Bitcoin	Ether	Cryptopunks	BAYC
DATASET 1	(1,0,0)	(2,0,1)	(5,0,1)	
DATASET 2	(1,0,0)	(0,0,0)	(3.0.1)	(4,1,1)

Appendix 2

Code used to calculate the values in descriptive statistics, EGARCH and DCC-GARCH were done through the programing language R in Rstudio. Code used to calculate Wavelet Coherence were done through Matlab. x, y and z denote variables used in the calculations, i.e the time series of returns for the variables in this thesis.

2.1 R-Studio

```
#Viewing and attaching the dataset
library(haven)
DatasetR <- read_dta("C:/Users/XXX/XXXX/XXXX/DATASET")
View(DATASET)
attach(DATASET)

#Installing and attaching the packages needed
install.packages("rugarch")
install.packages("PerformanceAnalytics")
install.packages("xts")
install.packages("quantmod")
install.packages("Spillover")
install.packages("seastests")
install.packages(“tseries”)
install.packages(“FinTS”)
install.packages("rmgarch")
install.packages("forecast")
install.packages("fBasics")
install.packages("ggplot2")

library(rugarch)
library(PerformanceAnalytics)
library(xts)
library(quantmod)
library(Spillover)
library(seastests)
library(tseries)
library(FinTS)
library(rmgarch)
library(forecast)
library(fBasics)
library(ggplot2)
```

```
#DESCRIPTIVE STATISTICS

#Augmented Dickey-FulLer test
adf.test(x)
#Ljung–Box Q-statistics
Box.test(x, lag = 36, type = "Ljung")
#Jarque-Bera test
jarque.bera.test(x)
#Augmented Dickey-Fuller test
adf.test(x)
#ARCH-LM test
ArchTest(x, lags = 36, demean = FALSE)
#Pearson's product-moment correlation
cor(DatasetR[, c('x', 'y', 'z')])
#Decomposing seasonality
x.ts <- ts(x, frequency = 7)
x.tsc <- decompose(x.ts)
plot(x.tsc)
#Histogram with density curve and normal distribution
chart.Histogram(x, methods = c("add.density", "add.normal"))

#VAR AND SPILLOVER INDEX

#Granger Causilty Test
grangertest(x ~ y, order = 3)
#Creating a varset
varset.bv <- cbind(x,y,z)
#Selection criteria akaike, hanna-quinn, schwartz etc.
lagselect <- VARselect(varset.bv, lag.max = 10, type= "const")
lagselect$selection
#Creating our VAR model
Model1<- VAR(varset.bv, p=1, type = "const", season = NULL, exog = NULL)
summary(Model1)
#Checking for autocorrelation
serial1 <- serial.test(Model1, lags.pt = 12, type = "PT.asymptotic")
serial1
#Testing for heteroscedasticity
Arch1 <- arch.test(Model1, lags.multi = 12, multivariate.only = TRUE)
Arch1
#Testing for Normal Distribution of the residuals
N
Norm1
#Variance Decomposition
FEVD1 <- fevd(Model1, n.ahead = 30)
plot(FEVD1)
#Spillover index
G.spillover(Model1, n.ahead = 30, standardized = TRUE)

#EGARCH and DCC-GARCH
#Autocorrelation function
acf(x)
#Partial autocorrelation function
pacf(x)
#Arima test
auto_model <- auto.arima(x)
summary(auto_model)
coeftest(auto_model)
#EGARCH Model (Normal Distribution), mean model(1,0,1) variance model (1,1)
```

```
model1 <- ugarchspec(mean.model = list(armaOrder = c(1,1)), variance.model = list(garchOrder=c(1,1),model =
"eGARCH"),distribution.model = "norm")
#Using specified model on different assets
m <- ugarchfit(data = x, spec = model1)
#DCC EGARCH
modelspec=dccspec(uspec = multispec(replicate(3,model1)), dccOrder = c(1,1), distribution = "mvnorm")
modelfit=dccfit(modelspec,data=data.frame(x,y,z))
modelfit
#Correlation Matrix
correlation=rcor(modelfit)
dim(correlation)
correlation[,,dim(correlation)[3]]
#Plotting correlation between x and y
cor.x_y=correlation[1,2,]
plot.ts(cor.x_y)
```

2.2 Matlab

```
#LOADING DATA
X=load('Dataset N - X - Time series.txt');
Y=load('Dataset N - Y - Time series.txt');

#CREATING RETURN
rX= tick2ret(X);
rY= tick2ret(Y);

#WAVELET COHERENCE MODEL
figure('color',[1 1 1]);
wtc(rX,rY);
title(['Wavelet Coherence: X and Y'])
```