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An Empirical Study of Cryptocurrency Market Interdependence: Insights from Return and Volatility Spillover Analysis

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Preface

This thesis represents the culmination of our Master of Science in Economics and Business Administration program, with a specialisation in Finance, at the Norwegian University of Life Sciences (NMBU). The journey towards completing the thesis has proven to be a formidable and demanding endeavour, nevertheless an enriching and immensely rewarding experience. Numerous hours have been devoted to research, writing, programming, and resolving intricate tasks in the pursuit of this thesis.

We express our utmost gratitude for the unflagging support rendered by our esteemed friends and cherished family, particularly during instances of ambiguity and bewilderment encountered in the course of this academic pursuit. Furthermore, we would like to extend our gratitude to Associate Professor Muhammad Yahya for his suggestions and guidance, and to our academic comrade Thomas Vik for his feedback on our innovative similarity index.

Whilst the initial emphasis furnished meaningful insights into the dynamics of the cryptocurrency market, we perceived the necessity of tackling additional challenges that encompassed the formulation of functions to achieve optimal model selection, proposed an innovative framework for analysing spillovers in a broader context, and suggested effective ways of integrating robust techniques to accommodate intricate error structures in multivariate time series.

As we contemplate upon our accomplishments, we are reminded of the significance of pursuing our passions with assiduity and commitment. We sincerely aspire that some of the findings presented herein can serve as a source of inspiration, not only to delve deeper into the realm of cryptocurrencies, but also to the field of applied econometrics.

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Abstract

This study examines spillover effects of returns and volatility among 48 of the most significant cryptocurrencies, selected based on their market capitalisation as of January 31st, 2023. By utilising a generalised Vector Autoregressive (VAR) framework that maintains the invariance of forecast-error variance decompositions to variable ordering, this study quantifies both total and directional spillovers of returns and volatility. The methodology is employed on daily return data covering the period from November 9th, 2017, to January 31st, 2023. In order to reveal latent patterns and tendencies that may be imperceptible in the dataset, we adopt a temporal segmentation approach by partitioning the data into annual sub-periods extending from 2018 to 2022, encompassing a quinquennium. The study shows that, (i) contrary to some prior literature, Bitcoin does not exert dominant influence on return and volatility spillovers among the sampled cryptocurrencies; (ii) Ethereum (ETH) and Qtum (QTUM) appears to exhibit a dominant influence on return and volatility spillovers among the selected cryptocurrencies during most periods; (iii) the sampled cryptocurrencies demonstrate a remarkably high degree of spillovers; (iv) a clear pattern in the main drivers of spillovers is not readily discernible, albeit some cryptocurrencies stands out. In addition, our results indicate that constructing models using exclusively cryptocurrency data may pose inherent difficulties owing to the resemblances in return characteristics among numerous digital assets, which may subsequently undermine the precision of these models.

Sammendrag (Norwegian)

Denne studien undersøker smitteeffekter av avkastning og volatilitet blant de 48 mest betydningsfulle kryptovalutaene, basert på markedsverdi per 31. januar 2023. Ved å benytte et generalisert Vector Autoregressive (VAR) rammeverk som opprettholder invariansen av prognosefeil ved variansdekomponeringer i henhold til variablers rekkefølge, kvantifiserer denne studien både totale og retningsbestemte smitteeffekter av avkastning og volatilitet. Metoden er brukt på daglig avkastningsdata fra perioden 9. November 2017 til 31. Januar 2023. For å avdekke tendenser som kan være mindre synlig i den totale undersøkte perioden, deler vi dataene inn i årlige subperioder som strekker seg fra 2018 til 2022, og omfatter en femårsperiode. Studien viser at (i) i motsetning til noen tidligere studier, utøver ikke Bitcoin en dominerende innflytelse på smitteeffekter av hverken avkastning eller volatilitet blant de utvalgte kryptovalutaene, (ii) Ethereum (ETH) og Qtum (QTUM) ser ut til å ha en dominerende innflytelse på smitteeffekter av avkastning og volatilitet blant de utvalgte kryptovalutaene i de fleste periodene, (iii) de utvalgte kryptovalutaene demonstrerer en bemerkelsesverdig høy grad av smitteeffekter, (iv) et klart mønster i hoveddriverne av smitteeffekter er ikke lett å identifisere, selv om noen kryptovalutaer skiller seg ut. Videre indikerer våre resultater at å konstruere modeller som utelukkende bruker kryptodata kan medføre innbygde vanskeligheter på grunn av likhetene i avkastningsegenskapene blant de utvalgte kryptovalutaene, noe som kan underminere presisjonen av disse modellene.

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1. Introduction

The emergence of cryptocurrencies has undoubtedly disrupted the traditional world of investment, creating new opportunities for investors as capital continues to pour into these digital assets. Despite their lacking tangibility and intrinsic value, cryptocurrencies have managed to captivate the attention of numerous actors, with their potential for high returns and their unique features of decentralisation and transparency. Nonetheless, the market remains highly volatile, with prices prone to rapid fluctuations triggered by various factors, such as regulatory announcements, news events, and shifts in investor sentiment. The lack of clear regulatory oversight also adds to the uncertainty and complexity of this emerging market. As such, understanding the dynamics of the cryptocurrency market has become an area of interest and importance for investors, portfolio managers, and academics alike.

The extant empirical literature on cryptocurrencies displays a twofold pattern. Firstly, it tends to concentrate primarily on Bitcoin, the pioneer and preeminent cryptocurrency, at the expense of other digital assets. This trend could be attributed to Bitcoin's substantial market share and long-standing dominance in the cryptocurrency space. Secondly, the majority of studies concentrate on the explicability or predictability of cryptocurrency price time series, typically utilising econometric techniques to scrutinise the data. While such studies have undoubtedly provided valuable insights into the behaviour of cryptocurrencies, they may fall short of capturing the entire spectrum of the underlying dynamics and interconnections of diverse cryptocurrencies in the broader landscape. These shortcomings serve as motivation for the study. As the cryptocurrency market continues to mature, it is imperative for actors to broaden their purview and adopt more inclusive methodologies to acquire a comprehensive understanding of the behaviour of cryptocurrencies beyond just Bitcoin.

Given the aforementioned developments, the current research endeavours to provide research on the intricate dynamics and interdependencies among the 48 foremost cryptocurrencies, as measured by their market capitalisation as of late January 2023. First, we conduct a literature review on the topic, accentuating the principal discoveries while identifying any conceivable gaps in the extant research. Second, we provide an overview of the data collected for the study, which includes descriptive statistics, correlations, and other stylised facts. Third, we employ the framework proposed by (Diebold and Yilmaz 2012) to evaluate the interdependencies among the cryptocurrencies returns and volatilities. Specifically, we utilise a Vector Autoregressive (VAR) model and a generalised forecast error variance decomposition method, as proposed by (Koop, Pesaran and Potter 1996) and (Pesaran and

Shin 1998) to quantify spillovers of returns and volatility. We address the challenges posed by the time-varying and fat-tailed nature of cryptocurrency returns through the use of exponential generalised autoregressive conditional heteroscedasticity (eGARCH) filtered volatilities. The filtered volatilities are subsequently integrated into the spillover framework as an input, granting us the capacity to more effectively seize the interdependency dynamics among cryptocurrencies. Fourth, empirical results are presented followed by robustness evaluations to ensure the accuracy and reliability of our findings. Finally, we discuss the implications of our results and provide suggestions for further research in the field of cryptocurrency analysis.

Overall, the research seeks to make a substantive contribution to the ever-evolving field of cryptocurrency research by delving into the interdependence among them. By examining the relationship between various cryptocurrencies, this study offers insights that can enhance our understanding of the underlying idiosyncratic mechanisms that drive return and volatility movements. Furthermore, these findings can furnish valuable insights to investors, portfolio managers, and researchers, providing crucial implications for the development of risk management and diversification strategies. This research is particularly timely and relevant given the exponential growth of the cryptocurrency market and the increasing interest and investment in this space by both institutional and retail investors. Through a rigorous analysis of cryptocurrency data, this study aims to provide a comprehensive understanding of this dynamic and highly unpredictable market, thereby enriching the current academic literature and contributing to the broader discourse surrounding cryptocurrencies.

1.1 Background information

Cryptocurrencies are virtual or digital currencies that utilise cryptographic techniques to ensure the security and verification of transactions. Blockchain technology forms the foundation of most cryptocurrencies, as it provides a decentralised and transparent ledger that is enforced by a network of computers (Frankenfield 2023). Unlike most traditional currencies, which are centralised and controlled by governments or financial institutions, cryptocurrencies are decentralised and operate without intermediaries or trusted third parties. This means that transactions can be conducted directly between users, without the need for banks or other financial institutions. The technology ensures that the ledger is distributed across a diverse range of computers, making it exceedingly challenging and computationally expensive to manipulate. Consequently, the blockchain is highly resistant to hacking and fraud, which enhances the integrity and reliability of transactions. For instance, since its introduction in 2008, the Bitcoin network has maintained an impeccable record of security, remaining impervious to any successful attempts at hacking or compromise (Groves 2023).

The groundwork for blockchain technology can be traced back to the late 1970s and 2000s, when several researchers and developers explored the concepts of distributed systems using cryptography. (Chaum 1979) proposed a framework for establishing secure and trusted communication channels between parties over an insecure network, using a combination of public-key cryptography and digital signatures. (Haber and Scott 1991) proposed the concept of a digital timestamp, which is a method for proving that a digital document existed at a particular point in time. These early concepts of secure and decentralised record-keeping systems have made significant contributions to solving critical problems that enable pure peer-to-peer transactions and the development of modern blockchain systems. However, it was not until 2008 that these ideas were fully realised on a global scale.

Following the 2008 global financial crisis, a message signed by an enigmatic figure named Satoshi Nakamoto emerged and spread rapidly through a public mailing list. Nakamoto's message[1] contained an idea that would eventually capture the attention of the whole financial world - Bitcoin. A decentralised, peer-to-peer electronic cash system that operates without intermediaries or trusted third parties, such as banks or governments. The system bases itself on the ideas developed by (Chaum 1979, Haber and Scott 1991), namely blockchain technology. Since the publication of Nakamoto's white paper on Bitcoin in 2008, the cryptocurrency ecosystem has grown significantly, with the creation of thousands of cryptocurrencies and blockchain projects. As demand for these digital assets increased, investors began to see them as a new asset class with the potential for returns and diversification benefits. This led to the creation of cryptocurrency exchanges, where investors could buy and sell various cryptocurrencies in a similar manner to traditional financial markets to optimise their portfolios.

[1] The original email sent by Satoshi Nakamoto, the anonymous creator of Bitcoin, is provided in Appendix B.1.

2. Literature review

In recent times, the cryptocurrency market has experienced significant growth, with hundreds of new digital assets being introduced to the market. The upsurge in popularity of cryptocurrencies has not only garnered widespread public attention but has also sparked a notable increase in academic interest, as evident by the emerging body of literature on the subject. The upsurge has given rise to a multitude of studies examining various aspects of the market, including its behaviour, price dynamics, and beyond. Amidst the growing mainstream adoption and the entry of some institutional investors (Fidelity Digital Assets 2022), academic research has intensified its focus on the dynamics of the market. Understanding how returns and volatility in the cryptocurrency market behave has shown to be essential for developing investment strategies, managing risk, and assessing the long-term viability of the asset class.

Although there has been a growing body of literature on spillovers between the cryptocurrency and other markets (Iyer 2022, Corbet, et al. 2018, Caferra 2022, Cao and Xie 2022, Yousaf and Yarovaya 2022, Mo, Meng and Zhen 2022, Al-Shboul, Assaf and Mokni 2023), there has been relatively little research on spillovers within the cryptocurrency market itself (Koutmos 2018, 122). There are likely several reasons for this. One plausible explanation is that actors who are adapting to the cryptocurrency market are still exploring how cryptocurrencies fit into their existing investment strategies, rather than exclusively investing in the cryptocurrency market. That being said, as the cryptocurrency market continues to mature and gain wider adoption, it is reasonable to expect an increase in research in this domain.

Fundamental work in fields such as sociology, economics, and network theory has long recognised the importance of interconnectivity in shaping the behaviour and dynamics of social and economic systems. Similarly, digital currencies also exhibit their own degree of interconnectivity, both within their own market and in relation to other assets. (Iyer 2022) investigates the presence of spillovers between the cryptocurrency and equity markets. The paper employs the framework proposed by (Diebold and Yilmaz 2012), and finds evidence suggesting that cryptocurrency and equity markets have become increasingly interconnected across economies over time. (Corbet, et al. 2018), also employing the (Diebold and Yilmaz 2012) framework, suggest interconnectedness with each other, and that they have similar patterns of connectedness with other asset classes.

(Koutmos 2018) employs an older framework (Diebold and Yilmaz 2009), and measures interdependencies among 18 major cryptocurrencies. The study found that Bitcoin is the dominant contributor of return and volatility spillovers among all the sampled cryptocurrencies, and that spillovers have risen over time, with spikes during major news events. (Palamalai and Maity 2019) employs a Vector Error Correction approach and Diagonal BEKK Multivariate GARCH model on the top eight most highly capitalised cryptocurrencies. They also found evidence of interdependencies and volatility co-movements among the different cryptocurrencies. Additionally, the study suggests that the window for obtaining short-term portfolio diversification benefits from the chosen large-cap cryptocurrency markets is limited. (Kumar and Anandarao 2019) focused specifically on the dynamics of volatility spillover by employing a IGARCH (1,1)-DCC (1,1) multivariate model on the top four cryptocurrencies in terms of market capitalisation. The study's findings indicate that there is limited evidence of volatility spillovers, but there is an increase in volatility spillovers after 2017. Additionally, the study suggests the possibility of herding behaviour in cryptocurrency markets. (Katsiampa 2019) examines the volatility dynamics by employing an asymmetric Diagonal BEKK model, on five major cryptocurrencies. The study revealed that the conditional variances of all five cryptocurrencies were significantly influenced by both previous squared errors and past conditional volatility. Additionally, the study found that asymmetric past shocks had a significant impact on the current conditional variance.

(Zięba, Kokoszczyński and Śledziewska 2019) examines interdependencies between a wide range of cryptocurrencies log-returns, with a special focus on Bitcoin. The study's findings also suggest market interdependencies between different cryptocurrencies playing a significant role in shaping the behaviour of the market. Unlike (Koutmos 2018), the study does not find evidence to support the notion that Bitcoin exerts a dominant and significant influence on other cryptocurrencies.

Based on relevant academic literature and empirical results, (Kyriazis 2019) presents a systematic survey of the return and volatility spillovers in cryptocurrencies. The paper highlights the use of Vector Autoregressive (VAR) schemes using (Diebold and Yilmaz 2009), and forecast error variance decomposition (FEVD) based on (Diebold and Yilmaz 2012) in papers such as (Gillaizeau, et al. 2019). Additionally, the paper highlights that Autoregressive Conditional Heteroscedasticity (ARCH) methodologies, particularly the exponential generalised autoregressive conditional heteroskedasticity (eGARCH) and the

Glosten-Jagannathan-Runkle (GJR)-GARCH specifications, also has been utilised to capture volatilities and leverage effects in papers such as (Bouri, Das, et al. 2018).

Most of the spillover studies we observe employs some version of the framework proposed by Diebold and Yilmaz, where they alter between (Diebold and Yilmaz 2009), and (Diebold and Yilmaz 2012). Their methodology allows for the measurement of spillover effects between multiple assets in a comprehensive and systematic way, which is why we believe the framework has been widely adopted for investigating interconnectivity in financial markets. However, it's worth noting that the methodology proposed in (Diebold and Yilmaz 2012), is a significant upgrade[2] compared to that of (Diebold and Yilmaz 2009).

To summarise, the growing popularity of cryptocurrencies has led to an increase in academic interest, particularly in understanding their behaviour, price dynamics, and interconnectivity with other markets. While there has been a considerable amount of research on spillovers between cryptocurrencies and other markets, there has been relatively little on spillovers within the cryptocurrency market itself. Various studies have examined interdependencies and volatility co-movements among different cryptocurrencies, with Bitcoin found to be the dominant contributor of return and volatility spillovers (i.e., in some studies). The framework proposed by Diebold and Yilmaz appears to be a widely used method for analysing spillovers, as evidenced by its frequent citation and utilisation in studies. As the cryptocurrency market continues to mature and become more widely adopted, it is likely that we will see more research in this area. Moreover, there is evidence of volatility co-movements and limited short-term diversification benefits from large-cap cryptocurrency markets. The possibility of herding behaviour and the significant role of market interdependencies in shaping the behaviour of the cryptocurrency market are also commonly reported. Overall, the literature suggests that the cryptocurrency market is highly interconnected, with some studies pointing to Bitcoin exerting a significant influence on other cryptocurrencies and the market as a whole. Below, we include a table summarising the key studies on interconnections in the cryptocurrency market.

[2] Diebold Yilmaz 2012 (DY 2012) addresses the issue of variable ordering in spillover analysis by introducing a generalised framework that is invariant to the ordering of variables. Therefore, compared to DY 2009, DY 2012 provides a more robust and accurate framework for spillover analysis, particularly in the context of high-dimensional datasets where variable ordering can have a significant impact on the results.

Table 1: Studies on return and volatility dynamics in the cryptocurrency market

No.	Cite	Data	Method	Findings
1	(Koutmos 2018)	18 of the largest cryptocurrencies based on market capitalization. Daily observations form Aug. 2015 to Jul. 2018.	Uses framework of Diebold and Yilmaz (2009) to measure interdependencies among cryptocurrency returns and volatilities, respectively. Volatilities are estimated using the Parkinson (1980) estimator (High and low). Also, GARCH-based measures are used.	Finds that Bitcoin is the dominant transmission catalyst for shocks in the remaining sampled currencies. The result of the study suggests that the cryptocurrencies are becoming more connected.
2	(Palamalai and Maity 2019)	8 of the largest cryptocurrencies based on market capitalisation. Daily observations from Apr. 2013 to May. 2019.	Vector Error Correction approach and Diagonal BEKK Multivariate GARCH model to measure return and volatility spillovers.	Evidence of interdependencies and volatility co-movements among the various pairs of cryptocurrency markets. Limited window of opportunity for the short-term portfolio diversification.
3	(Kumar and Anandarao 2019)	Bitcoin, Ethereum, Ripple and Litecoin (4 major) Daily observations from Aug. 2015 to Jan. 2018.	IGARCH (1,1)-DCC (1,1) to measure volatility spillovers.	significant volatility spillover from Bitcoin to Ethereum and Litecoin. moderate return co-movement among the crypto-currency returns. results indicate the possibility of turbulence in the crypto-currency markets and point towards the possibility of herding behavior in crypto-currency markets.

4	(Katsiampa 2019)	Bitcoin, Ether, Ripple, Litecoin, and Stellar Lumen (5 major). Daily observations from Aug. 2015 to Feb. 2018.	Asymmetric Diagonal BEKK model to examine volatility dynamics.	Most asymmetric past shocks have a significant effect in the current conditional variance. time-varying conditional correlations exist and are mostly positive.
5	(Zięba, Kokoszczyński and Śledziewska 2019)	78 cryptocurrencies. Daily observations from Sep. 2015 to May. 2018.	Minimum Spanning Tree (MST) method to study hierarchical structure and topological properties. Vector Autoregression (VAR) model with a simple impulse response function.	Changes in Bitcoin price do not affect and are not affected by changes in prices of other cryptocurrencies. Results obtained indicate that there are strong relationships between some cryptocurrencies.
6	(Omane-Adjepong and Alagidede 2019)	7 leading cryptocurrencies. Daily observations from May. 2014 to Feb. 2018.	Wavelet-based methods are used to examine market connectedness.	Connectedness and volatility causal linkages are found to be sensitive to trading scales and the proxy for market volatility. Probable diversification benefits are confined from intraweek to monthly scales for specific market pairs.

7	(Bouri, Shahzad and Roubaud 2019)	7 of the largest cryptocurrencies based on market capitalisation. Daily observations from Aug. 2015 to Dec. 2017.	logistic regression to uncover evidence of co-explosivity across cryptocurrencies.	Results show evidence of a multidirectional co-explosivity behaviour that is not necessarily from bigger to smaller and younger markets.
8	(Moratis 2020)	30 of the largest cryptocurrencies based on market capitalisation. Daily observations from Oct. 2016 to May. 2020.	Quantifies spillover effects in the cryptocurrency market using a rolling-window Bayesian Vector Autoregressive Model.	Bitcoin dominates the spillover in the cryptocurrency market. Total spillover increased severely after the surge of 2017.

3. Data

This section provides an overview of the data used in the thesis, including important characteristics and relevant descriptive statistics. Additionally, it outlines the computer programs that were utilised for collecting, analysing, and interpreting the data. Attaining a comprehensive understanding of the data characteristics is useful, not only for assessing the credibility of the analysis, but also for enabling informed decision-making, risk assessment, and facilitating actors in comprehending the components influencing the market movements.

We provide selected stylised figures from the total investigated period. However, due to the vast number of cryptocurrencies analysed, it is not feasible to provide a comprehensive overview that includes them all. Rather than attempting to provide a comprehensive overview of all the cryptocurrencies analysed, we have opted to present select representative cryptocurrencies alongside the total results in quantiles. This approach provides a more comprehensive understanding of the data without overburdening the main body of the text with excessive details. A detailed presentation of the descriptive statistics for the static period can however be found in Appendix A.1.

3.1 Data Collection and Frequency

Cryptocurrency data has become an increasingly important and valuable asset in recent years, as cryptocurrencies have gained wider recognition and acceptance as a form of investment and payment (Gil-Cordero, Cabrera-Sánchez and Arrás-Cortés 2020). However, working with cryptocurrency data can also present some challenges and risks, due to the nature of the cryptocurrency market and the volatility of cryptocurrency prices. Thus, taking the time to explore and thoroughly analyse the data is in our beliefs essential in order to mitigate risks and ensure the integrity of the results. Additionally, a rigorous analysis of the data could also guide model selection and enhance the overall quality of the research.

The data for this study was sourced from Yahoo Finance, a reputable financial news, and data website, using the open-source Python package "yfinance" and the unauthorised Python API "Yahooquery". Although Yahoo-Finance source most of its historical data on cryptocurrencies from the world's most-referenced price-tracking website CoinMarketCap (CoinMarketCap n.d.), we retrieve the data from Yahoo-Finance, due to the easy-to-use API applications. The code used to obtain the data from Yahoo Finance can be found in Appendix B.2. On January 31st, 2023, we extracted daily price observations in US dollars for 250 of the most significant cryptocurrencies ranked by market capitalisation. The data on the respective market capitalisation and the cryptocurrencies themselves are presented in Appendix A.3. We have opted to utilise price data spanning from November 9th, 2017, to January 31st, 2023, in order to encompass a broad selection of cryptocurrencies. This particular time frame coincides with a significant period of growth and progress in the cryptocurrency market, which was marked by the introduction of numerous new cryptocurrencies through Initial Coin Offerings (ICOs) on different exchanges and data platforms (Kauflin 2018). Moreover, we are of the opinion that five years' worth of data is adequate to conduct a dependable analysis of market trends and dynamics. Our chosen time frame strikes a balance between the quantity of observations and variables considered in our study, resulting in daily price observations for 48 of the largest cryptocurrencies as of January 31st, 2023. It should be noted that 2 observations were missing for the cryptocurrency, Ergo (ERG). Despite a diligent search, alternative sources could not be found to fill the void. As a solution, we opted to substitute the missing data with a 20-day moving average. While a 20-day moving average may not be the best method, we believe it is adequate when replacing the two missing values. This is especially true when the missing values represent less than one percent of the total observations. The missing observations in question appeared on 29.09.2018, and 17.10.2018.

The study relies on daily price observations, mostly due to the limited availability of data. Even though utilising higher frequency data could result in a more comprehensive understanding of intense volatility, we believe that daily data is deemed adequate for capturing short-term fluctuations and serves the purpose of this study most effectively. It's also worth mentioning that using high frequency data, such as minute data, can be a tedious and computationally intensive process. The sheer amount of data generated from high frequency sources means that processing and analysing this data requires significant computational power and storage capacity. Furthermore, daily data might also capture changes that might go unnoticed with higher frequency data. While higher frequency data could be beneficial in some studies, daily data serves the purpose of this study effectively.

In addition to our static full-sample data, covering the total investigated period, we further divide our time-series data into yearly sub-samples, or temporal periods, to enhance our understanding of the time-varying spillover dynamics in the cryptocurrency market. Our temporal periods span a five-year period, from 2018 to 2022, and provide us with daily price observations for each year, allowing us to discern patterns and trends that may not be immediately evident in the overall dataset. To maintain consistency throughout the yearly temporal periods, we chose to exclude both 2017, and 2023 as they do not encompass a full year. Inadequacy arises from the generalisation of yearly sub-sampled periods with non-calendar year periods, as such periods may overlook potential seasonal effects. This methodological approach facilitates a more refined comprehension of the data, which can enable more informed decision-making based on our analysis.

3.2 Measuring Returns

In finance and economics, price observations are commonly utilised to conduct analyses of asset returns. For most economists, returns are often computed as natural logarithmic changes in prices, which are known as log returns. This measurement methodology is preferred over simple returns in many cases due to several reasons. Firstly, an important benefit of using log returns is that they are time-additive and have the desirable property of being equivalent to continuously compounded returns, allowing for fair comparison between different assets (Brooks, Introductory Econometrics for Finance 2014, 8). The so-called simple returns, conversely, are multiplicative in nature and thus come with certain limitations. One such limitation is that they tend to amplify the impact of outliers in the data, making them less suitable for use with data that exhibits high levels of skewness and kurtosis. log returns are in our case preferred over simple returns as they offer a more accurate representation of the returns of cryptocurrencies over time, especially in light of the possibility of large outliers in the highly volatile cryptocurrency data.

Without delving too much into the technicalities, we can compute the daily return r at time t, by taking the natural logarithm of the ratio of the current price p_t to the previous price p_{t-1}.

$$r = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{1}$$

The natural logarithm of the ratio is simply the logarithm to the base of the mathematical constant e. This is what essentially provides the convenient and accurate representation of continuously compounded returns, as it considers the compounding effect over time.

3.3 Overview of the cryptocurrency market

In this chapter, we present an overview of the selected cryptocurrency studied. Providing the performance of each individual cryptocurrency is not feasible due to practical reasons, as there are a large number of cryptocurrencies included in the analysis. To address this issue, we propose an equally weighted index approach, which provides a comprehensive overview of the average performance of the selected cryptocurrencies.

The equally weighted index consolidates the performance of the study's selected cryptocurrencies into a singular metric, wherein each cryptocurrency holds an equal weight, regardless of its market capitalisation or trading volume. Furthermore, one should note that the cryptocurrency market exhibits high concentration, with only a handful of cryptocurrencies accounting for a significant share of the market. Consequently, it is probable that our equally weighted index will be influenced by this concentration. To showcase the market dominance of our chosen cryptocurrencies, we present in Figure 1 the top five selected currencies with the largest market capitalisation.

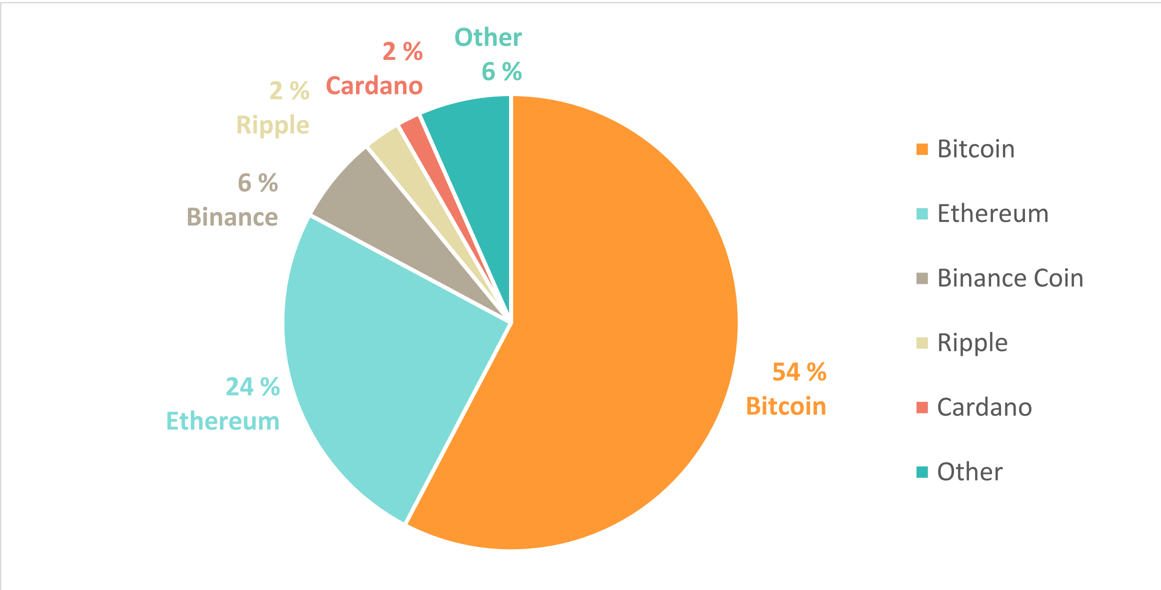

Figure 1: Top five Cryptocurrencies with the largest market capitalisation

Note: The Figure shows market capitalisation dominance considering the top five cryptocurrencies with the largest market capitalisation within our studies selected currencies. "Other", measures the sum of the rest of the cryptocurrencies within our selected currencies.

Remarkably, Bitcoin (BTC) is by far the largest cryptocurrency in terms of market capitalisation, representing more than 50% of the total market capitalisation of all our selected cryptocurrencies. This dominance is likely due to its first-mover advantage and high level of adoption, as well as its widespread recognition as a store of value and medium of exchange.

Similarly, Ethereum (ETH) stands as another cryptocurrency with significant dominance, boasting a substantial market capitalisation. This is plausibly due to its wide application as the most utilised blockchain platform for constructing decentralised applications (Malanii 2023).

A graphical depiction of the equally weighted prices, along with a measure of volatility, can be seen in Figure 2. As in Equation (1), the volatility measure is computed by utilising natural log changes on the index. The figure indicates that the cryptocurrencies examined in our study displayed considerable volatility peaks in multiple periods, notably at the beginning of 2018, mid-2020, and several others spanning from mid-2021 to the end of 2022. While the cryptocurrencies may be subject to transmission effects of returns and volatility among themselves, it is important to note that other factors also contribute to changes in both price and volatility observations. Consequently, to improve the understanding of components that may influence the market's return observations, we have identified some factors that have demonstrated a discernible impact on the market movements. We evaluate factors such as economic and political events, investor sentiment, and micro-events briefly. This understanding is crucial for informed decision-making by stakeholders in the cryptocurrency market.

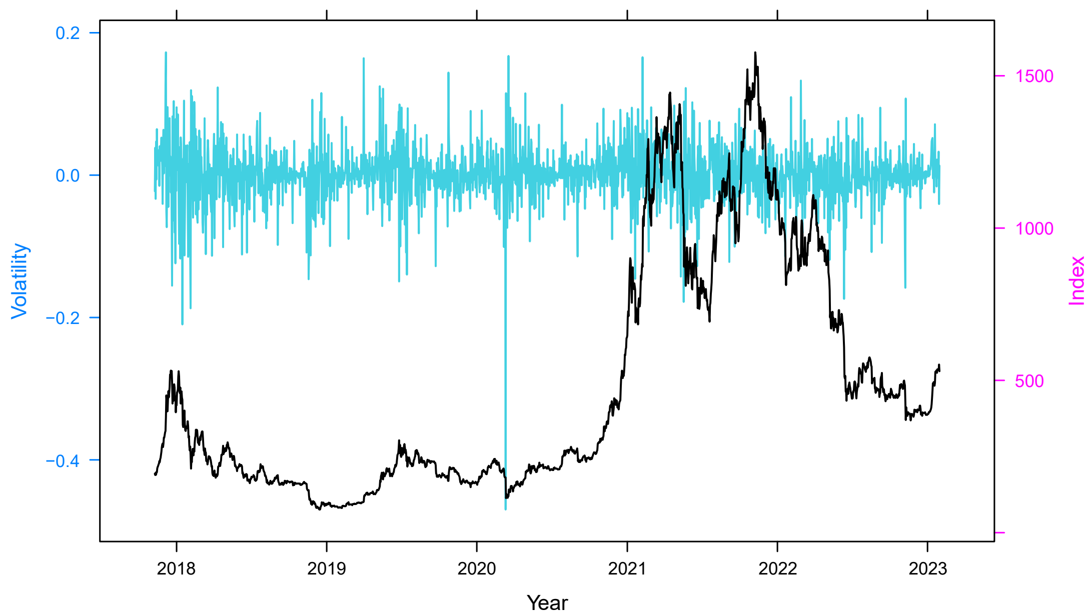

Figure 2: Equal-weighted cryptocurrency index

Note: The x-axis coordinates indicate the start of the respective year. Also, each of the 48 currencies are equally weighted. The "Volatility" is measured using natural log returns as described in Equation (1).

In 2017, the emergence of initial coin offerings (ICOs) and increased adoption of cryptocurrencies by individuals and businesses fuelled a surge in the cryptocurrency market. This period, also known as the "Initial Coin Offering (ICO) Bubble" (Swartz 2022), is the reason why the data used in this study starts at this year.

Most notable is the shock occurring on 12.03.2020, with our equally weighted index falling approximately 53 percent from the prior day. The U.S. announces a 30-day ban on travel (Maass 2020), and the global COVID-19 outbreak was declared as a global pandemic by the World Health Organization (WHO) the day before (World Health Organization 2020). Additionally, Bitcoin, the largest cryptocurrency in terms of market capitalisation, underwent a "halving" in May 2020, which reduced the rate at which new Bitcoins are created, something that may also have been a contributing factor to the increased volatility during this period (Godbole 2020). Halving is an event in the Bitcoin protocol that occurs approximately every four years. It is a built-in mechanism that reduces the rate at which new Bitcoins are created and helps to ensure a limited supply of the digital currency. The findings of (Meynkhard 2019) demonstrate that the market value of the cryptocurrency increases as a result of the so-called Halving effect.

The environmental impact of Bitcoin mining[3] has been a topic of discussion in recent times, particularly in mid-2021. This was prompted by a surge of news coverage, including a public announcement, by Tesla CEO Elon Musk, that his company would no longer accept Bitcoin as payment due to concerns about the environmental consequences of mining (Kolodny 2021). The effects of Musk's statement were studied by (Lennart 2023), who found a significant correlation between tweets from Musk and abnormal Bitcoin returns during that period. These findings imply that the impact Musk's tweets, may have played a role in the increased volatility of Bitcoin during the aforementioned period. Moreover, it is noteworthy to mention that during this period, the stringent regulatory actions of China's most prominent authorities against cryptocurrencies escalated, with a comprehensive prohibition on all crypto transactions and mining. The impact of this move has also been visible on cryptocurrency and blockchain-related stocks, which experienced significant downward pressure (John, Shen and Wilson 2021).

[3] Bitcoin mining is the process of creating new Bitcoin units by solving complex mathematical problems using specialised computers. These computations are resource-intensive and require substantial energy consumption.

More recently, the cryptocurrency market has experienced a substantial setback, as evidenced by the loss of 60 percent in value for Bitcoin (DeVon 2022) and a corresponding 53 percent decline in our equally weighted index (Figure 2). The economic growth of the United States has decelerated significantly, and the Federal Reserve continued to raise interest rates, resulting in increased uncertainty and risk aversion among investors (U.S. Bank 2023). Additionally, the market has witnessed a spate of failures and bankruptcies among cryptocurrency companies, causing further distress in the market (Gura 2022). It suggests that the cryptocurrency market is not immune to economic and systemic risks, and that the performance of the selected currencies in your study is influenced by various factors such as economic growth, interest rates, and the stability of cryptocurrency-related companies.

To summarise, various factors can influence market sentiment and the price fluctuations of particular cryptocurrencies. These factors may include market demand, government regulations, technological developments, and media coverage. Moreover, the cryptocurrency market is known for its volatility, making it highly susceptible to rapid transformations in response to diverse factors.

3.4 Descriptive statistics

Table 2 exhibits summary statistics for the static period. We have selected a subset of cryptocurrencies that we believe to be adequate representatives of the dataset. However, it is important to acknowledge that Table 2 may not fully capture the variability present in the entire population of the selected cryptocurrencies. To address this limitation and provide a more comprehensive understanding of the summary statistics for the remaining data, we present the summary statistics in quantiles for all periods in Table 3. This may offer additional insights into the summary statistics for the data, without burdening the main text with an excess of tables.

Table 2: Descriptive statistics for a subset of cryptocurrencies (09.11.2017 - 31.01.2023)

Ticker	Mean	StdDev	Min	Max	Kurtosis	Skewness	Sharpe
ADA	0.47	1.28	-0.50	0.86	24.51	1.94	0.37
BNB	0.97	1.11	-0.54	0.53	15.00	0.37	0.87
BTC	0.22	0.77	-0.46	0.23	12.04	-0.83	0.29
ETC	0.08	1.21	-0.51	0.35	7.77	-0.10	0.07
LTC	0.07	1.05	-0.45	0.39	8.64	-0.14	0.07
XRP	0.11	1.21	-0.55	0.61	16.6	0.83	0.09

Note: Mean and standard deviation (StdDev) figures are presented in annualised terms. "Kurtosis" computes the estimator of Pearson's measure of kurtosis in excess of a normal distribution.

From Table 2, we observe that the return observations exhibit considerably high volatility measured by the standard deviation (StdDev), leptokurtic kurtosis (i.e., high kurtosis), and a moderately skewed distribution. These characteristics are not unique to the displayed cryptocurrencies during the static period, as it is found in most of the other observations as well (see full table in Appendix A.1).

For the total investigated period, we observe that half of the dataset displays a somewhat symmetrical distribution, with skewness values falling within the range of -0.5 to 0.5. The rule of thumb seems to suggest that the range of skewness values between -0.5 to 0.5 indicates a relatively symmetrical distribution (McNeese 2016). We also find that 37% of the skewness observations have negative values, while 63% have positive values. This finding suggests that the static period dataset exhibit a tendency towards higher values, as indicated by the larger proportion of positive skewness observations.

We observed that the kurtosis values in the dataset exhibit leptokurtic characteristics, with extreme values being present, even in the lower end of the distribution. Remarkably, during the entire investigated period, the lowest recorded excess kurtosis value was 5.44, which is considered to be a very high value (Hayes 2021). This finding suggests that the dataset may have a heavy-tailed distribution with a higher concentration of observations in the central region, accompanied by infrequent, but extreme, observations in the tails of the distribution. Figure 3 illustrates how the average skewness and kurtosis has developed over time. The purpose of the graph is to offer insight into the average occurrence of outliers, and their direction.

As noted previously, 2020 is a noteworthy period. The significant negative skewness and positive kurtosis values observed in Figure 3 could potentially be attributed to several factors, such as the impact of COVID-19 on the market, increased volatility and uncertainty, changes in investor behaviour, and the influx of new market participants. These factors may have led to a more pronounced distribution tail, resulting in the observed skewness and kurtosis values. This finding could indicate a potentially greater risk in the market during periods of systematic extreme events, and it highlights the importance of proper risk management and diversification strategies.

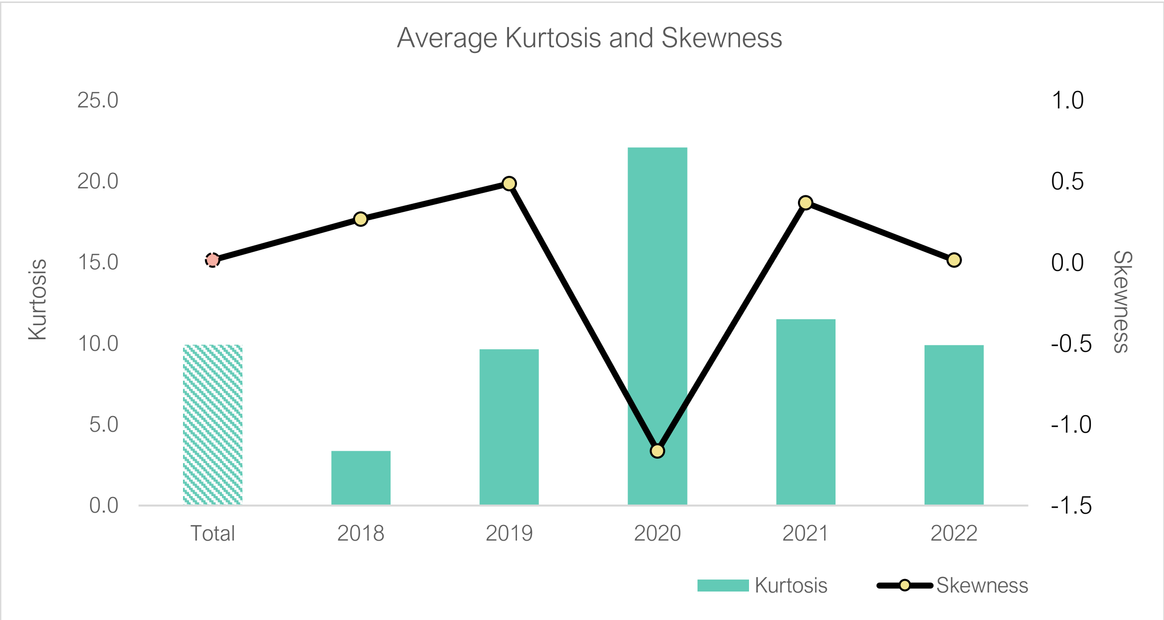

Figure 3: Average development in excess kurtosis (LHS) and skewness (RHS) for all 48 cryptocurrencies

Note: The term 'Total' refers to the total investigated period and is considered as the static period.

This information could be useful to understanding the overall risk of the market for cryptocurrencies. The presence of high kurtosis and negative skewness in tandem implies a more volatile and increased level of downside risk in the cryptocurrency market during 2020.

To improve our comprehension of the descriptive features of the complete dataset, and our temporal yearly sub-samples, we present the descriptive statistics for all 48 cryptocurrencies grouped into quantile ranges. To clarify, the presented quantile ranges[4] are based on how each measure distributes across all the observed currencies given the specific period. This approach allows us to examine the descriptive statistics for the various cryptocurrencies without compromising on the information provided. Also, given the large number of currencies included in the study, it is not feasible to present every measure for all periods, for all currencies. For instance, by observing the standard deviation (StdDev) during 2020 in Table 3, we can tell that the standard deviation was high across a large number of currencies.

[4] Not to be confused with the quantile ranges of the specific measures.

Table 3: Descriptive statistics for the static and temporal periods presented in quantiles

Year	Quantile	Mean	StdDev	Min	Max	Kurtosis	Skewness	Sharpe
	25 %	-2.8	1.3	-0.4	0.3	1.9	-0.1	-1.9
2018	50 %	-2.2	1.4	-0.3	0.3	2.9	0.2	-1.6
	75 %	-1.7	1.6	-0.3	0.5	5.7	0.5	-1.0
	25 %	-0.7	0.8	-0.2	0.2	2.4	-0.1	-0.8
2019	50 %	-0.4	0.9	-0.2	0.2	3.6	0.2	-0.4
	75 %	0.1	1.0	-0.2	0.3	5.6	0.7	0.1
	25 %	0.5	1.1	-0.6	0.2	14.7	-2.1	0.4
2020	50 %	0.9	1.2	-0.5	0.3	17.9	-1.6	0.7
	75 %	1.4	1.3	-0.5	0.4	22.4	-0.2	1.1
	25 %	0.7	1.4	-0.5	0.3	4.1	-0.3	0.5
2021	50 %	1.4	1.5	-0.4	0.4	5.8	0.1	0.8
	75 %	1.8	1.7	-0.4	0.5	8.7	0.7	1.2
	25 %	-1.9	0.9	-0.3	0.2	2.7	-0.6	-1.8
2022	50 %	-1.5	1.0	-0.3	0.2	4.7	-0.3	-1.4
	75 %	-1.2	1.1	-0.2	0.4	7.6	0.4	-1.3
	25 %	-0.2	1.2	-0.6	0.4	7.8	-0.1	-0.1
Total	50 %	0.0	1.3	-0.5	0.5	10.5	0.2	0.0
	75 %	0.2	1.4	-0.5	0.7	16.0	1.3	0.1

Note: Mean and standard deviation (StdDev) figures are presented in annualised terms. "Kurtosis" computes the estimator of Pearson's measure of kurtosis in excess of a normal distribution. "Total" uses the total/ static period, which contain the total investigated period.

With the exception of 2020, the average skewness of the return distributions during the total period and most of the sub-periods tends to be positive, indicating that the returns in general are skewed towards higher values and that there are more positive returns than negative returns. Furthermore, the kurtosis of the return distributions during the total period and most of the sub-periods tends to inhibit extreme leptokurtic behaviour, meaning that the distributions have fatter tails than the normal distribution. Thus, it can be inferred that the likelihood of experiencing extreme returns is higher compared to what is expected under a normal distribution. Among all the selected cryptocurrencies, the sub-period of 2020 exhibits the highest overall kurtosis in comparison to the other sub-periods. These extreme observations are also seen in Figure 2 and Figure 3 respectively.

It appears that for the year 2018, the mean returns are negative across all three quantiles. In contrast, for 2019, while the mean returns are negative for the 25th and 50th percentiles, they become positive for the 75th percentile, indicating that the upper range of cryptocurrencies had positive returns that year. Similarly, for 2020 and 2021, the returns are positive across all three quantiles, suggesting a general positive trend in returns among all currencies during these periods. However, for 2022, the mean returns are negative across all three quantiles, indicating a downturn in returns for a large range of currencies for that year.

The standard deviation appears to remain relatively consistent within each year across the different quantile ranges. This suggests that the cryptocurrencies analysed share similar volatility characteristics within each year. However, it's important to note that the standard deviation does vary between years, indicating that the overall volatility of the cryptocurrencies may change over time.

Overall, Table 3 indicate that the selected cryptocurrencies are characterised by significant volatility and the presence of large outliers. We see that most measures share similar quartile ranges within each year with the exception of kurtosis. While kurtosis remains high across all periods, it seems that the lower quartile ranges deviate more from the upper quantiles compared to other measures. This suggests that a few currencies may be more prone to experiencing a large magnitude of extreme losses or gains, whereas others may experience a lower magnitude.

3.5 Correlations

To gain insights into the relationships between the cryptocurrencies in our study, we present an overview of the correlations between them. Despite the fact that the findings of the analysis may not be regarded as conclusive nor robust, they can serve as a preliminary step in identifying potential relationships or patterns in the data that may necessitate further scrutiny. It is also important to note that correlation does not imply causation. A high correlation between two variables does not necessarily mean that one variable causes the other, or that there is a direct relationship between the two. Market conditions or external events may impact both variables, creating the illusion of causation.

In light of the non-normal distribution of the return series, as indicated by the descriptive statistics, we have chosen to use Spearman's rank correlation instead of the more commonly used Pearson correlation coefficients. By employing Spearman's correlation robust measure of correlation, we can somewhat more effectively evaluate the relationship between variables without making assumptions about the underlying distribution of the data. If referring to a set of n number of x_i, and y_i variables, we can formulate the correlation function, first by ranking values in order, then taking the difference of the ranking coordinates, denoting them as d_i, and squaring them. We can formulate the formula as such:

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{2}$$

Using Equation (2), we compute coefficient matrices for the total, and various sub-periods. We visually interpret the results by crating the lower triangular correlation matrix as a graphical representation in Figure 4. We do not discover values for any subperiods that are significantly different than that of the total investigated period. Thus, Figure 3 should yield the same interpretation. Additionally, although not consider as robust, Person correlations also render quite similar results.

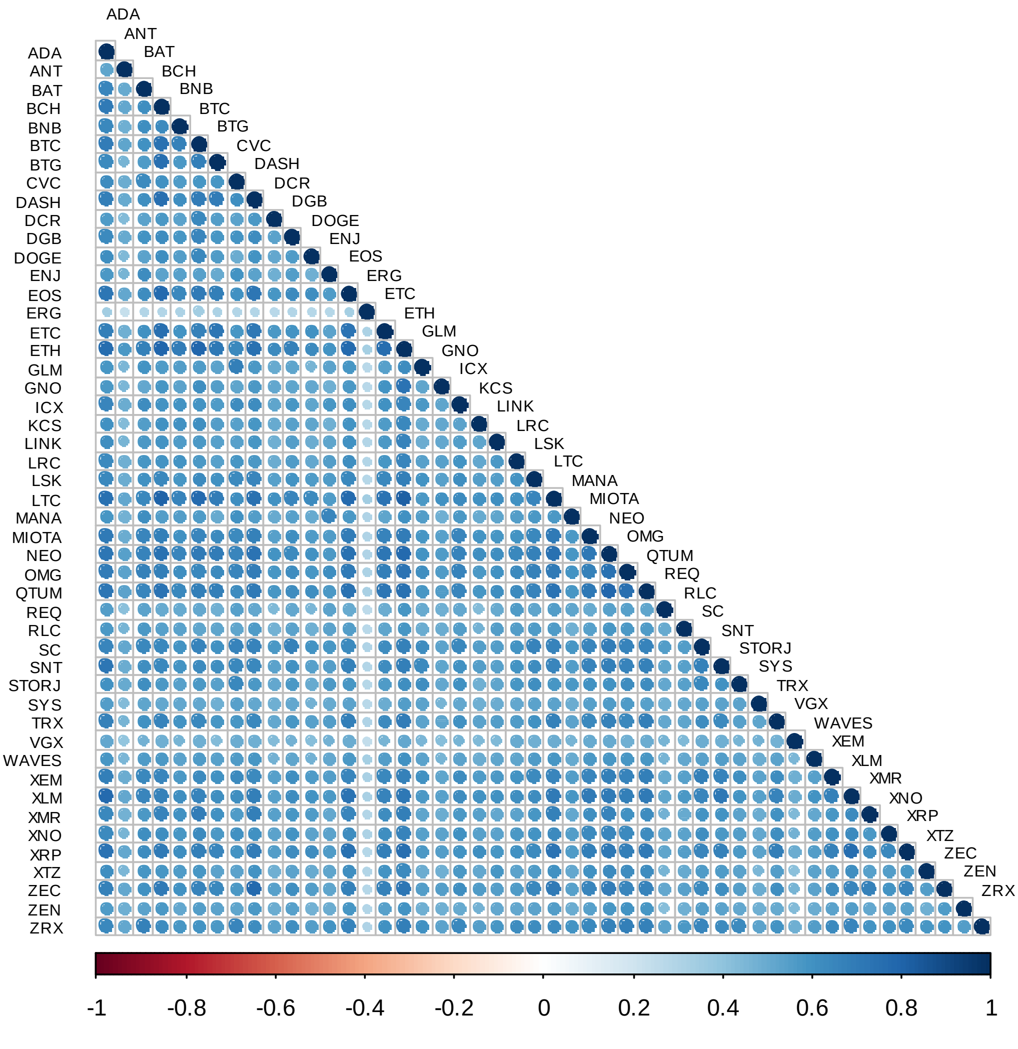

Figure 4: Graphical display of correlation matrix for total period investigated

Note: The Spearman's correlation matrix in the lower triangular form is displayed. Strong positive correlations are represented in large blue circles, while strong negative correlations are indicated in large red circles. The diagonal of the matrix is equal to 1, as it represents the correlation of each variable with itself.

By examining the graphical representation of the correlation matrix in Figure 4, it is apparent that most cryptocurrencies in the dataset display a significant degree of correlation with one another. Nevertheless, some cryptocurrencies stand out with a degree of uniqueness, including Ergo (ERG), Request (REQ), and Voyager Token (VGX), as can be observed. These cryptocurrencies may have unique market characteristics or factors driving their prices, which set them apart from the rest of the cryptocurrencies in the dataset. It may be worth exploring these unique characteristics further to gain a better understanding of their performance in the market. Upon visual examination of multiple price and return observations, we find that most cryptocurrencies exhibit similar characteristics. However, as mentioned earlier, there are some unique aspects to certain cryptocurrencies.

4. Methodology

In this chapter, we outline the methodologies employed to evaluate the intricate dynamics and interdependencies of return and volatility spillovers. First, we describe our approach to measuring spillover effects and then detail the method for obtaining the latent volatility component of a marginal model to serve as input in the spillover framework. Second, we present the methods used for conducting post-estimation diagnostic tests, which involve assessing serial correlation, heteroskedasticity, normality, and structural changes. Third, we introduce an innovative framework for identifying similarities in spillover effects across multiple time periods. Finally, we address concerns regarding serial correlation and heteroskedasticity, and propose a method to tackle these issues by employing heteroskedasticity and autocorrelation-consistent standard errors.

4.1 Measuring spillovers

In financial markets, the term "spillovers" often refers to the occurrence of shocks or information impacting one market or asset, which then spread or spill over to other markets or assets, ultimately causing alterations in their returns or volatility. Spillovers can occur through a variety of channels, including trade linkages, financial linkages, and information linkages, and can have significant effects on the functioning and stability of financial markets. Return and volatility spillovers are crucial features of financial markets that have garnered significant interest from both academic researchers and industry practitioners. Over the years, several theoretical frameworks have been developed to study types of connectiveness, including contagion theory, Granger causality, co-integration analysis, spillover index models, and connectedness index models, among others. While these frameworks differ in their assumptions and methodologies, they all seek to shed light on the complex interrelationships, and to identify the channels through which shocks are transmitted across them.

The framework of (Diebold and Yilmaz 2009, 2012, 2014, 2015) is widely used in empirical studies aimed at examining the transmission of shocks across various entities in financial markets. The framework provides a unified and flexible approach to measuring spillovers, allowing for a comprehensive analysis of the interdependencies between different assets or markets. Given the large number of variables involved in our study, estimating spillover effects in a multivariate setting is a necessity, and the framework at hand proves to be particularly well-suited for this purpose.

Utilising a generalised vector autoregressive framework, as introduced in (Diebold and Yilmaz 2012), where forecast-error variance decompositions are invariant to variable ordering, we can measure both total and directional return and volatility spillovers. Neglecting the often-used Cholesky factor identification of the Vector Autoregressive (VAR) model allows us to overcome the sensitivity of variance decompositions to variable ordering, and to examine directional spillovers. The variance decomposition, or more specifically, variance decomposition of the forecast errors, allow us to parse the forecast error variances of each variable into parts that are attributable to the various system shocks, providing important information about the interdependence among the variables and the relative importance of each variable in driving the dynamic behaviour of the system. We can derive a matrix containing the proportion of forecast error variance of each cryptocurrency that can be attributed to its own innovations, and the innovations from other cryptocurrencies by extending the familiar N-variable Vector Autoregressive (VAR) model. As in (Diebold and Yilmaz 2012), we consider a covariance stationary, N-variable, VAR model. We can formulate the VAR(p) model as such:

$$x_t = \sum_{i=1}^{p} \Phi_p x_{t-1} + \epsilon_t \tag{3}$$

where x_t is stationary, and obtains an infinite moving average representation equal to $\sum_{i=0}^{\infty} A_i \epsilon_{t-1}$, in which $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, and $\mathrm{A_i}$ is a $N \times N$ coefficient matrix. We posit that the error term, denoted as ϵ, follows a multivariate normal distribution with a mean of zero and a covariance matrix of $\sum$. This implies that the errors are assumed to be independent and identically distributed (i.i.d.), making them homoscedastic and without any serial correlation. The utilisation of the multivariate normal distribution properties to estimate the parameters of the VAR(p) model and test hypotheses regarding dynamic relationships among variables is enabled by the assumption of normality and homoscedasticity of the error term.

We quantify the contribution of each variable's forecast errors to the overall forecast error of the system using a decomposition method. Specifically, we can measure the "own variance shares" of each variable, which represent the proportion of the variable's forecast error that is caused by shocks to the variable itself. In addition, we can also measure the "cross variance shares" or "spillovers" of each variable, which represent the proportion of the variable's forecast error that is caused by shocks to other variables in the system. To calculate these shares, we utilise the generalised variance decomposition as proposed by (Koop, Pesaran and Potter 1996) and (Pesaran and Shin 1998), hereinafter referred to as KPPS. The KPPS H-step-ahead generalised forecast error variance decomposition can be expressed as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' \, e_i)} \tag{4}$$

where $\sum$ is the variance matrix for the error vector, σ_{jj} is the standard deviation of the error term for the j^{th} equation, A_h, is the coefficient matrix for the h^{th} lag of the VAR model, and e_i' the transpose of the residual vector for variable i. e_i, a selection vector, with one as the i^{th} element and zeros otherwise. However, as the shock to each variable is not orthogonalized, it's important to note that $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$.

The numerator represents the sum of squared contributions of all shocks to variable j up to the forecast horizon H, on the forecast error of variable i. This can be thought of as the total variance of the forecast error of variable i that is explained by the shocks to variable j. The denominator of the equation represents the sum of the squares of the impulse responses of variable i to all shocks in the VAR model. The impulse responses are the dynamic responses of variable i to a one-unit shock to each of the variables in the VAR model, and they capture the effect of each shock on variable i over time. Thus, the equation gives the proportion of the total variance of the forecast error of variable i that is explained by shocks to variable j up to the forecast horizon H. In selecting the forecast horizon, we have considered a range of horizons from 5 to 20 steps ahead. We found that the results are relatively robust to different forecast horizons, with similar patterns and magnitudes of spillover effects observed across the different horizons. We have decided to follow the convention of similar studies and use a forecast horizon of 10 steps ahead. This choice of forecast horizon is consistent with the practice in the literature and allows us to capture the medium-term spillover effects between the variables of interest. To supplement, we consider an example. If the diagonal element $\theta_{ij}^{g}(H)$ for variable j is 0.8 at forecast horizon h, it means that 80% of the forecast error variance of variable j at horizon h can be attributed to its own innovations, while 20% can be attributed to the innovations of the other variables in the system. Additionally, we could normalise each entity of the variance decomposition matrix to the row sum as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{5}$$

Such that $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$.

4.1.1 Total spillovers

With the KPPS variance decomposition, it is possible to create an aggregate spillover index. The spillover index can be perceived as a measure of the total interdependence among the variables in the model. It considers the direct and indirect effects of shocks to each variable on the forecast errors of all other variables in the system. The spillover index is obtained by summing up the cross-variance shares for each variable i in the system, i.e., the fractions of the H-step-ahead forecast error variances of x_i that are due to shocks to all other variables in the system. The spillover index can be used to identify the most important variables in the system and to assess the degree of interconnectedness among them. We can formulate the total spillover index as such:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq 1}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100 \tag{6}$$

4.1.2 Directional spillovers

The generalised VAR approach provides us with insight into the direction of spillovers. The generalised impulse responses and variance decompositions are not affected by the arrangement of variables, allowing us to determine the directional spillovers by using the normalised elements of the generalised variance decomposition matrix. We quantify the directional volatility spillovers received by market i from other markets j, or vice versa as such:

$$S^{H}_{i\to j \mid i\leftarrow j}(H) = \frac{\sum_{\substack{i,j=1\\ i\neq 1}}^{N} \tilde{\theta}^{g}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^{g}_{ij}(H)} \cdot 100 = \frac{\sum_{i,j=1}^{N} \tilde{\theta}^{g}_{ij}(H)}{N} \cdot 100 \tag{7}$$

The directional spillover measure is particularly useful when analysing the currencies that have the highest contribution to other currencies and those that are most affected by shocks from other currencies. This information can help in identifying similarities across different periods and gain insights into the aggregate behaviour of individual cryptocurrencies and their relationship to the market.

Additionally, we include the net spillovers from market i to all other markets j. The net spillovers refer to the difference between the spillover shocks transmitted, and those received from all other markets. We can simply write them as:

$$S^{g}_{i} = S^{H}_{i\to j} - S^{H}_{i\leftarrow j} \tag{8}$$

This makes it easy for us to determine if asset i is responsible for the spillovers to/from other assets j or just receiving them.

4.2 Model selection

Before applying our main Vector Autoregressive (VAR) model, we need to select an appropriate lag order. To determine the optimal lag length, we employ a model selection method based on an information criterion. The information criterion is a method for selecting the best statistical model among a set of candidate models by comparing their relative goodness of fit and complexity.

Considering the intricacy of our model, encompassing 48 variables, we posit that the Hannan-Quinn (HQ) criterion is an appropriate selection. The model jointly evaluates the model's goodness-of-fit and its complexity, to identify the most appropriate lag order. Although the Hannan-Quinn (HQ) is little used in practice (Burnham and Anderson 2002, 287), we favour it because it takes a more conservative approach to penalising more complex models. This means that HQ is less likely to overfit the data and more likely to select simpler models that generalise better to new data. However, this criterion offers several other advantages beyond its ability to handle large numbers of variables. HQ is a modified version of the Akaike Information Criterion (AIC), which is widely used to select the optimal lag order in VAR models. HQ, however, includes a penalty term for the number of parameters in the model, which is more severe than that used by the AIC. This helps to avoid overfitting and to select a more parsimonious model. To evaluate the performance of our selected model, we computed several information criteria, including the HQ criterion, and the final prediction error. Specifically, we compute:

$$HQ(n) = \ln\det\left(\tilde{\Sigma}_u(n)\right) + \frac{2\ln(\ln(T))}{T} nK^2 \tag{9}$$

Where $\tilde{\Sigma}_u(n)$ is the residual covariance matrix of the VAR model with lag order n. It is obtained by estimating the VAR model and extracting the residuals, which capture the unexplained variation in the data. The tilde notation above the Σ indicates that it is a corrected estimator that accounts for the finite sample size. $\tilde{\Sigma}_u(n) = T^{-1}\sum_{t=1}^{T} \hat{u}_t \hat{u}'_t$ and n^* is the total number of parameters in each equation and n assigns the lag order. k is the number of model parameters, det is the determinant function which calculates the determinant of the matrix, T is the sample size or number of observations in the dataset. Additionally, as we compare the results, the following information criteria, and the final prediction error are computed, using the same notations:

$$AIC(n) = \ln\det\left(\Sigma_{\tilde{u}}(n)\right) + \frac{2}{T} nK^2$$

$$\mathrm{SC(n)} = \ln\det\left(\Sigma_{\tilde{u}}(n)\right) + \frac{\ln(T)}{T} nK^2 \tag{10}$$

$$FPE(n) = \left(\frac{T+n^*}{T-n^*}\right)^K \det\left(\Sigma_{\tilde{u}}(n)\right)$$

These measures allow us to assess the goodness-of-fit of our model and to compare it with alternative models.

4.3 Marginal model

Given the moderate skewness and the consistent leptokurtic distributions observed in the various time series, we believe that the traditional linear models may not fully capture the volatility dynamics and spillover effects between the variables of interest. Therefore, we propose employing a Generalised Autoregressive Conditional Heteroscedasticity (GARCH)-

type specification when modelling volatility spillovers. The GARCH-type models are widely used in finance and econometrics to capture the time-varying volatility and the asymmetric responses to shocks. Incorporating past observations and past squared errors, these models account for the dependence of the conditional variance of errors and can effectively capture the persistence and clustering of volatility shocks that are frequently seen in economic and financial time series. We select the most appropriate model from a pool consisting of: Generalized Autoregressive Conditional Heteroscedasticity (GARCH), Exponential GARCH (EGARCH), and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH).

We determine optimal orders for model parameters using the Akaike's information criterion (AIC), a widely accepted criterion for model selection that has been shown to perform well in various contexts. AIC is particularly suitable for modeling individual time series when applied to less complex models. However, we have noticed that researchers traditionally use a trial-and-error approach or have avoided disclosing their methodology for model selection. To address this issue, we propose a function that automates the process of selecting the optimal model. We develop a function that systematically evaluates all possible combinations of n, m, p, and q for GARCH and Autoregressive Moving Average (ARMA) model selection. To prevent overly complex models, we set constraints on the parameter values. Specifically, m, n, and p must fall within the range of 0 to 3 (inclusive), while q must be at least 1 and at most 3. If q is set to 0, it would indicate the absence of any ARCH terms in the model, resulting in the conditional variance being solely dependent on the squared residuals from the previous lags. Through the process of iterating through these combinations, we can determine the model that is most appropriate based on the AIC criteria, which allows for the development of more precise models. It is important to recognise that this is a challenging task that demands substantial computational resources. For instance, when limiting our max order to 3, for all possible combinations of n, m, p, and q for the GARCH and ARMA selection we still obtain 192 different combinations. Consequently, this yields in total 9 216 combinations for our 48 variables. Therefore, as a result of computational complexity, we recommend using high-performance computing (HPC) resources such as a cluster of computers or a cloud-based computing platform with sufficient processing power and memory capacity.

We discover that an $ARMA(m,n)\ - eGARCH(p,q)$, is the most sufficient model when estimating the conditional volatility component. This model facilitates the extraction of the latent conditional volatility, which is subsequently incorporated as an input in the framework of (Diebold and Yilmaz 2012). Moreover, we find that the eGARCH model is a more flexible version of the standard GARCH model, which assumes that negative and positive shocks have different effects on conditional volatility. The eGARCH model allows for asymmetric effects of shocks on volatility, meaning that positive and negative shocks do not have equal impacts on the conditional variance of the variable of interest. By allowing for such asymmetric effects, the eGARCH model can better capture the empirical properties of the time series, such as the leverage effect, where negative shocks have a greater impact on volatility than positive shocks of the same magnitude. In contrast, the standard GARCH model assumes symmetric effects of shocks on volatility, which may not adequately capture the volatility dynamics observed in many financial and economic time series. Although trying various variants of the GARCH model we find that the eGARCH representation consistently produces most adequate results. We can formulate the eGARCH model as such:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{q} \alpha_i \left[\frac{|\epsilon_{t-i}|}{\sigma_{t-i}} - E\left\{ \frac{|\epsilon_{t-i}|}{\sigma_{t-i}} \right\} \right] + \sum_{j=1}^{q} \beta_i \log \sigma_{t-j}^2 + \sum_{k=1}^{q} \gamma_k \left(\frac{\epsilon_{t-k}}{\sigma_{t-k}} \right) \quad (31)$$

The intercept of variance is denoted by ω, while the eGARCH and ARCH components of volatility are represented by the parameters α_i and β_i respectively. Additionally, the leverage effects are captured by the parameter γ_k. When $\gamma_k < 0$, a positive shock will result in a relatively smaller increase in conditional volatility compared to an equal magnitude negative shock. This model's conditional volatility is as aforementioned utilised as an input in the (Diebold and Yilmaz 2012) frameworks to evaluate volatility spillover among the various cryptocurrencies. The specification of the marginal model for the returns r_t is a time series model that includes both an autoregressive component and a moving average component, and is given by:

$$r_t = \Omega + \sum_{i=1}^{m} \phi_i r_{t-i} + \sum_{j=1}^{n} \theta_j \epsilon_{t-j} + \epsilon_t \quad (12)$$

Here, Ω represents the intercept term, ϕ_i are the autoregressive coefficients of order m, r_{t-i} are the lagged values of the returns, θ_j are the moving average coefficients of order n, ϵ_{t-j} are the lagged values of the error terms, and ϵ_t is the current error term.

Despite the abundance of proposed models within the ARCH family e.g., (Bera and Higgins 1993, Bollerslev, Engle and Nelson 1994, Diebold and Lopez, Modeling Volatility Dynamics 1995), current research has almost universally acknowledged the superior performance of the standard GARCH(1,1) model, over attempts to determine the appropriate lag values (Javed

2011, Miah and Rahman 2016, Lunde and Hansen 2005). The plausible reason for this might be the high degree of similarity among the data used for testing the model, or perhaps due to the simplicity of employing that model. Although previous research has established that the standard GARCH(1,1) model performs well, we still believe that there is a benefit of using an information criteria for selecting the optimal model. The reason for this is that information criteria enable an objective and formal comparison of various models and can aid in avoiding overfitting in more intricate models.

4.4 Post estimation diagnostic tests

To ensure the accuracy and reliability of our analysis, it is crucial to conduct post-estimation diagnostic tests on our models. These tests allow us to evaluate any potential issues that may compromise the reliability of the model, allowing for appropriate steps to be taken to address them. We explore the methodology behind various post-estimation diagnostic tests that we have conducted on both the main and marginal model. These methods and auxiliary techniques include assessments for serial correlation, heteroskedasticity, and normality, among others. By carefully examining the results of these tests, we can ensure that our models are appropriately specified and provide accurate insights into the data.

4.4.1 Serial correlation

The assumption of uncorrelated errors across equations implies that the errors or disturbances of one equation do not depend on the errors of another equation. In other words, there is no contemporaneous correlation between the errors of different equations. However, in practice, it is common for the errors of different equations to be correlated at the same point in time (Brooks, Introductory econometrics for finance 2019, 274). This can happen, for example, if there are omitted variables that affect both equations, or if there is some form of feedback or interaction between the variables. It is important to detect and address serial correlation in the model, as failing to do so can lead to biased and inconsistent parameter estimates, as well as incorrect inference. Given a regression model, the Breusch-Godfrey test is a commonly used and well-recognised test for serial correlation. The test can detect higher-order serial correlation beyond the first order. The Breusch-Godfrey LM test can be expressed as follows:

$$\hat{u}_t = A_1 y_t + \cdots + A_p y_p + CD_t + B_1 \hat{u}_{t-1} + \cdots + B_h \hat{u}_{t-h} + \epsilon_t \qquad (13)$$

Where $\hat{u}_t$ is the residual at time t, after regressing y_t on its lags and any exogenous variables. y_{t-1} to y_{t-p} are lagged values of the dependent variable. A_1 to A_p are coefficients for the lagged dependent variable values. CD_t represents a matrix of exogenous variables at time t. B_1 to B_h are coefficients for lagged residuals from the time series regression. $\hat{u}_{t-1}$ to $\hat{u}_{t-h}$ are lagged residuals from the time series regression. ϵ_t is the error term at time t. Following, the null hypothesis:

$$H_0: B_1 = \ldots = B_h = 0$$
$$H_1: \exists B_i \neq 0, \quad \text{for} \quad i = 1,2, \dots, h \tag{14}$$

And, the test statistic can be written as:

$$LM_h = T\left(K - tr\left(\tilde{\Sigma}_R^{-1}\tilde{\Sigma}_e\right)\right) \tag{15}$$

Where $\tilde{\Sigma}_R^{-1}$ and $\tilde{\Sigma}_e$ assign the residual covariance matrix of the restricted and unrestricted model, respectively. Determination of significance is evaluated with a 90, 95, and 99 percent confidence interval. This ensures that our test is sufficiently rigorous and reliable, allowing us to make confident conclusions about the validity of our regression model. Ultimately, the results of the Breusch-Godfrey LM test will provide valuable insights into the accuracy and reliability of our main VAR model, allowing us to make informed decisions about our data analysis.

For the marginal model (i.e., the GARCH-type specification employed to extract latent volatility components for input in the Diebold Yilmaz framework), we use the Ljung-Box test instead of the Breusch-Godfrey test to test for autocorrelation in the residuals. The Breusch-Godfrey test assumes that the residuals are independent and identically distributed (i.i.d.) and have a constant variance. While this assumption may hold for some models, it may not hold for GARCH-type models, as they are designed specifically to capture the non-constant variance and non-i.i.d. behaviour. Therefore, using the Breusch-Godfrey test to test for autocorrelation in the residuals of our marginal model may not be the most appropriate choice. We can formulate the Ljung-Box test statistic as:

$$Q(m) = n(n+2)\sum_{k=1}^{m}\left(\frac{r_k^2}{(n-k)}\right) \tag{16}$$

Where $Q(m)$ is the test statistic for lag m, n is the sample size (i.e., the number of residuals) r_k is the sample autocorrelation at lag k. $\sum$ represents the sum from $k = 1$ to m. Under the null hypothesis of no autocorrelation, $Q(m)$ follows a chi-square distribution with $m - p - q$ degrees of freedom, where p and q are the number of parameters estimated in the ARMA and eGARCH models, respectively. This means that we can calculate the critical values for $Q(m)$ from the chi-square distribution with $m - p - q$ degrees of freedom. A rule of thumb suggested by (Hyndman 2014) is to select the maximum lag as $m = min\left(10, \frac{n}{5}\right)$, where, again, n is the sample size. This method selects a maximum lag that is proportional to the sample size, with a maximum value of 10.

4.4.2 Heteroskedasticity

Testing for heteroskedasticity in our model means checking whether the variance of the errors or disturbances of the model is constant over time. The presence of heteroskedasticity in the errors of the model may result in biased or inefficient estimates of its parameters and can potentially compromise the reliability of the model's results. One way to test for heteroskedasticity in the model is to use the Autoregressive Conditional Heteroscedasticity LM test (ARCH). The ARCH test checks for conditional heteroskedasticity, which means that the variance of the errors is assumed to be dependent on the past values of the errors. The ARCH test estimates the degree of autoregression in the conditional variance of the errors and provides a statistical test of whether the errors are heteroskedastic or not. The ARCH test is not directly testing for heteroskedasticity in the VAR model, but rather for conditional heteroskedasticity. However, the ARCH test is often used as a proxy for testing for heteroskedasticity in the VAR model because it is a commonly used and well-established method for checking for heteroskedasticity in time series models, and because it can provide useful information on the dynamics of the variance of the errors over time.

The multivariate ARCH-LM test is based on the following regression:

$$vech(\hat{u}_{t-1}\hat{u}'_{t-1}) = \beta_0 + B_1 vech(\hat{u}_{t-1}\hat{u}'_{t-1}) + \cdots + B_q vech(\hat{u}_{t-1}\hat{u}'_{t-1} + v_t) \qquad (17)$$

The model under consideration assumes a spherical error process assigned to the vector v at time t, (i.e., the error terms are assumed to be independently and identically distributed with constant variance over time). To represent the covariance structure of this process, we use the $vech$ operator to stack the columns of symmetric matrices, starting from the main diagonal downwards. The coefficient matrix β_0 has dimensions that depend on the number of variables in the model, denoted by K. Specifically, the dimension of β_0 is $\frac{1}{2}K(K+1)$. For each of the coefficient matrices B_i (where i ranges from 1 to q), the dimensions are $\frac{1}{2}K(K+1) \times \frac{1}{2}K(K+1)$. We write the subsequent hypothesis as follows:

$$H_0: B_1 = B_2 = \ldots = B_q = 0$$
$$H_1: B_1 \neq 0 \; or \; B_2 \neq 0 \; or \ldots or \; B_q \neq 0 \tag{18}$$

The test statistic itself can be narrowed down to:

$$VARCH_{LM}(q) = \frac{1}{2}TK(K+1)R_m^2$$

With:

$$R_m^2 = 1 - \frac{2}{K(K+1)}tr(\hat{\Omega}\hat{\Omega}_0^{-1}) \tag{19}$$

Where $\hat{\Omega}$ assigns the covariance matrix of the above defined regression model. The test statistic is distributed as $\chi^2\left(\frac{qK^2(K+1)^2}{4}\right)$.

4.4.3 Normality

One popular method for testing normality is the Bera-Jarque (BJ) test, which is widely used in statistical analysis. The BJ test relies on the fact that the mean and variance of normally distributed data can fully characterise its distribution, making it a powerful tool for assessing the normality of a dataset. Often, we determine whether a distribution follows that of normality by evaluating its kurtosis and skewness. (Jarque and Bera 1980) formalised testing whether the coefficient of skewness and the coefficient of excess kurtosis are jointly zero (Brooks, Introductory econometrics for finance 2019, 287). If denoting the errors by ϵ and their variance by σ^2, the coefficients of skewness and kurtosis can be expressed, respectively, as:

$$b_1 = \frac{E[\epsilon^3]}{(\sigma^2)^{\frac{3}{2}}} \quad \text{and} \quad b_2 = \frac{E[\epsilon^4]}{(\sigma^2)^2} \tag{20}$$

The multivariate Jarque-Bera test statistic is based on the skewness and kurtosis of the residuals. Let R be an $n \times p$ matrix of residuals from a model, where n is the sample size and p is the number of variables in the model. The kurtosis of the normal distribution we know is 3 thus, excess kurtosis: $(b_2 - 3) = 0$. Then the multivariate Jarque-Bera test statistic is given by:

$$BJ = T\left[\left(\frac{b_1^2}{6}\right) + \left(\frac{(b_2 - 3)^2}{24}\right)\right] \quad (21)$$

Where S is a p-dimensional vector of skewness of the residuals, K is a p-dimensional vector of excess kurtosis (kurtosis minus 3) of the residuals, and C is the sample covariance matrix of the residuals. The superscript T denotes the transpose of a vector. The test statistic JB follows a chi-squared distribution with $2p$ degrees of freedom under the null hypothesis of normality. The null hypothesis is of normality, and this would be rejected if the residuals from the model were either significantly skewed or leptokurtic/platykurtic (or both). The null hypothesis is that of normality in the residuals of the model. If the residuals are significantly skewed, or have an excessive leptokurtic/platykurtic kurtosis, the null hypothesis would be rejected.

We specifically employ the Shapiro-Wilk test of normality for our marginal model, which in our study refers to the GARCH-type model used as an auxiliary model to extract the latent volatility components. This is because the Shapiro-Wilk test is a more general test for normality. We employ this method to determine if a given random sample, denoted by $x_1, x_2, \ldots, x_n$, is drawn from a normal Gaussian distribution with a true mean of μ and variance of σ^2. In other words, we want to test the hypothesis that x follows a normal distribution $N(\mu, \sigma^2)$: $H0$: $x \sim N(\mu, \sigma^2)$, or Ha: $x \neq \sim N(\mu, \sigma\text{^}2)$. As in (Ramachandran and Tsokos 2020, 484), the test statistic for the Shapiro–Wilk test can be formulated as:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (22)$$

Here, $x_{(i)}$ represents the ordered sample values, and a_i are constants that are generated by the expression:

$$(a_1, a_2, \ldots, a_n) = \frac{m^T V^{-1}}{(m^T V^{-1} m)^{\frac{1}{2}}} \quad (23)$$

Where $m = (m_1, m_2 \ldots, m_n)^T$ are the expected values of the ordered statistics, which are independent and identically distributed (i.i.d.) random variables that follow the standard normal distribution, $N(0,1)$. The covariance matrix of the order statistics is denoted by V. We use an algorithm that is a C translation of the Fortran code described in (Royston 1995). For sample sizes of $n = 3$, the calculation of the p-value is exact. However, for larger sample sizes, approximations are used. These approximations are applied separately for sample sizes between 4 and 11, and sample sizes of 12 and greater. The use of this algorithm and its associated approximations allows us to perform the Shapiro-Wilk test of normality with a high degree of accuracy, even for larger sample sizes where exact calculation of the p-value is not feasible. This helps ensure that our analysis of the eGARCH model is based on reliable statistical methods and that any conclusions drawn from the model are well-supported.

4.4.4 Structural changes

Structural changes in time series analysis refer to changes in the underlying properties of a stochastic process over time, such as changing levels, variances, or autocorrelations. These changes can have a significant impact on the behaviour of the process and failing to account for them can lead to erroneous conclusions and forecasts. Structural change analysis can help to identify when and how the relationships between variables in the model have changed, allowing for appropriate adjustments to be made to the model, e.g., adding dummy variables, dividing the data into homogeneous segments before modelling, and so on.

Using the empirical fluctuation process according to a specified method from the generalised fluctuation test framework, we employ the OLS-CUSUM method to identify potential structural breaks in a time series model. It works by estimating a cumulative sum of recursive residuals for our VAR(p) model and comparing it to a critical value calculated based on the assumption of no structural breaks. If the cumulative sum exceeds this critical value, it suggests evidence of a structural break. To assess structural stability, we visually examine the Empirical Fluctuation Processes (EFP) for any significant deviations. The OLS-CUSUM type empirical fluctuation process is defined, as in (Zeileis, et al. 2002), by:

$$W_T^0(t) = \frac{1}{\hat{\sigma}_e \sqrt{n}} \sum_{i=1}^{[nt]} \hat{u}_i \qquad (0 \leq t \leq 1) \tag{24}$$

$\hat{\sigma}_e$ is the estimated variance of the error term in the regression model. It is used to standardise the residuals so that they have a mean of 0 and a variance of 1. n is the sample size, or the number of observations in the time series. $\hat{u}_i$ is the standardised OLS residual, which is the difference between the actual value of the dependent variable and the predicted value of the dependent variable based on the regression model, divided by the estimated standard error of the regression model. Standardising the residuals in this way ensures that they have a mean of 0 and a variance of 1. $[nt]$ denotes the integer part of nt, which is used to calculate the cumulative sum of the standardised residuals up to a certain point in time. Boundaries are used to determine whether the changes in the data are improbably large and hence reject the null hypothesis of no change. The standard boundaries for the OLS-CUSUM are of the linear type and can be expressed as $b(t) = \lambda \cdot (1 + 2t)\ for\ 0 \leq t \leq 1$. Where λ is a constant that determines the confidence level. We plot the OLS-CUSUM process and its corresponding boundaries at a confidence level of 5 percent. This allows us to visually inspect whether the path of the process crosses over the boundaries or not.

4.5 Similarity index

The similarity between spillovers across different periods can be quantified using a mathematical approach. We let k be an element in two permutation sequences, i and j, each of length n. $D_{ij}(k)$ represents the distance between k in list j and item k in list i, $rank_i(k)$ is the rank of item k in list i, and $max(n - rank_i(k), rank_i(k) - 1)$ is a normalisation term to account for ties in the ranking. For any k observation existing in list i and j, we can measure their similarity by:

$$S_{ij}(k) = \frac{\left|D_{ij}(k) - rank_i(k)\right|}{max(n - rank_i(k), rank_i(k) - 1)} \tag{25}$$

The overall similarity between the two permutated lists can be obtained by the average of all individual similarities as such:

$$S_{ij} = 1 - \frac{1}{n}\sum_{k=1}^{n} \frac{\left|D_{ij}(k) - rank_i(k)\right|}{max(n - rank_i(k), rank_i(k) - 1)} \tag{26}$$

This formula calculates the average absolute difference in the rank of each item between the two lists, normalised by the maximum possible difference in rank. The similarity index takes a value of 1 for identical lists, while a lower value indicates greater dissimilarity between the two lists. However, the similarity index, as defined, cannot take on a value of 0 for $n > 2$. This is because there cannot be more than one pair of observations with the maximum distance from each other. A mathematical minimum value for the similarity index function given a specific n is yet to be discovered. Thus, the minimum value of any similarity index can be obtained by calculating the similarity index for all possible permutations of the second list relative to the first list and selecting the minimum value obtained. However, this becomes computational impossible when $n \rightarrow \infty$. If we reverse on of the lists and compute the similarity index for a given observation, we expect to see a value of 1 when the middle value is being compared to itself. This is because the distance between the two sequences, in this case, is minimised in the middle and maximised at the edges. Although we can obtain smaller values by doing small alteration near the middle position, a reversed order could be used to estimate the approximate lowest attainable value for the similarity index.

An additional limitation of the function is its apparent sensitivity to variable ordering. Specifically, we observe that the function's output may vary slightly depending on the order in which data are inputted (e.g., comparing list i to j as opposed to j to i). However, it should be noted that these differences are relatively small in magnitude and do not alter the overall indication of similarity between the inputted set of sequences. Overall, employing the similarity index may serve as an indication of the degree of similarity between e.g., directional spillovers across multiple periods. While the similarity index may not be a perfect measure of similarity, it can still be a useful tool for comparing sequences, particularly if one is interested in identifying patterns of similarity of two sequences.

4.6 Unit root test

One of the prerequisites for estimating the Vector Autoregression (VAR) model is that the variables incorporated in the model should display stationarity. However, in the case of our return observations, as measured in Equation (1), it is quite likely that the data exhibit stochastic behaviour and possess a unit root. However, we still evaluate the presence of unit roots formally by employing an Augmented Dickey-Fuller test (ADF) on the time series. As the time series might inhibit traits of non-stationarity, we can apply certain transformations techniques (e.g., logarithmic or power transforms, differencing) to achieve stationarity. However, it's worth noting that higher-order transformations can result in a loss of data and introduce spurious and unreliable results.

The Augmented Dicky-Fuller test extends the original Dickey-Fuller test by accounting for higher-order autoregressive structures and allowing for serial correlation in the errors. The test works by estimating the degree of differencing required to transform a non-stationary series into a stationary one. We test for the null hypothesis that the time series inhibits a unit root, i.e., non-stationary and has a stochastic trend. The alternative hypothesis is that the time series is stationary and does not have a unit root. More specifically, the null hypothesis is that the coefficient of the lagged first difference term, which represents the presence of a unit root, is equal to zero (i.e., $\delta = 0$ in the equation). The alternative hypothesis is that the coefficient is negative (i.e., $\delta < 0$), indicating that the time series is stationary. We can express the equation as follows:

$$\Delta y_t = \alpha_0 + \alpha_1 t + \gamma y_{t-1} + \sum_{j=1}^{p} \delta_j \Delta y_{t-j} + \epsilon_t \quad (27)$$

Where Δy_t is the first difference of variable y at time t, y_{t-j} the variable lagged j times, α_0, a constant term, α_1 the coefficient on a time trend t, γ is the coefficient of the lagged level of the series, δ_j represent the slope parameters for the j^{th} lagged differences of the time series, and ϵ_t the error term. As suggested by (Banerjee, et al. 1993), to determine the optimal number of lags to include in the regression, the Dickey-Fuller test uses a default value of $k = \left\lfloor (T - 1)^{\frac{1}{3}} \right\rfloor$ where T is the sample size of the time series data, and $\lfloor\ \rfloor$ denotes the floor function, which rounds the result down to the nearest integer. The upper bound on the rate at which the number of lags, k, should be made to grow with the sample size for the general ARMA(p,q) setup. This is used to avoid overfitting the model and to strike a balance between including enough lags to capture the serial correlation in the data and avoiding spurious regression caused by including too many lags.

4.7 Heteroskedasticity-consistent standard errors

In traditional linear regression models, the standard errors of the estimated coefficients are based on the assumption that the error terms are normally distributed with constant variance, and that there is no correlation among the errors. However, in some cases, these assumptions may not hold, leading to biased standard errors. This, in turn, may affect the significance of the estimated coefficients. To address this issue, we propose employing heteroskedasticity and autocorrelation consistent standard errors (HAC). Although Employing HAC on the residuals of the e.g., Vector Autoregressive (VAR) model does not change the actual estimated coefficients or the decomposition results, it provides a more accurate assessment of the statistical significance of the estimated coefficients and decomposition results.

To obtain the robust standard errors, we can use a matrix equation (i.e., White/ Huber/ a.k.a. sandwich estimator). The coefficient matrix's covariance matrix can be computed using:

$$V(\beta) = (X^T X)^{-1} X^T S X (X^T X)^{-1} \quad (28)$$

Where X is the design matrix of the regression model, which contains the explanatory variables and an intercept term. S is the covariance matrix of the residuals, which captures the correlation structure of the error terms. Under the assumption that the residuals have a mean of 0 and are not autocorrelated, i.e. $E[e] = 0$ and $E[ee^T] = 0$, S is the diagonal matrix whose diagonal elements are e_i^2. We may employ different version of S:

$$HC1: \quad S = \frac{n}{n-k} e_i^2$$

$$HC2: \quad S = \frac{e_i^2}{1-h_i} \tag{29}$$

$$HC3 = S = \frac{e_i^2}{(1-h_i)^2}$$

HC1 is a "naive" estimator that only accounts for heteroscedasticity, but not for any other forms of model misspecification. It assumes that the errors are uncorrelated and have different variances for each observation, but that the variance is constant across all regressors. HC2 is a more robust estimator that accounts for both heteroscedasticity and possible serial correlation in the errors. It assumes that the errors are uncorrelated but have different variances that can be estimated consistently by a long-run variance estimator, such as the Newey-West estimator. It is a more efficient estimator that accounts for heteroscedasticity, serial correlation, and the possibility of endogeneity in the regressors. We have decided to use the HC2 estimator in all our models due to its advantages over the other two alternatives. While HC1 may lead to inflated standard errors in the presence of outliers, HC3 can be overly sensitive to them and result in overly small standard errors, despite being empirically proven to be a better estimator (Zaiontz 2020). HC2, on the other hand, strikes a good balance between robustness and efficiency and provides reliable estimates of standard errors. As a result, we believe that HC2 is the most suitable choice for our standard error estimation.

Overall, using robust standard errors can help to improve the reliability of the estimated coefficients in the VAR model, particularly in cases where the assumptions of normality and homoscedasticity may not hold. Additionally, it is important to note that statistical significance is not the only factor to consider when evaluating a model. Even if the coefficients are not significant, there may still be some meaningful relationships between the variables that are not captured by the model. Additionally, if the purpose of the spillover index is to capture the transmission of shocks or spillovers between the variables, it may still be worth exploring even if the coefficients in the VAR model are not significant.

5. Empirical analysis

In this chapter, we report the outcomes of our empirical analysis. Owing to the considerable number of cryptocurrencies in our study, some results are furnished in appendices, rather than being presented in the primary text[5]. Our focus in this chapter is primarily on the results, with their implications and interpretations elucidated in the ensuing discussion section. First, we present the results from the static period, followed by the temporal periods. Second, we extrapolate our analysis by examining rolling spillovers, which enable us to identify shifts or trends in the spillover patterns over time. This analysis provides us with valuable insights into how the spillover effects evolve over the course of the study period. Finally, our evaluation of the spillover dynamics is concluded with a discussion of the robustness of our findings.

5.1 Static spillovers

We present the various outcomes from the spillover tables bellow Appendix A.4. These values are obtained from the generalised forecast error variance decomposition method, which was detailed in the methodology chapter. Each entry in the table corresponds to the estimated contribution to the forecast error variance of currency i, resulting from shocks to currency j. The off-diagonal column and row sums, which represent the contribution from and to other variables, are displayed in the far-right column and bottom row, respectively. The latter is accompanied by "contribution to self and others", along with "net spillovers". Table 4 and 5 display the top ten contributors of both return and volatility, along with their measures on received shocks and net spillovers. These tables provide a concise overview of the most significant contributors to spillovers in the cryptocurrency market, allowing us to view the most influential variables.

5.1.1 Return spillovers

By examining the table outlining the spillovers of return, we observe that the innovations to Ethereum (ETH) returns are accountable for 3.51% of the error variance when forecasting the 10-day-ahead Bitcoin (BTC) returns, while they only account for 1.97% of the error variance when forecasting Ergo (ERG) returns. The magnitude of the spillover effect from ETH returns

[5] Spillover tables for different temporal periods are furnished under Appendix A.4.2 due to their considerable size. Directional and net spillovers for every period are added under Appendix A.5 for readers' reference.

on BTC and ERG returns can be interpreted as a measure of interdependence between the assets. A higher proportion of the error variance explained by ETH returns when forecasting BTC returns, compared to when forecasting ERG returns, indicates that there is a stronger relationship between ETH and BTC returns, than between ETH and ERG returns. This relationship can be interpreted as a measure of how much information about the returns of one asset (in this case, ETH) can be used to make predictions about the returns of another asset (BTC or ERG). However, it is important to note that the generalised forecast error variance decomposition method does not directly provide forecasts of future forecast error variance. Instead, it provides information about the relative contributions of different variables to the forecast error variance, which can help us better understand the relationships between variables and their impact on forecasting accuracy.

As mentioned earlier, given the vast amount of data and complexity involved, analysing each individual shock transmission is infeasible. Therefore, we present a comprehensive table that ranks the top ten cryptocurrencies by their respective magnitudes of directional return spillovers onto other currencies. The table includes additional metrics such as their received shocks, i.e., contributions from other currencies, and their respective net spillovers. Furthermore, we provide the mean, minimum, and maximum values of each metric to facilitate comparative analysis.

Table 4: Top ten cryptocurrencies ranked by magnitude of return spillovers to other currencies.

Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers
1	ETH	133.6	95.3	38.3
2	NEO	125.6	95.0	30.6
3	LTC	122.8	94.9	27.9
4	QTUM	118.0	94.8	23.3
5	OMG	116.0	94.6	21.3
6	BTC	115.1	94.6	20.5
7	EOS	114.5	94.6	20.0
8	MIOTA	113.1	94.5	18.6
9	XMR	112.0	94.4	17.6
10	ZEC	111.4	94.4	17.0
.	.	.	.	.
.	.	.	.	.
48	ERG	14.6	66.3	-51.7
Mean		92.7	92.7	0.0
Min		14.6	66.3	-51.7
Max		133.6	95.3	38.3

Note: The table displays the off-diagonal column and row sums of the return spillover table, along with their difference, namely net spillovers. The Mean, Min, and Max rows represents the average, the minimum, and the max of each respective row.

Upon inspecting the “contributions to others” metric, it becomes evident that ETH significantly transmits a higher number of return shocks compared to other currencies (133.6 percent). A contribution value of 133.6 would imply that shocks in ETH's returns account for 133.6% of the forecast error variance of the other currencies in the system. Conversely, upon inspecting the "contributions from others" metric, ETH also happens to be the principal recipient of shocks, with a magnitude of 95.3 percent. Despite ETH's position as the foremost recipient and contributor of spillovers, it still yields the highest net spillover of 38.3 percent.

Ergo (ERG) ranks the lowest among all cryptocurrencies studied in terms of its contribution to and from other currencies, as well as net spillovers. The static spillover of returns table yields a spillover index of 92.7%, indicating a substantial proportion of the overall forecast variance originating from spillover. The index can be interpreted as the proportion of the total forecast error variance in the system that is explained by spillover effects from other variables, whereas the remaining 7.3% can be attributed to the respective currency's internal shocks, (i.e., contribution to itself). In fact, we can derive the overall forecast variance originating from self-shocks by substituting the $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)$ term computed in the spillover index computation, with the trace of the matrix.

5.1.2 Volatility spillovers

Static spillovers of volatility are furnished below Appendix A.4.1. This table is also derived from the generalised forecast error variance decomposition of the Vector Autoregressive model, although the input utilises latent volatility components from the marginal mode, (i.e., the conditional standard deviation of the model's residuals). As we did for spillovers of returns, we present a table featuring the top ten cryptocurrencies ranked by the magnitude of directional volatility spillovers they generate to other currencies.

Table 5: Top ten cryptocurrencies ranked by magnitude of volatility spillovers to other currencies.

Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers
1	OMG	146.0	91.0	55.0
2	DASH	143.0	91.1	51.9
3	EOS	137.1	89.9	47.3
4	ETH	137.0	91.8	45.1
5	QTUM	131.1	90.5	40.6
6	BAT	130.5	89.6	41.0
7	BCH	125.1	89.0	36.1
8	LSK	124.9	90.7	34.2
9	ICX	124.7	90.3	34.4
10	XRP	122.5	88.2	34.4
.	.	.	.	.
.	.	.	.	.
48	ERG	0.6	8.5	-7-9
Mean		83.9	83.9	0.0
Min		0.6	8.5	-56.7
Max		146.0	91.8	55.0

Note: The table displays the off-diagonal column and row sums of the volatility spillover table, along with their difference, namely net spillovers. The Mean, Min, and Max rows represents the average, the minimum, and the max of each respective row.

Here, we observe that ETH, similar to the previous return spillovers, is a significant contributor. The highest contributor to others is OMG (146 percent), while ETH is the highest recipient of shocks (91.8 percent). The highest net spillover is observed for OMG (55 percent), followed by DASH (51.9 percent), and EOS (47.3 percent). On the other hand, ANT has the lowest net spillover (-56.7 percent), indicating that it is more likely to receive, than to transmit volatility shocks to other cryptocurrencies. Similar to the findings in the return spillovers, ERG's contribution to spillovers in the market is found to be the lowest, accounting for only 0.6 percent. The volatility spillover table yields a total spillover index of 83.9%, 8.8% lower than that of the total spillover index of return, suggesting that there is a higher degree of return transmission in the market compared to that of volatility.

By using the similarity index proposed in Equation (26), we can gain insight into the degree of similarity between the directional spillovers. The analysis indicates that there are similarities between the static spillovers of return and volatility. Examining the similarities in the "contribution to others", "contribution from others", and "net spillovers" between the return and volatility model, we observe that there exists a degree of similarity. The similarity index computes values of 0.74, 0.80, and 0.71, respectively. A similarity coefficient of 1 would indicate perfect similarity, meaning that our observed similarity coefficients are notable but not identical. However, it should be emphasised that when $n > 2$, the similarity index cannot be zero. And as mentioned in the methodology chapter for the similarity index, the minimum value of any similarity index can be obtained by calculating the similarity index for all possible permutations of the second list relative to the first list and selecting the minimum value obtained. However, the number of possible combinations of our list containing 48 unique cryptocurrencies are 48! (48 factorial), which is approximately $1.24 \; x \; 10^{61}$. To put it in perspective, if we could generate and test 1 billion (10^9) combinations per second, it would take us approximately $3.93 \; x \; 10^{42}$ years to try them all. This is many orders of magnitude longer than the current age of the universe, which is estimated to be around 13.7 billion years (Weintraub 2011). By utilising both a random selection simulation method[6] and manual manipulation of orders, we have determined that the minimum achievable value with 48 observations is approximately 0.37. Consequently, it seems that there are some resemblances between the spillovers of returns and volatilities.

However, dissimilarities exist. For instance, Bitcoin (BTC) exhibits a high ranking as the sixth largest contributor of return with 115.1 percent. On the other hand, Bitcoin's contribution to volatility is relatively low and ranks at 27th place. With respect to the static period, an examination of our similarity index as in Equation (25) reveals that BTC exhibits the lowest individual value of 0.21, indicating that its return and volatility dynamics are notably dissimilar in comparison to the other currencies. Notably, our analysis indicates that innovations to BTC returns have a greater influence on error variance than BTC volatility. It is also noteworthy that BTC exhibits negative net spillovers of volatility during this period, implying that it receives more volatility from the market than it contributes. However, the

[6] The method relies on randomly selecting permutation orders for a list j, n times, and returning the minimum value. While testing this method over a million times, obtaining the minimum value is unlikely. However, the results obtained from this method closely approximate those obtained from reversing the order of the list.

same cannot be said for returns, as BTC is found to rank sixth on the list of largest net spillovers in this regard.

5.2 Temporal spillovers

This section aims to extend the examination of spillovers by scrutinising the temporal dynamics of the cryptocurrency market. By partitioning our data into yearly subsamples spanning the period from 2018 to 2022, we may identify any discernible patterns or trends and assess how the market has evolved over time. Using the same methodology as before, we apply the generalised variance forecast error decomposition to each sub-sample to investigate spillovers of both return and volatility. This method enables us to acquire more insights into the relative impact of individual cryptocurrencies on driving spillovers and the extent to which these effects have varied over different time frames.

In the context of overall spillovers, both the static and temporal periods demonstrate a substantial degree of spillovers, as substantiated by the total spillover index located in the lower right corner of each respective spillover table. Notably, all spillover indices of the temporal periods exhibit values greater than 94%, denoting an elevated level of spillovers throughout all temporal periods. This highlights the significant interdependence and interconnectedness of the various currencies within the system. In the subsequent chapter, these values are also aggregated when analysing them in rolling-windows.

Assessing contribution of both return and volatility shocks to the system, it can be deduced that Ethereum (ETH) and Qtum (QTUM) has had a noteworthy impact. In most subsamples, except for 2022, the empirical results suggest that ETH has been a significant contributor of volatility, and overall, except for 2019, a large contributor of returns. Additionally, during all periods except for 2019, QTUM appears to have sustained its dominance in terms of contributing to both return and volatility spillovers. These findings suggests that both ETH and QTUM has played a critical role in shaping the overall dynamics of the sampled cryptocurrencies. Bitcoin (BTC) appears to exhibit a noteworthy impact on the market's return, albeit solely for the static and 2020 subsamples. Despite exhibiting relatively diminished influence on market volatility as compared to other currencies, Bitcoin emerges as one of the dominant contributors of volatility, albeit solely in the subperiod of 2019. In contrast to some literature (Koutmos 2018, Kumar and Anandarao 2019), but like the findings of (Zięba, Kokoszczyński and Śledziewska 2019), our findings suggest that Bitcoin may not be the most significant contributor of either return or volatility. Nevertheless, our analysis indicates that the Bitcoin exhibits noteworthy influence, only during certain periods. Specifically, during the static and 2020 sub-periods for return, as well as 2019 and 2022 sub-periods for volatility spillovers.

In order to identify the most prominent currencies that have caused shocks in the system, we have created a visual representation displaying the top three currencies with the highest contribution of shocks for each period. The plot depicts currencies in the system that exert a discernible impact on the overall spillover of return (Figure 5), and volatility (Figure 6), thereby facilitating the identification of underlying patterns or trends. First, we present the top three contributors of return shocks for each currency, followed by the three most significant contributors of volatility shocks to the system.

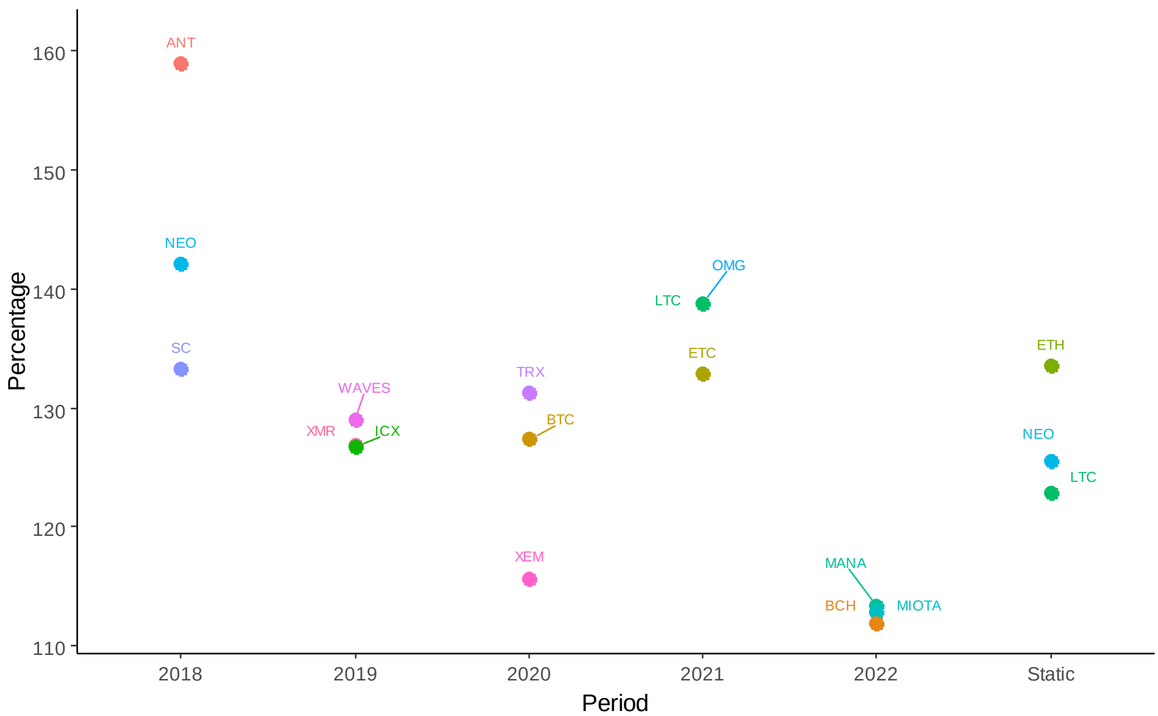

Figure 5: The Static and Temporal Periods' Top 3 Contributors of Return Shocks

Note: The Figure displays various colours for each observed ticker, with the same colour assigned to tickers that are the same. For example, Neo is displayed in both 2018 and the static period and has the same colour in both periods. The graph explicitly measures the directional transmission of shocks to other currencies in the market.

From Figure 5, it is difficult to discern any clear patterns in terms of the three largest contributors of return shocks among the various currencies. The only currency that appears twice in Figure 5 was NEO, while the other currencies appear only once. This suggests that there is no particular currency or group of currencies that dominate the contributions of return shocks relative to the others. Therefore, it is challenging to draw any conclusive insights from the graph in terms of identifying the most significant contributors to return shocks in the system.

Considering all the sampled currencies, we can explore potential similarities across the observed periods by employing the similarity index in a matrix format. Due to the variable ordering issues, we only interpret the lower triangular matrix. Furthermore, the diagonal elements will always be equal to 1 since $S_{ii} = 1$.

Table 6: Similarity index applied to directional return contribution to the market

i, j	Static	18	19	20	21	22
Static	1					
18	0.68	1				
19	0.62	0.59	1			
20	0.58	0.55	0.51	1		
21	0.73	0.54	0.61	0.56	1	
22	0.66	0.64	0.55	0.67	0.60	1

Note: Each entry represents the average similarities between the directional transmission of shocks to others for each respective period. Each entry is calculated as in Equation 25.

Table 6 reveals some level of similarity, although some of it may be attributed to random variation. Notably, the similarities between the static period and the 2021 sub-period are the most prominent, suggesting that the 2021 period may share some similarities with those observed in the static period. Furthermore, the results do not indicate evidence of significant similarities in the transmission of return shocks among the different periods examined in the study.

To identify the primary directional transmitters of volatility shocks to the system, we utilise the same methodology employed in Figure 5. Again, we notice the appearance of some similar coins, while no distinct pattern. From Figure 6, it can be observed that only Bitcoin appears twice as one of the top three contributors of volatility shocks in both 2019 and the 2022 sub-sample. This finding indicates that no specific currency or group of currencies stands out as being the dominant contributor of volatility shocks, when compared to the other currencies.

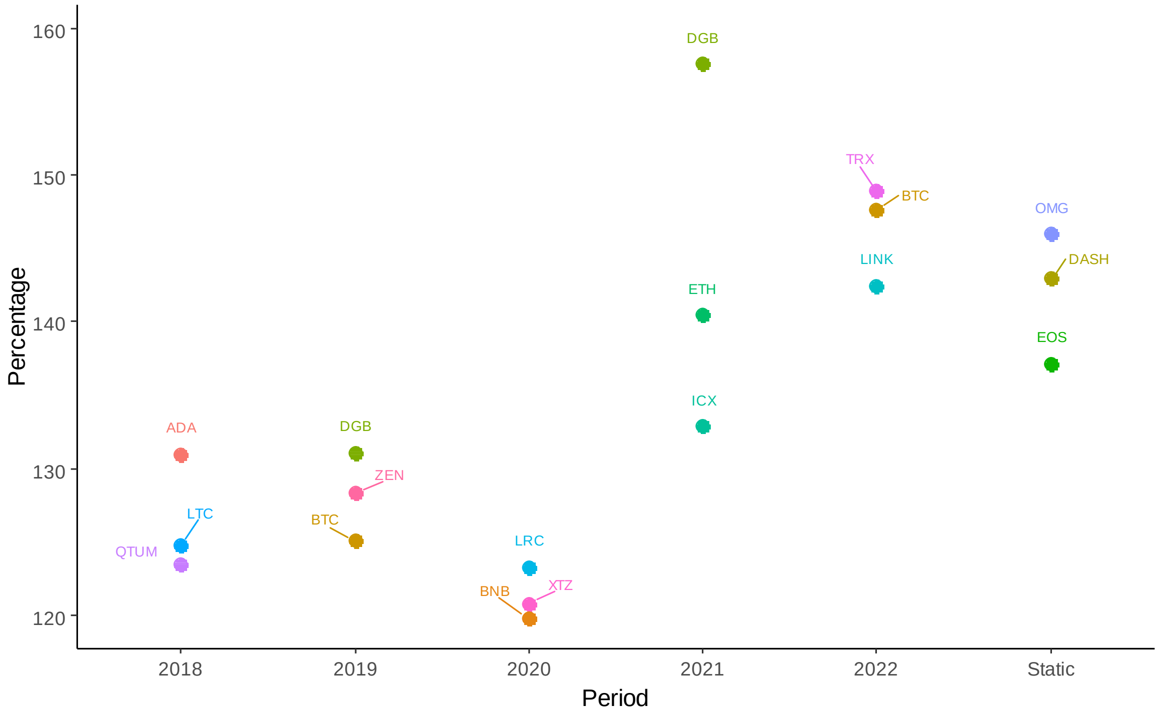

Figure 6: Top 3 Largest Contributors of Volatility Shocks for Static and Temporal Periods

Note: The Figure displays various colours for each observed ticker, with the same colour assigned to tickers that are the same. For example, Bitcoin is displayed in both 2019 and 2022 and has the same colour in both periods.

Another interesting discovery is that Ergo (ERG) is found to be one of the lowest contributors of return shocks in all temporal sub-samples, with some exception of 2019 and 2021. It also shows that ERG's contribution to volatility shocks is also relatively low, particularly during the 2019 and 2020 subsamples. These results imply that ERG may be less connected or less impacted by spillovers of returns and volatility from other cryptocurrencies in the market.

As for the directional transmission of return shocks, we explore potential similarities between volatility contributions to the market across the observed periods by, again, employing the similarity index in a matrix format.

Table 7: Similarity index applied to directional volatility contribution to the market

i, j	Static	18	19	20	21	22
Static	1					
18	0.57	1				
19	0.58	0.58	1			
20	0.63	0.60	0.56	1		
21	0.68	0.57	0.60	0.61	1	
22	0.65	0.62	0.55	0.59	0.55	1

Note: Each entry represents the similarities between the directional transmission of shocks to others for each respective period. Each entry is calculated as in equation 26.

Similar to the findings on the directional transmission of return shocks, there is little evidence of strong similarities across the various periods examined in this study with respect to the transmission of volatility shocks to the market. These findings suggest that, on average, currencies do not exhibit a specific position in terms of their spillover contributions to other currencies during each respective period. Albeit some currencies might contribute to more similarities than others.

Overall, while it is challenging to discern any clear-cut dominant patterns, we observe that currencies such as Ethereum (ETH) and Qtum (QTUM) are large contributors of both return and volatility shocks to the market. The largest cryptocurrency in terms of market cap, namely Bitcoin show dominance, but only for sub-periods. Another intriguing finding is related to Ergo (ERG), which seems to exhibit limited linkage with the market for the majority of the observed periods.

5.2.1 Rolling spillovers

Following the computation of spillover indices as in Equation (6), we proceed to estimate the rolling spillovers for both return and volatility spillovers. We employ rolling periods of 100, 200, and 300 days. We have opted for these rolling periods to estimate the rolling spillovers for both returns and volatility, as several similar studies have utilised these window lengths. Also, the 100-day period we believe provides a more near-term perspective, while the 200- and 300-day periods capture medium and longer-term trends, respectively. Examining these rolling periods enables us to achieve a more refined understanding of the spillover effects over time, and to identify shifts or trends.

The graphical representation denoted as Figure 7 illustrates that the return spillovers exhibit a persistent high level throughout all the periods. Nonetheless, it is noteworthy that two distinct peaks of spillovers stand out, which occurred around mid-2020 and mid-2021, respectively. Our findings reveal a slight increase in spillover effects from mid-2021 to the most recent observations in 2023. Nevertheless, it is important to note that despite this trend, spillovers remain consistently high throughout all periods. For instance, the total spillover plot demonstrates that there are no observations of spillovers below 85 percent, which indicates a persistent level of high interdependence among the cryptocurrencies in our study.

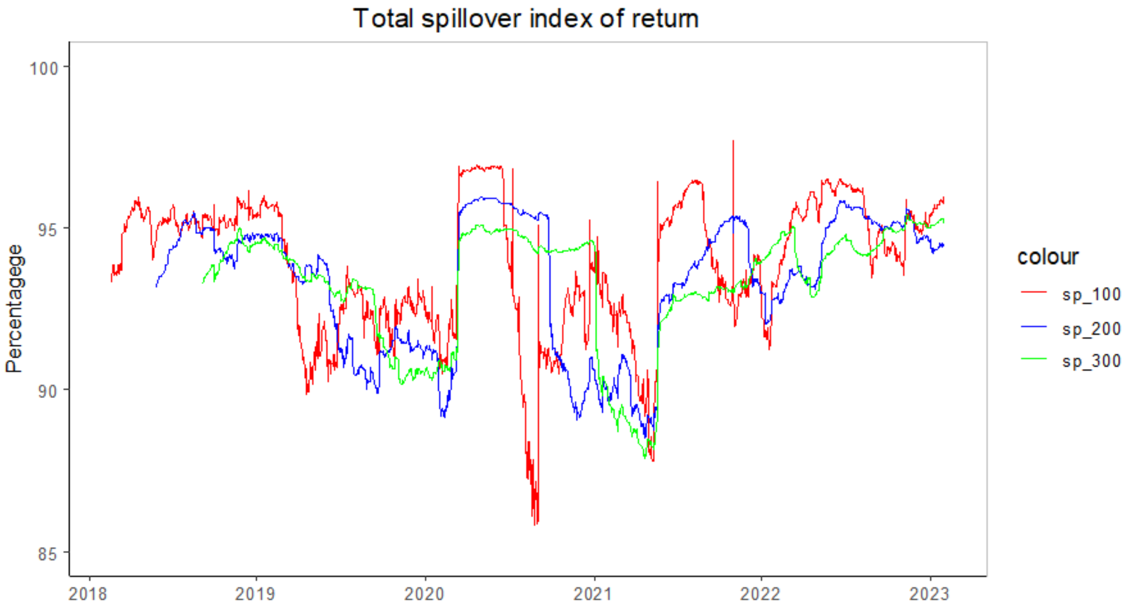

Figure 7: Rolling return Spillover index

Note: The Figure illustrates the total return spillover index over time. The results are computed using the forecast error variance decomposition of a 10-step-ahead forecast horizons. 100-, 200-, and 300-days rolling windows were used to generate the plot.

In Figure 2, where the prices were combined into an index with equal weights, a period of turmoil followed by a sharp decline in prices was revealed. It appears that the spillovers increased significantly, particularly after the significant return shock on 12.03.2020, and around the shock around mid-2021. The increase in spillovers following these periods may suggest that the shock had a significant impact on the overall market, causing more volatility and spillover effects. This could also indicate that the shock was transmitted across multiple currencies or assets, leading to increased correlations and spillovers among them.

Comparable patterns to the rolling spillover plot of returns are discerned in the rolling spillovers of volatilities; nevertheless, the latter evinces somewhat greater fluctuations. Figure 8 depicts the total spillover index of volatilities, which offers insight into the extent of volatility spillovers that have occurred in the market over the examined time period.

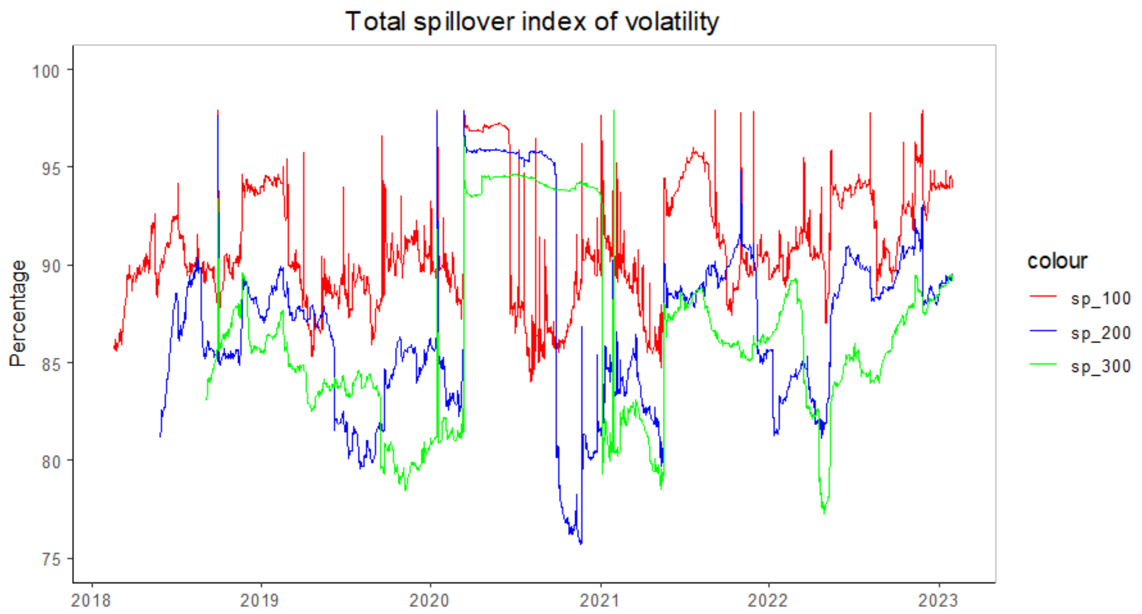

Figure 8: Rolling volatility Spillover index

Note: The Figure illustrates the total volatility spillover index over time. The results are computed using the forecast error variance decomposition of a 10-step-ahead forecast horizon. 100-, 200-, and 300-days rolling windows were used to generate the plot.

Despite their relatively small magnitudes, our analysis reveals consistently high levels of spillovers in both volatility and returns across all time periods, with some small, but notable deviations occurring around mid-2020 and mid-2021 for both return and volatility.

5.3 Marginal model

The marginal model, specifically the eGARCH model, has been employed in order to extract the latent conditional volatility components with the intent of subsequently incorporating them into the Vector Autoregression (VAR) model for decomposition purposes. As briefly explained in the methodology section, we select the most appropriate model from a pool of Generalized Autoregressive Conditional Heteroscedasticity (GARCH), Exponential GARCH (eGARCH), and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) models. Amongst those, we select the optimal lag orders by iterating through every possible combination of orders of n, m, p, and q for the GARCH and ARMA orders in the model. To limit the amount of time required for solving numerous potential combinations, we have imposed constraints on the parameter values. Specifically, variables m, n, and p have been limited to the range of 0 to 3, while variable q is restricted to a range between 1 and 3. Setting q to 0 would imply that there are no ARCH terms in the model, and the conditional variance would only depend on the lagged squared residuals.

We also employ a simple GARCH(1,1) model, as suggested by (Javed 2011, Miah and Rahman 2016, Lunde and Hansen 2005), but discover that the eGARCH specification is more preferable. The results for the optimal model selection can be found in Appendix A.2, whereas estimates and respective p-values for the significance test could be found in Appendix A.6. From the estimated coefficients, we consider a model statistically significant at a 5% significance level. It's also important to note that some models have different coefficients than others, since they might have higher orders (i.e., m, n, p, q).

We find that 86% of the GARCH (β), and 78% ARCH (α) component are statistically significant at a 5% threshold level. This suggests that both the lagged squared shocks from the previous period and the persistence in conditional volatility for all underlying series have a significant impact on the current conditional volatility. We also discover that the previously mentioned leverage effect γ is statistically significant for 94% of the currencies, which suggests that there is a strong relationship between the volatility of the returns and the magnitude of negative returns. In practical terms, this means that when the market experiences a large negative shock, the volatility of the returns is likely to increase more than it would if the shock were positive. We also discover that almost all autoregressive parameters (i.e., 94%) are statistically significant for each currency, implying that the previous returns are highly influential in explaining the current returns.

5.4 Model selection for the Vector Autoregressive (VAR) model

While our primary Vector Autoregression (VAR) model is based on the Hannan-Quinn information criterion, we also consider other model selection criteria, such as the Akaike information criterion, the Schwarz Criterion (SC), and Akaike's Final Prediction Error (FPE). We perform the function outlined in Appendix B.3[7] for a range of possible lags, up to a maximum of 10 lags, to identify the optimal lag length for the model. The optimal lag length

[7] The function in question is the one labelled "criterion_table" in the code.

is the one that minimises the criterion, which in turn represents a balance between model fit and model complexity. When applying this process to our VAR, the lag length is chosen simultaneously for all variables in the system. This means that the same lag length is used for all variables in the model, and the goal is to find the optimal lag length that provides the best overall fit for the entire system. Tables 8 and 9 exhibit the pertinent lag orders for the VAR model, which takes into consideration both our model encompassing returns and the model entailing latent volatility components.

Table 8: Optimal lag orders for the VAR model of returns

Criterion	Total	2018	2019	2020	2021	2022
AIC	2	7	7	7	7	7
HQ	1	7	7	7	7	7
SC	1	7	7	7	7	7
FPE	2	7	7	7	7	7

Note: The selected orders are based on: Akaike Information Criterion (AIC) Hannan-Quinn Criterion (HQ) Schwarz Criterion (SC) Final Prediction Error (FPE).

It is interesting to note that for the total sample period of the return model, as indicated by 'Total', the Hannan-Quinn Criterion (HQ) and Schwarz Criterion (SC) both suggests a lag of 1, while Akaike Information Criterion (AIC) and Final Prediction Error (FPE) suggest a lag of 2. This is due to the fact that the Hannan-Quinn Criterion (HQ) Schwarz Criterion (SC) criterion penalise complex models more heavily than the Akaike information (AIC) and Final Prediction Error (FPE) criterion.

Table 9: Optimal model lag orders for the VAR model of Volatility

Criterion	Total	2018	2019	2020	2021	2022
AIC	5	7	7	7	7	7
HQ	4	7	7	7	7	7
SC	1	7	7	7	7	7
FPE	5	7	7	7	7	7

Note: The selected orders are based on: Akaike Information Criterion (AIC) Hannan-Quinn Criterion (HQ) Schwarz Criterion (SC) Final Prediction Error (FPE).

Although the results are a bit more drastic for the volatility model, we see that both Hannan-Quinn Criterion (HQ) and the Schwarz Criterion (SC) suggest lower orders compared to that of Akaike Information Criterion (AIC), and Final Prediction Error (FPE). On the other hand, the HQ deviates more from SC. This is because the Hannan-Quinn Criterion (HQ) typically penalises less than the Schwarz Criterion (SC). HQ, although higher is closer to that of AIC, and FPE and is thus chosen as lag-length for the static (total) period.

For all of the sub-periods examined, all of the information criteria suggest a lag of 7. This result may seem surprising, given the relatively large number of variables in our model. Nevertheless, it is important to note that the selected lag length is the one that optimises the balance between model complexity and goodness of fit. In this regard, the selected lags can be seen as providing a trade-off between overfitting the data and underfitting it. Overall, the selected lag lengths should provide a good balance between these two concerns and should provide a robust framework for our subsequent analysis.

5.5 Robustness

The study conducts various robustness diagnostic tests, as detailed in the methodology section. As a result of the voluminous data, most outcomes are not presented in the main body of the text but are instead furnished in the Appendix. Results for the main Vector Autoregressive (VAR) model are reported for the static period, for both return and volatility in Appendix A.7. The results of the VAR results for the temporal period are not included in the thesis due to the extensive number of tables. Although these results share quite similar results to that of the static period, they may be provided upon request[8].

Conducting the Augmented Dickey-Fuller (ADF) test on all individual input objects of the VAR model, including the return series and the latent conditional volatility component of the marginal model, we observe that all observations are stationary. This result confirms that the assumption of stationary input variables in the VAR model is met. However, this observation is not unexpected since it is well-known that financial return series tend to be stochastic and display mean-reverting behaviour over time. The ADF test's optimal lag order is determined by the Akaike Information Criterion (AIC). To this end, a simple autoregressive (AR) model is estimated for each variable, enabling the identification of the most suitable lag length. The results for the Augmented Dicky-Fuller can be found in Appendix A.8.

After performing the Breusch-Godfrey test for serial correlation on the main VAR model, we found that all models displayed significant serial correlation during the static period. Estimating serial correlation in the temporal periods presents a significant challenge due to the covariance matrix of the residuals being close to singular. This suggests high correlation between the variables in the model. As a result, we assume that these periods show similar

[8] Extracting p-values from the VAR model can also be achieved using the code in appendix B.3 on page 160.

serial correlation features as those observed in the static period. The assumption of analogous serial correlation features to that of the static period is not too far-fetched, as these types of return series are known to exhibit mean-reverting behaviour, indicating a high likelihood of serial correlation. Additionally, we investigated various lag orders, ranging from 1 to 10, for both the VAR model incorporating return and latent volatility components. Our findings suggest that the null hypothesis can be rejected in all cases, indicating a significant degree of serial correlation in the model, where each observed value seems to be dependent on its past values.

Additionally, we used the Ljung-Box test to investigate whether there was autocorrelation present in the residuals of the marginal model. The results of this analysis can be found in Appendix A.9. Similar to the Vector Autoregressive (VAR) model, it is worth noting that a large proportion of the residuals from the marginal model also showed evidence of serial correlation. However, among all the cryptocurrencies studied, only Status (SNT), Bitcoin Cash (BCH), and OMG Network (OMG) can reject the null hypothesis that the residuals of their respective marginal models are independently distributed, based on the Ljung-Box test with a 5% significance level. However, despite the evidence of serial correlation, we still provide the estimates of the marginal model using robust standard errors[9].

We conducted an Autoregressive Conditional Heteroscedasticity (ARCH) test on the Vector Autoregression (VAR) model to assess the presence of ARCH-effects. We primarily assessed the same lag order as that of their respective VAR model, as this approach provides a more coherent understanding of the dynamics between the return and volatility series. However, we expanded our analysis by exploring a range of lag orders from 1 to 10, which allowed us to obtain a comprehensive understanding of the magnitude and presence of these effects. The results revealed that the ARCH-effects were absent in the first order for both the return and volatility models. However, for lag orders ranging from 2 to 10, the existence of these effects was identified, indicating heteroscedasticity. However, detecting such effects in the temporal periods poses a similar challenge to that encountered when testing for serial correlation. As a result, we assume that the temporal periods may display heteroskedastic features that deviate from those of the static period. Therefore, the results are interpreted with a certain degree of caution.

[9] In R, the robust estimates are obtained from a quasi-maximum likelihood estimation, and can be accessed using the @fit$robust.matcoef command.

To address our limitations of inhibiting serial correlations and heteroskedastic features in our model, we incorporate heteroskedasticity and autocorrelation robust standard errors (HAC). This approach adjusts for the bias in the standard errors of the estimated coefficients. To technically achieve this, we modify the VAR model to incorporate the type of robust standard error used, such as HC0, HC1, and so on. As we consider the appropriate standard errors to use for different periods, we find that HC2 standard errors are a suitable choice in most cases. This approach balances robustness and efficiency, resulting in more reliable estimates of standard errors. Thus, the p-values for the VAR result in Appendix A.7 are reported with these robust standard errors.

We also examined the normality assumption of the VAR model, in which all three tests conducted - the Bera-Jarque (BJ) test, Skewness, and Kurtosis - rejects the null hypothesis at a 5% threshold. We also examined the distribution of residuals in the marginal model by conducting the Shapiro-Wilk Normality Test. The results showed that the p-values were below the 5% threshold, again, indicating the rejection of the null hypothesis of normality. This implies a departure from the normality assumption in both models. While the rejection of the null hypothesis of normality in both models indicates a departure from normality in the residuals, it is important to note that this violation is not significant enough to invalidate our results. In fact, it is not uncommon for financial data to exhibit non-normality due to the presence of heavy tails and skewness. Therefore, it is more appropriate to use robust standard errors and employ techniques that are robust to deviations from normality. Nonetheless, the violation of normality assumptions in the residuals serves as a reminder to exercise caution when interpreting the results. The results for the normality test of the VAR model are presented below, whereas the Shapiro-Wilk Normality Test for the marginal model is furnished in Appendix A.10.

Table 10: Normality test return model

Values	JB Test	kurtosis	skewness
test statistic	4072776	3980486	92290
p-value	0.000	0.000	0.000

Note: Test for the Vector autoregressive model of returns

Table 11: Normality test Volatility model

Values	JB Test	kurtosis	skewness
test statistic	639150558	637106680	2043877
p-value	0.000	0.000	0.000

Note: Test for the Vector autoregressive model of volatility

We additionally explore the possibility of structural breaks in our analysis by implementing the OLS-CUSUM empirical fluctuation process, as described in 4.4.4. Our results indicate that from the VAR model containing log returns, only Nano (XNO) exhibited a minor structural break. Although the OLS-CUSUM empirical fluctuation process identified a structural break in one of the currencies in the VAR model containing log returns, the significance and magnitude of the structural break were found to be minuscule. Thus, it is unlikely to have a significant impact on the overall analysis. Figure 9 depicts the OLS-CUSUM plot of the VAR model containing log returns, which revealed a small structural break in XNO.

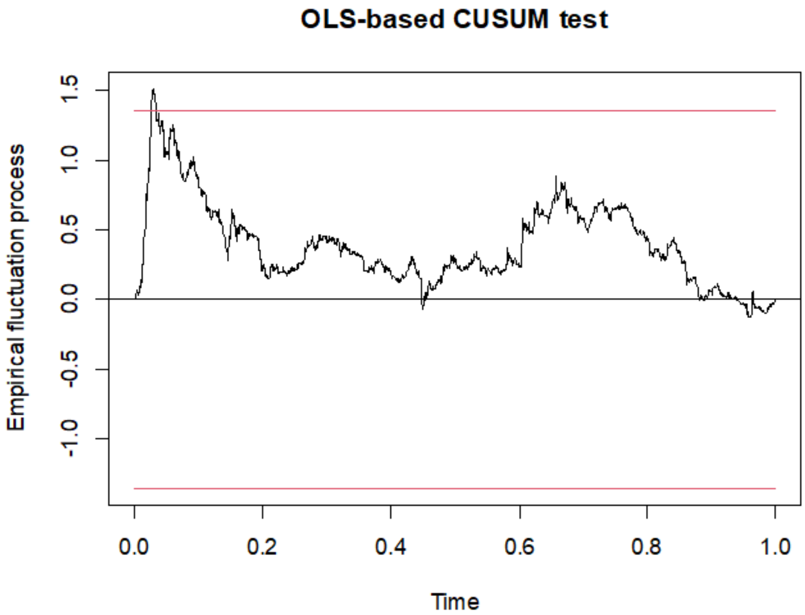

Figure 9: OLS-CUSUM plot of Nano (XNO).

Note: The plot depicts an empirical fluctuation process using the OLS-CUSUM test. It indicates a structural break that occurred around the beginning of 2018.

Although no other structural breaks were found, we have included the plots for both the model of volatility and returns under Appendix A.11, for the sake of completeness and transparency in our analysis.

Upon evaluating the statistical significance of the coefficients in the static period by employing HC2 standard errors, we observe low levels of significance across the numerous lags in the matrix system. More specifically, we discover that on average, mere 8% of regressors are statistically significant using a 5% threshold, while 12% show statistical significance at a 10% threshold for the volatility model. Similarly, for the return model, we find that only 6% of regressors exhibit statistical significance at a 5% threshold, whereas 11 of regressors are statistically significant at a 10% threshold. We find similar characteristics when examining the other temporal sub-periods, indicating that a considerable number of regressors remain insignificant at both 5% and 10% thresholds. The P-values for these estimates are furnished in Appendix A.7. Although temporal periods results are not presented, the results share similar characteristics.

Overall, the data material displays favourable attributes of stationarity for both the return series and the latent volatility component of the marginal model. Nevertheless, the Vector Autoregressive (VAR) model presents certain challenges, as the outcomes exhibit characteristics of serial correlation and non-normality. Despite the absence of ARCH-effects in the first order of the return and volatility models during the static period, we recognise the potential presence of serial correlation and certain ARCH-effects in the temporal periods. To address these challenges, we adopt the strategy of employing robust standard errors (HC2) that account for heteroskedasticity and autocorrelation. This approach enables us to obtain more precise estimates of the standard errors of the coefficients in our model, thereby allowing for more accurate and unbiased inferences regarding the significance of individual variables. We acknowledge the unique properties of cryptocurrency time series data, which exhibit traits of large volatility, leptokurtic kurtosis, and moderate skewness are somewhat challenging to model.

6. Discussion

The concluding section of this thesis serves to provide a comprehensive overview and analysis of the primary findings presented in the preceding sections, along with their practical implications. Moreover, the study's limitations and potential shortcomings will be critically evaluated and discussed, highlighting areas where further research could be undertaken to enhance the study's comprehensiveness and generalisability. Ultimately, this section aims to provide readers with a clear and concise understanding of the study's implications, limitations, as well as potential avenues for future research.

The findings for both the static and temporal periods are multifaceted, and a clear pattern in the main drivers of spillovers is not readily discernible. However, certain cryptocurrencies emerge as more influential than others, considering both the static and temporal periods. Notably, Ethereum (ETH) and Qtum (QTUM) is found to have exerted a significant impact, as evidenced by the high levels of spillovers of both volatility and return it transmits. Conversely, Ergo (ERG) appears to be the least connected within the sample, something hinted at us in the Spearman's rank correlation matrix displayed in Figure 4. While market capitalisation may not necessarily be the sole driver of spillover effects among cryptocurrencies, it provides an important metric for assessing a cryptocurrency's relative value. For instance, ETH currently boasts a market capitalisation of 194.9 billion USD, positioning it as the second-largest cryptocurrency by market capitalisation after Bitcoin. This impressive market valuation reflects Ethereum's status as a widely-traded and highly valued cryptocurrency that is likely to exert significant influence on the broader cryptocurrency market. Bitcoin (BTC) being the largest cryptocurrency with a market capitalisation of 447.6 billion, however, does not appear to have the same strong influence as Ethereum. One possible explanation is the difference in the underlying technologies and use cases of the two cryptocurrencies. Ethereum was designed to be a platform for building decentralised applications and smart contracts. This means that it has a wider range of use cases beyond simply serving as a digital currency. As a result, there are more decentralised applications built on the Ethereum network, and more developers building on the platform. This greater activity and development on the Ethereum network may lead to more spillovers, as changes and developments on the Ethereum network are more likely to have ripple effects on other cryptocurrencies and the broader blockchain ecosystem. In contrast, Bitcoin was designed primarily as a digital currency and store of value. While it is widely traded and accepted as a means of payment, it does not have the same range of use cases as Ethereum. As a result, changes and developments on the Bitcoin network may have less of an impact on other cryptocurrencies and the broader blockchain ecosystem.

Furthermore, the findings reveal that QTUM, despite its relatively lower market capitalisation compared to other major cryptocurrencies, stands out as a significant contributor to both returns and volatility shocks in the market, for both the static and several temporal periods. Notably, in the Vector Autoregressive (VAR) model containing latent volatility components for the static period, QTUM emerges as the coin with the most statistically significant regressors, providing the strongest evidence against the absence of a relationship between the variables. One possible explanation for the dominant position obtained by QTUM could be its unique combination of characteristics that make it particularly influential in the cryptocurrency market. For example, QTUM is a hybrid blockchain platform that combines the security of Bitcoin's blockchain with the smart contract functionality of Ethereum's blockchain (Cryptopedia Staff 2021). This means that it has the potential to attract users and developers from both Bitcoin and Ethereum communities, which could contribute to its higher spillover effects. In contrast to some previous research, which posits that Bitcoin is the primary driver of spillovers, our analysis suggests that clear dominant contributor of spillovers are not easily discernible. Nonetheless, our findings are in line with other studies such as (Zięba, Kokoszczyński and Śledziewska 2019, Koutmos 2018, Palamalai and Maity 2019, Kumar and Anandarao 2019) which suggests high degree of interdependence in the market. (Kumar and Anandarao 2019), also points out the presence of herding behaviour which might be a plausible cause of the high levels of market integration. The cryptocurrency market consists of numerous idiosyncratic and highly connected risk components, albeit certain cryptocurrencies appear to be more exposed than others.

To achieve full exposure to the cryptocurrency market, investors should take a careful approach when constructing their portfolios, prioritising coins with lower spillover effects for potential diversification benefits. Based on our findings, it appears to be challenging to achieve diversification benefits, although their existence cannot be completely ruled out. Conversely, (Palamalai and Maity 2019) suggests that diversification benefits can be obtained from a few selected large-cap cryptocurrency, although, only for a narrow time frame. Thus, also insinuating challenges of efficiently mitigating risk through diversification. Investors aiming for diversification benefits may need to adopt a careful and selective approach when constructing their portfolios, for instance supplementing their portfolios with other diversification-providing assets.

The information on spillovers of return and volatility can be utilised to create investment strategies that considers the interconnectivity between cryptocurrencies. For instance, identifying cryptocurrencies that have a low susceptibility of shocks from other cryptocurrencies, can provide diversification benefits to a portfolio. Additionally, investors can identify which coins have a significant impact on the returns of other coins and adjust their portfolio accordingly. For example, if a particular coin has a significant positive spillover effect on another coin, an investor can create a type of synthetic position by holding one coin. This strategy allows investors to benefit from the price movements of multiple coins while avoiding direct exposure to specific coins. Moreover, a multitude of strategies are available for investors to choose from, and the specific configuration ultimately depends on the preferences and objectives of each individual investor.

The significance of the model's results, despite their relatively lower statistical significance at a 5% threshold[10], should not be dismissed, as they may provide valuable insights. Our study

[10] The main Vector Autoregressive model for both return and volatility presents lower degree of significance at a 5% and 10% threshold.

suggests that the cryptocurrency market exhibits a considerable level of interconnectivity. The presence of comparable findings in the existing literature further supports this conclusion. As such, it is crucial to consider the potential economic significance of our results and their practical implications for investment strategies. The findings highlight the importance of adopting a cautious approach when building cryptocurrency portfolios, emphasising coins that exhibit lower spillover effects and offer potential diversification benefits.

6.1 Suggestion for future research

Despite finding results that points towards high interconnectivity in the cryptocurrency market we suggest establishing more efficient methods to overcome the potential issues of omitted variable bias and multicollinearity. Future research may consider introducing additional explanatory variables into the analysis or exploring alternative modelling techniques that are equipped to handle high-dimensional datasets with numerous potential predictors.

For instance, approaches such as the use of a principal component analysis (PCA) or ridge regression could be considered. The utilisation of PCA to analyse cryptocurrency returns may pose significant difficulties due to the presence of a considerable number of outliers. Thus, reducing the influence of outliers is necessary to ensure that the principal components accurately capture the underlying structure of the data. When applying outlier reduction techniques to address the issue of outliers in returns, it is important that the time sequences are aligned. This is particularly important considering time-series analysis, as the sequential order of observations matters. Hence any reduction in observations for a particular cryptocurrency due to an outlier removal could lead to the loss of the entire row of data at that time point. Moreover, as outliers may, or likely occur at different time points across multiple currencies, applying outlier removal rules would result in significant information loss, potentially leading to a reduction in the reliability of the analysis. To address this issue, an alternative approach could be to introduce a variable that reduces the impact of outliers without compromising the relevant information. This could potentially be accomplished by employing a trimming method, such as Winsorization, that reduces the spurious outliers without compromising the integrity of the non-anomalous observations. Such an approach could improve the reliability of the analysis and potentially enhance our understanding of the interconnectivity of the cryptocurrency market.

To expand on these findings, future studies could include a more extensive set of coins beyond the top market-cap weighted ones. By including a wider variety of coins, such as those with different levels of market capitalisation, trading volumes, and technological features, a more comprehensive analysis of the cryptocurrency market's interconnections could be achieved. This, in turn, could provide a more nuanced understanding of the dynamics of the whole market and inform more effective investment strategies.

6.2 Limitations

Despite the rigorous methodology employed, several limitations exist within this study. We briefly provide a discussion of these limitations, and their implications. Firstly, the current study employs daily historical price observations for 48 of the largest cryptocurrencies, determined by market capitalisation, as of 31 January 2023. The decision to reduce the number of cryptocurrencies from our originally selected 250 currencies was made in order to only include coins with at least five years of historical data, thus ensuring a more robust and reliable analysis. By only including a select number of cryptocurrencies, there is the possibility that we may not have captured the full extent of spillover effects that may exist in the broader cryptocurrency market. Therefore, our findings may not be generalisable to the wider cryptocurrency market, despite having introduced more cryptocurrencies than most studies.

Secondly, the challenges in identifying a definitive pattern of spillovers may be attributed to the omission of relevant variables and high levels of multicollinearity. It is important to note that our study exclusively utilises the generalised Vector Autoregressive (VAR) framework proposed by (Diebold and Yilmaz 2012), and does not explore alternative models for examining spillovers. The choice of solely relying on the generalised vector autoregressive framework for examining spillovers in the cryptocurrency market was influenced by a range of factors, including the framework's well-established use in the field, its simplicity, and its effectiveness in handling multivariate analyses.

Thirdly, we have decided to partition our time series into yearly sub-samples rather than examining specific periods of, for example, turmoil. While this allows for a broad overview of spillover effects over time, it may not provide an accurate representation of spillovers during specific periods of market stress. Examining spillovers during specific periods of market stress may reveal insights that may be masked by the broader overview provided by yearly sub-samples.

Finally, an additional limitation of our study is its sole focus on the cryptocurrency market, neglecting the impact of other external factors that could influence the performance of cryptocurrencies. The volatile nature of cryptocurrencies and the possibility of market manipulation by large holders, make it difficult to gauge the real impact of these factors on the cryptocurrency market. Nevertheless, the inclusion of other external factors could have offered more insights into the determinants of cryptocurrency returns. For instance, the impact of economic indicators such as GDP growth rates, inflation, interest rates, and geopolitical factors could play a significant role in shaping cryptocurrency returns. Additionally, the study could have considered factors such as regulatory changes, technological advancements, and adoption rates of cryptocurrencies in different regions. Although the inclusion of these external factors may introduce more complexities into the analysis, their incorporation could provide a more comprehensive understanding of the cryptocurrency market. However, due to time and resource constraints, we have not explored these factors in detail.

7. Conclusion

This study examines the return and volatility spillover effects within the cryptocurrency market, focusing on the 48 largest cryptocurrencies in terms of market capitalisation, as of January 31st, 2023. We employ a generalised Vector Autoregressive (VAR) framework, as proposed by (Diebold and Yilmaz 2012) to examine the direction and magnitude of spillovers across the selected cryptocurrencies. In detail, we scrutinise both a static period ranging from November 9th, 2017, to January 31st, 2023, as well as five-year sub-periods spanning from January 2018 to December 2022, in effort to capture the temporal evolution of these spillover effects.

The empirical findings can be presented as follows. First, in contrast to certain studies (e.g., (Koutmos 2018, Kumar and Anandarao 2019)), which posited Bitcoin dominance as the main driver of spillovers, our scrutiny did not reveal a primary cryptocurrency responsible for the observed spillovers, but rather the involvement of several cryptocurrencies. Cryptocurrencies like Ethereum (ETH) and QTUM demonstrated a substantial magnitude of shock transmission of both return and volatility for both the static and temporal periods. Meanwhile, coins such as Ergo (ERG) exhibited a notable degree of disconnection from the market. Second, the observed total spillovers of both returns and volatility showed an increase following the significant return shock on 12.03.2020 and the shock in mid-2021. Implying that total spillovers may intensify during periods of turmoil. Finally, we observe remarkable levels of spillovers in both returns and volatility throughout all the investigated periods, implying that attaining diversification benefits from the selected cryptocurrencies might be a formidable task. This observation is consistent with the conclusions of (Zięba, Kokoszczyński and Śledziewska 2019, Koutmos 2018, Palamalai and Maity 2019, Kumar and Anandarao 2019), who also discovered indications of a significant level of interdependence in the market.

Our study provides important insights into the dynamics and interdependencies among the largest cryptocurrencies in the market. The results of our investigation could be valuable to stakeholders, such as investors, portfolio managers, and researchers, who may find them relevant for their respective activities. For instance, investors and portfolio managers may find it valuable to ascertain the connections between assets as a means of diversifying their investments and reducing risk, or to formulate investment strategies.

8. References

Al-Shboul, Mohammad , Ata Assaf, and Khaled Mokni. 2023. “Does economic policy uncertainty drive the dynamic spillover among traditional currencies and cryptocurrencies? The role of the COVID-19 pandemic.” *Research in International Business and Finance* 64: 101824. doi:https://doi.org/10.1016/j.ribaf.2022.101824.

Banerjee, Anindya, Juan J. Dolado, John W. Galbraith, and David Hendry. 1993. *Co-Integration, Error Correction, And the Econometric Analysis of Non-Stationary Data.* Oxford: Oxford University Press.

Bera, Anil K., and Matthew L. Higgins. 1993. “ARCH MODELS: PROPERTIES, ESTIMATION AND TESTING.” *Journal of economic surveys* 7 (4): 305-366. doi:https://doi.org/10.1111/j.1467-6419.1993.tb00170.x.

Bollerslev, Tim, Robert F. Engle, and Daniel B. Nelson. 1994. “Chapter 49 Arch models.” *Handbook of Econometrics* 4: 2959-3038. doi:https://doi.org/10.1016/S1573-4412(05)80018-2.

Bouri, Elie, Mahamitra Das, Rangan Gupta, and David Roubaud. 2018. “Spillovers between Bitcoin and other assets during bear and bull markets.” *Applied Economics* 5935-5949. doi:https://doi.org/10.1080/00036846.2018.1488075.

Bouri, Elie, Syed Jawad Hussain Shahzad, and David Roubaud. 2019. “Co-explosivity in the cryptocurrency market.” *Finance Research Letters* 29: 178-183. doi:https://doi.org/10.1016/j.frl.2018.07.005.

Brooks, Chris. 2019. *Introductory econometrics for finance.* New York: Cambridge University Press.

—. 2014. *Introductory Econometrics for Finance.* Vol. 3. New York: Cambridge University Press.

Burnham, Kenneth P., and David R. R. Anderson. 2002. *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach.* Berlin: Springer.

Caferra, Rocco. 2022. “Sentiment spillover and price dynamics: Information flow in the cryptocurrency and stock market.” *Physica A: Statistical Mechanics and its Applications* 593: 126983. doi:https://doi.org/10.1016/j.physa.2022.126983.

Cao, Guangxi, and Wenhao Xie. 2022. "Asymmetric dynamic spillover effect between cryptocurrency and China's financial market: Evidence from TVP-VAR based connectedness approach." *Finance Research Letters* 49: 103070. doi:https://doi.org/10.1016/j.frl.2022.103070.

Chaum, David Lee. 1979. *Computer Systems established, maintained and trusted by mutually suspicious groups.* California: Electronics Research Laboratory, University of California.

CoinMarketCap. n.d. *coinmarketcap.* Accessed 02 22, 2023. https://coinmarketcap.com/about/.

Corbet, Shaen, Andrew Meegan, Charles Larkin, Brian Lucey, and Larisa Yarovaya. 2018. "Exploring the dynamic relationships between cryptocurrencies and other financial assets." *Economics Letters* 165: 28-34. doi:https://doi.org/10.1016/j.econlet.2018.01.004.

Cryptopedia Staff. 2021. "Qtum tackles governance with QTUM coin." *Gemini.* 21 10. Accessed 05 02, 2023. https://www.gemini.com/cryptopedia/qtum-crypto-and-blockchain-evm.

DeVon, Cheyenne. 2022. "Bitcoin lost over 60% of its value in 2022—here's how much 6 other popular cryptocurrencies lost." *CNBC*, 23 12. https://www.cnbc.com/2022/12/23/bitcoin-lost-over-60-percent-of-its-value-in-2022.html.

Diebold, Francis X., and Jose A. Lopez. 1995. "Modeling Volatility Dynamics." *Macroeconometrics* 427-472. doi:https://doi.org/10.1007/978-94-011-0669-6_11.

Diebold, Francis X., and Kamil Yilmaz. 2012. "Better to give than to receive: Predictive directional measurement of volatility spillovers." *International Journal of Forecasting* 57-66.

Diebold, Francis X., and Kamil Yılmaz. 2015. *Financial and macroeconomic connectedness: A network approach to measurement and monitoring.* New York: Oxford University Press, USA.

Diebold, Francis X., and Kamil Yilmaz. 2009. “Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets.” *The Economic Journal* 119: 158–171. doi:https://doi.org/10.1111/j.1468-0297.2008.02208.x.

Diebold, Francis X., and Kamil Yılmaz. 2014. “On the network topology of variance decompositions: Measuring the connectedness of financial firms.” *Journal of Econometrics* 182 (1): 119-134. doi:https://doi.org/10.1016/j.jeconom.2014.04.012.

Fidelity Digital Assets. 2022. “2022 institutional investor digital assets study.” *Fidelity Digital Assets.* 27 10. Accessed 05 03, 2023. https://www.fidelitydigitalassets.com/research-and-insights/2022-institutional-investor-digital-assets-study.

Frankenfield, Jake. 2023. *Cryptocurrency Explained With Pros and Cons for Investment.* 04 02. Accessed 05 03, 2023. https://www.investopedia.com/terms/c/cryptocurrency.asp.

Gil-Cordero, Eloy, Juan Pedro Cabrera-Sánchez, and Manuel Jesús Arrás-Cortés. 2020. “Cryptocurrencies as a financial tool: Acceptance factors.” *Mathematics* 1974. doi:10.3390/math8111974.

Gillaizeau, Marc, Ranadeva Jayasekera, Ahmad Maaitah, Tapas Mishra, Mamata Parhi, and Evgeniia Volokitina. 2019. “Giver and the receiver: Understanding spillover effects and predictive power in cross-market Bitcoin prices.” *International Review of Financial Analysis* 63: 86-104. doi:https://doi.org/10.1016/j.irfa.2019.03.005.

Godbole, Omkar. 2020. “Bitcoin Price May Drop After Halving, Historical Data Shows.” *CoinDesk,* 04 05. Accessed 02 22, 2023. https://www.coindesk.com/markets/2020/05/04/bitcoin-price-may-drop-after-halving-historical-data-shows/.

Groves, Kevin. 2023. “Can bitcoin be hacked & is bitcoin safe to use?” *HedgewithCrypto.* 14 03. Accessed 05 03, 2023. https://www.hedgewithcrypto.com/can-bitcoin-be-hacked/.

Gura, David. 2022. “Crypto company BlockFi declares bankruptcy in the first big aftershock of FTX's fall.” *npr,* 28 11. https://www.npr.org/2022/11/28/1139431115/blockfi-ftx-bankruptcy-chapter-11.

Haber, Stuart, and Stornetta W. Scott. 1991. “How to Time-Stamp a Digital Document.” *Advances in Cryptology-CRYPT0’ 90* (Springer Berlin Heidelberg) 437-455. doi:10.1007/3-540-38424-3_32.

Hayes, Adam. 2021. “Leptokurtic distributions: Definition, example, vs. Platykurtic.” *Investopedia.* 14 02. Accessed 03 03, 2023. https://www.investopedia.com/terms/l/leptokurtic.asp.

Hyndman, Rob J. 2014. “robjhyndman.com.” *Thoughts on the Ljung-Box test.* 24 01. Accessed 04 25, 2023. https://robjhyndman.com/hyndsight/ljung-box-test/.

Iyer, Tara . 2022. *Cryptic Connections: Spillovers.* Research paper, International Monetary Fund, 13.

Jarque, Carlos M., and Anil K. Bera. 1980. “Efficient tests for normality, homoscedasticity and serial independence of regression residuals.” *Economics Letters* 6 (3): 255-259. doi:https://doi.org/10.1016/0165-1765(80)90024-5.

Javed, Farrukh. 2011. “GARCH-Type models and Performance of Information Criteria.” *SSRN Electronic Journal* 18. doi:10.2139/ssrn.1856054.

John, Alun, Samuel Shen, and Tom Wilson. 2021. “China's top regulators ban crypto trading and mining, sending bitcoin tumbling.” *Reuters.* 24 09. Accessed 05 14, 2023. https://www.reuters.com/world/china/china-central-bank-vows-crackdown-cryptocurrency-trading-2021-09-24/.

Katsiampa, Paraskevi. 2019. “An empirical investigation of volatility dynamics in the cryptocurrency market.” *Research in International Business and Finance* 322-335. doi:https://doi.org/10.1016/j.ribaf.2019.06.004.

Kauflin, Jeff. 2018. “Where Did The Money Go? Inside the Big Crypto ICOs of 2017.” *Forbes.* 29 10. Accessed 05 06, 2023. https://www.forbes.com/sites/jeffkauflin/2018/10/29/where-did-the-money-go-inside-the-big-crypto-icos-of-2017/?sh=5a2fe44261bb.

Kolodny, Lora. 2021. “Elon Musk says Tesla will stop accepting bitcoin for car purchases, citing environmental concerns.” *CNBC,* 12 05. Accessed 02 22, 2023. https://www.cnbc.com/2021/05/12/elon-musk-says-tesla-will-stop-accepting-bitcoin-for-car-purchases.html.

Koop, Gary, M. Hashem Pesaran, and Simon M. Potter. 1996. "Impulse response analysis in nonlinear multivariate models." *Journal of Econometrics* 74 (1): 119-147. doi:https://doi.org/10.1016/0304-4076(95)01753-4.

Koutmos, Dimitrios . 2018. "Return and volatility spillovers among cryptocurrencies." *Economics Letters* 122-127. doi:https://doi.org/10.1016/j.econlet.2018.10.004.

Kumar, Anoop S., and S. Anandarao. 2019. "Volatility spillover in crypto-currency markets: Some evidences from GARCH and wavelet analysis." *Physica A: Statistical Mechanics and its Applications* 524: 448-458. doi:https://doi.org/10.1016/j.physa.2019.04.154.

Kyriazis, Nikolaos A. 2019. "A Survey on Empirical Findings about Spillovers in." *Journal of Risk and Financial Management* 12: 170. doi:https://doi.org/10.3390/jrfm12040170.

Lennart, Ante. 2023. "How Elon Musk's Twitter activity moves cryptocurrency markets." *Technological Forecasting and Social Change* 122112. doi:https://doi.org/10.1016/j.techfore.2022.122112.

Lunde, Asger, and Peter R. Hansen. 2005. "A forecast comparison of volatility models: does anything beat a GARCH(1,1)?" *Journal Of Applied Econometrics* 873-889. doi:https://doi.org/10.1002/jae.800.

Malanii, Oleh. 2023. "Top blockchain platforms 2023." *Hacken.* 05 10. Accessed 05 13, 2023. https://hacken.io/discover/blockchain-platforms/.

McNeese, Bill. 2016. "Are the skewness and kurtosis useful statistics?" *BPI Consulting.* 02. Accessed 03 03, 2023. https://www.spcforexcel.com/knowledge/basic-statistics/are-skewness-and-kurtosis-useful-statistics.

Meynkhard, Artur. 2019. "Fair market value of bitcoin: halving effect." *Investment Management and Financial Innovations* 16 (4): 72-85. doi:https://doi.org/10.21511/imfi.16%284%29.2019.07.

Miah, Mamun, and Azizur Rahman. 2016. "Modelling Volatility of Daily Stock Returns: Is GARCH(1,1) Enough?" *American Scientific Research Journal for Engineering, Technology, and Sciences* 29-39.

Mo, Bin, Juan Meng, and Liping Zhen. 2022. “Time and frequency dynamics of connectedness between cryptocurrencies and commodity markets.” *Resources Policy* 102731. doi:https://doi.org/10.1016/j.resourpol.2022.102731.

Moratis, George. 2020. “Quantifying the Spillover Effect in the Cryptocurrency Market.” *Finance Research Letters* 38: 101534. doi:https://doi.org/10.1016/j.frl.2020.101534.

Maass, Harold. 2020. “10 things you need to know today: March 12, 2020.” *The Week*, 03 12. Accessed 02 22, 2023. https://theweek.com/10things/901711/10-things-need-know-today-march-12-2020.

Omane-Adjepong, Maurice, and Imhotep Paul Alagidede. 2019. “Multiresolution analysis and spillovers of major cryptocurrency markets.” *Research in International Business and Finance* 49: 191-206. doi:https://doi.org/10.1016/j.ribaf.2019.03.003.

Palamalai, Srinivasan, and Bipasha Maity. 2019. “Return and volatility spillover effects in leading cryptocurrencies.” *Global Economy Journal* 19 (03): 1950017. doi:10.1142/s2194565919500179.

Pesaran, H. Hashem, and Yongcheol Shin. 1998. “Generalized impulse response analysis in linear multivariate models.” *Economics Letters* 58 (1): 17-29. doi:https://doi.org/10.1016/S0165-1765(97)00214-0.

Ramachandran, Kandethody M., and Chris P. Tsokos. 2020. *Mathematical Statistics with Applications in R.* London: Academic Press.

Royston, Patrick. 1995. “Remark AS R94: A Remark on Algorithm AS 181: The W-test for Normality.” *Journal of the Royal Statistical Society. Series C (Applied Statistics)* 44: 547-551. doi:https://doi.org/10.2307/2986146.

Swartz, Lana. 2022. “Theorizing the 2017 blockchain ICO bubble as a network scam.” *New Media & Society* 1695–1713. doi:https://doi.org/10.1177/14614448221099224.

U.S. Bank. 2023. “Are we going into a recession? | U.S. bank.” *U.S. Bank*, 30 01. https://www.usbank.com/investing/financial-perspectives/market-news/economic-recovery-status.html.

Weintraub, David A. 2011. *How Old Is the Universe?* New Jersey: Princeton University Press.

World Health Organization. 2020. *World Health Organization (WHO).* 12 03. Accessed 02 22, 2023. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-mission-briefing-on-covid-19---12-march-2020.

Yousaf, Imran, and Larisa Yarovaya. 2022. "Spillovers between the Islamic gold-backed cryptocurrencies and equity markets during the COVID-19: A sectorial analysis." *Pacific-Basin Finance Journal* 71: 101705. doi:https://doi.org/10.1016/j.pacfin.2021.101705.

Zaiontz, Charles. 2020. "Robust standard errors." *Real Statistics.* 30 05. Accessed 03 29, 2023. https://real-statistics.com/multiple-regression/robust-standard-errors/.

Zeileis, Achim, Friedrich Leisch, Kurt Hornik, and Christian Kleiber. 2002. "strucchange: An R Package for Testing for Structural Change in Linear Regression Models." *Journal of Statistical Software* 7: 1-38. doi:10.18637/jss.v007.i02.

Zięba, Damian, Ryszard Kokoszczyński, and Katarzyna Śledziewska. 2019. "Shock transmission in the cryptocurrency market. Is Bitcoin the." *International Review of Financial Analysis* 64: 102-125. doi:https://doi.org/10.1016/j.irfa.2019.04.009.

Appendix 1

A.1 Table of descriptive statistics for all 48 cryptocurrencies.

Descriptive statistics for 48 of the largest cryptocurrencies, based on their market capitalisation as of late February 2023. The Mean and Standard Deviation (StdDev) figures are presented in annualised terms. Additionally, the "Kurtosis" column computes the estimator of Pearson's measure of kurtosis in excess of a normal distribution.

Nr.	Ticker	Mean	StdDev	Min	Max	Kurtosis	Skewness	Sharpe
1	ADA	0.47	1.28	-0.50	0.86	27.53	1.94	0.37
2	ANT	0.13	1.43	-0.78	0.40	12.28	-0.51	0.09
3	BAT	0.08	1.24	-0.51	0.38	8.49	-0.12	0.07
4	BCH	-0.30	1.22	-0.56	0.43	14.16	0.03	-0.25
5	BNB	0.97	1.11	-0.54	0.53	18.00	0.37	0.87
6	BTC	0.22	0.77	-0.46	0.23	15.04	-0.83	0.29
7	BTG	-0.43	1.34	-0.54	0.72	23.69	1.29	-0.32
8	CVC	-0.21	1.53	-0.55	0.89	21.78	1.43	-0.14
9	DASH	-0.32	1.14	-0.47	0.45	13.18	0.18	-0.28
10	DCR	-0.07	1.14	-0.51	0.71	18.76	0.42	-0.06
11	DGB	-0.01	1.38	-0.54	0.52	10.51	0.42	-0.01
12	DOGE	0.80	1.49	-0.52	1.52	87.86	4.75	0.54
13	ENJ	0.55	1.54	-0.62	0.77	17.90	1.18	0.36
14	EOS	-0.02	1.25	-0.50	0.44	11.28	-0.04	-0.02
15	ERG	-0.32	2.55	-1.03	1.70	24.74	1.15	-0.13
16	ETC	0.08	1.21	-0.51	0.35	10.77	-0.10	0.07
17	ETH	0.30	0.98	-0.55	0.23	12.66	-0.91	0.31
18	GLM	0.01	1.31	-0.59	0.55	12.33	0.12	0.01
19	GNO	0.06	1.20	-0.43	0.51	10.56	-0.01	0.05
20	ICX	-0.35	1.40	-0.59	0.47	10.05	-0.25	-0.25
21	KCS	0.47	1.28	-0.50	0.67	17.30	1.30	0.36
22	LINK	0.66	1.34	-0.61	0.48	10.14	-0.08	0.49
23	LRC	0.12	1.52	-0.58	0.49	9.31	0.54	0.08
24	LSK	-0.38	1.22	-0.55	0.30	9.81	-0.42	-0.31
25	LTC	0.07	1.05	-0.45	0.39	11.64	-0.14	0.07
26	MANA	0.74	1.54	-0.63	0.94	26.21	1.81	0.48
27	MIOTA	-0.17	1.24	-0.54	0.38	11.34	-0.28	-0.13
28	NEO	-0.26	1.17	-0.47	0.34	9.13	-0.44	-0.22
29	OMG	-0.34	1.30	-0.56	0.54	10.69	-0.11	-0.26
30	QTUM	-0.29	1.32	-0.58	0.56	14.26	0.04	-0.22
31	REQ	0.09	1.59	-0.69	1.18	31.93	2.04	0.06
32	RLC	0.18	1.55	-0.74	0.72	13.97	0.23	0.12

Nr.	Ticker	Mean	StdDev	Min	Max	Kurtosis	Skewness	Sharpe
33	SC	-0.10	1.36	-0.62	0.58	12.69	0.05	-0.07
34	SNT	-0.05	1.35	-0.42	0.74	19.52	1.34	-0.04
35	STORJ	-0.10	1.51	-0.60	0.91	22.49	1.29	-0.06
36	SYS	-0.08	1.51	-0.58	0.70	13.23	0.57	-0.05
37	TRX	0.63	1.32	-0.52	0.79	29.38	1.96	0.48
38	VGX	-0.11	1.76	-0.73	0.77	14.42	1.35	-0.06
39	WAVES	-0.13	1.32	-0.49	0.53	11.54	0.37	-0.10
40	XEM	-0.34	1.27	-0.42	1.00	34.05	1.60	-0.27
41	XLM	0.16	1.16	-0.41	0.56	13.85	0.81	0.13
42	XMR	0.07	1.04	-0.53	0.34	13.83	-0.93	0.07
43	XNO	0.36	1.53	-0.59	0.75	16.96	1.39	0.24
44	XRP	0.11	1.21	-0.55	0.61	19.61	0.83	0.09
45	XTZ	-0.09	1.32	-0.61	0.57	12.32	-0.42	-0.07
46	ZEC	-0.34	1.15	-0.54	0.26	9.29	-0.57	-0.29
47	ZEN	-0.19	1.29	-0.55	0.38	8.74	-0.27	-0.15
48	ZRX	-0.01	1.30	-0.47	0.44	8.46	0.11	-0.01

A.2 Information criterion results

Table containing optimal orders for the marginal eGARCH model. The table displays the GARCH and ARCH orders that have been selected based on the Akaike's Information Criterion (AIC) for the corresponding time series in our study. The optimal orders have been obtained by iterating through all possible combinations of orders for any n sample of time series, and selecting the orders that result in the lowest AIC. The functions for this table can be found in Appendix B.3. Its named: "*ARMA-GARCH information criterion loop*"

Ticker	garchOrder	armaOrder	Hannan–Quinn information criterion	Ticker	garchOrder	armaOrder	Akaike information criterion
ADA	c(1,1)	c(1,0)	-3.00	ADA	c(1,1)	c(3,3)	-3.02
ANT	c(1,1)	c(0,0)	-2.64	ANT	c(2,3)	c(3,3)	-2.66
BAT	c(1,1)	c(1,0)	-2.88	BAT	c(3,3)	c(3,2)	-2.91
BCH	c(1,1)	c(1,0)	-3.14	BCH	c(1,3)	c(2,3)	-3.16
BNB	c(1,1)	c(1,0)	-3.33	BNB	c(1,3)	c(1,0)	-3.35
BTC	c(1,1)	c(0,0)	-3.96	BTC	c(3,3)	c(0,1)	-3.99
BTG	c(1,1)	c(0,1)	-3.08	BTG	c(1,2)	c(2,2)	-3.10
CVC	c(1,1)	c(1,1)	-2.70	CVC	c(3,3)	c(1,1)	-2.73
DASH	c(1,1)	c(0,1)	-3.18	DASH	c(3,3)	c(2,3)	-3.21
DCR	c(1,1)	c(0,1)	-3.13	DCR	c(1,3)	c(3,3)	-3.15
DGB	c(1,1)	c(0,1)	-2.79	DGB	c(1,2)	c(3,3)	-2.81
DOGE	c(2,1)	c(0,1)	-3.31	DOGE	c(3,3)	c(1,2)	-3.35
ENJ	c(1,1)	c(0,1)	-2.66	ENJ	c(1,2)	c(2,3)	-2.69
EOS	c(1,1)	c(1,0)	-3.06	EOS	c(3,2)	c(3,1)	-3.08
ERG	c(2,1)	c(0,1)	-1.86	ERG	c(3,2)	c(3,3)	-1.89
ETC	c(1,1)	c(0,1)	-3.13	ETC	c(3,3)	c(3,2)	-3.16
ETH	c(1,1)	c(1,0)	-3.35	ETH	c(3,3)	c(3,1)	-3.37
GLM	c(1,1)	c(0,1)	-2.89	GLM	c(3,3)	c(1,2)	-2.92
GNO	c(1,1)	c(0,0)	-3.08	GNO	c(1,1)	c(3,3)	-3.10
ICX	c(1,1)	c(1,0)	-2.70	ICX	c(1,3)	c(0,2)	-2.72
KCS	c(1,3)	c(0,0)	-3.23	KCS	c(3,3)	c(2,3)	-3.26
LINK	c(1,1)	c(0,0)	-2.72	LINK	c(1,1)	c(2,3)	-2.74
LRC	c(1,1)	c(0,1)	-2.56	LRC	c(1,3)	c(3,3)	-2.59
LSK	c(1,1)	c(0,1)	-3.03	LSK	c(1,3)	c(3,2)	-3.06
LTC	c(1,1)	c(0,1)	-3.24	LTC	c(3,3)	c(2,0)	-3.27
MANA	c(1,1)	c(1,1)	-2.70	MANA	c(3,1)	c(1,1)	-2.73
MIOTA	c(1,1)	c(1,0)	-3.00	MIOTA	c(3,3)	c(1,0)	-3.02

Ticker	garchOrder	armaOrder	Hannan–Quinn information criterion	Ticker	garchOrder	armaOrder	Akaike information criterion
NEO	c(1,1)	c(0,1)	-3.01	NEO	c(3,3)	c(3,3)	-3.04
OMG	c(1,1)	c(1,0)	-2.82	OMG	c(2,1)	c(3,2)	-2.85
QTUM	c(1,1)	c(0,1)	-2.91	QTUM	c(3,3)	c(3,2)	-2.95
REQ	c(3,1)	c(1,2)	-2.62	REQ	c(3,3)	c(1,2)	-2.66
RLC	c(1,1)	c(0,1)	-2.45	RLC	c(1,3)	c(3,2)	-2.48
SC	c(1,1)	c(0,1)	-2.84	SC	c(3,3)	c(0,3)	-2.87
SNT	c(1,2)	c(0,1)	-2.95	SNT	c(3,1)	c(3,3)	-2.99
STORJ	c(1,1)	c(0,1)	-2.67	STORJ	c(2,1)	c(2,3)	-2.70
SYS	c(1,1)	c(0,1)	-2.57	SYS	c(3,3)	c(0,1)	-2.60
TRX	c(1,1)	c(0,1)	-3.25	TRX	c(3,1)	c(3,2)	-3.28
VGX	c(1,2)	c(0,1)	-2.41	VGX	c(2,3)	c(3,3)	-2.43
WAVES	c(1,1)	c(0,0)	-2.92	WAVES	c(3,1)	c(3,2)	-2.94
XEM	c(1,1)	c(0,1)	-3.09	XEM	c(3,3)	c(2,0)	-3.12
XLM	c(1,1)	c(0,1)	-3.18	XLM	c(3,3)	c(0,1)	-3.20
XMR	c(1,1)	c(1,0)	-3.31	XMR	c(3,3)	c(1,3)	-3.33
XNO	c(1,1)	c(0,1)	-2.80	XNO	c(2,3)	c(0,1)	-2.83
XRP	c(1,1)	c(0,1)	-3.36	XRP	c(3,1)	c(3,3)	-3.39
XTZ	c(1,1)	c(0,1)	-2.85	XTZ	c(3,3)	c(1,1)	-2.88
ZEC	c(1,1)	c(1,0)	-3.00	ZEC	c(2,3)	c(3,2)	-3.03
ZEN	c(3,3)	c(1,0)	-2.81	ZEN	c(3,3)	c(1,1)	-2.85
ZRX	c(1,1)	c(0,1)	-2.80	ZRX	c(3,3)	c(2,3)	-2.84

A.3 List of every cryptocurrency with market capitalisation.

Nr.	Tickers	Full name	Market value in millions of US dollars	Nr.	Tickers	Full name	Market value in millions of US dollars
1	BTC	Bitcoin	447590	49	EOS	EOS	1158
2	ETH	Ethereum	194947	50	AXS	Axie Infinity	1140
3	USDT	Tether	67785	51	SAND	The Sandbox	1115
4	BNB	Binance Coin	48486	52	EGLD	MultiversX	1071
5	USDC	USD Coin	43066	53	FLOW	Flow	1070
6	XRP	Ripple	20443	54	THETA	Theta Network	1043
7	BUSD	Binance USD	15705	55	FRAX	Frax	1017
8	ADA	Cardano	13062	56	XTZ	Tezos	1013
9	DOGE	Dogecoin	11374	57	LUNC	Terra Classic	1006
10	MATIC	Polygon	9760	58	TUSD	TrueUSD	943
11	SOL	Solana	8995	59	HBTC	Huobi BTC	903
12	DOT	Polkadot	7239	60	CHZ	Chiliz	896
13	LTC	Litecoin	6638	61	USDP	Pax Dollar	884
14	SHIB	Shiba Inu	6371	62	TMG	T-mac DAO	833
15	WTRX	Wrapped TRON	6325	63	BSV	Bitcoin SV	825
16	AVAX	Avalanche	6291	64	HT	Huobi Token	820
17	DAI	Dai	5825	65	KCS	KuCoin Token	807
18	TRX	TRON	5689	66	GRT6719	The Graph	788
19	STETH	Lido Staked ETH	5544	67	FXS	Frax Share	754
20	UNI7083	Uniswap	5043	68	CRV	Curve DAO Token	727
21	HEX	HEX	4681	69	ZEC	Zcash	725
22	WBTC	Wrapped Bitcoin	4094	70	USDD	USDD	718
23	ATOM	Cosmos	3801	71	BTTOLD	BitTorrent	712
24	LINK	Chainlink	3575	72	BTT	BitTorrent-New	697
25	LEO	UNUS SED LEO	3370	73	MINA	Mina	689
26	XMR	Monero	3350	74	XEC	eCash	677
27	ETC	Ethereum Classic	3039	75	TWT	Trust Wallet Token	671
28	TON11419	Toncoin	2901	76	FTT	FTX Token	672
29	APT21794	Aptos	2824	77	CAKE	PancakeSwap	663
30	BCH	Bitcoin Cash	2556	78	MIOTA	IOTA	635
31	XLM	Stellar	2399	79	MKR	Maker	634
32	OKB	OKB	2260	80	XRD	Radix	624
33	APE18876	ApeCoin	2224	81	DASH	Dash	622
34	NEAR	NEAR Protocol	2053	82	KLAY	Klaytn	620
35	CRO	Cronos	1995	83	TNC5524	TNC Coin	607
36	FIL	Filecoin	1925	84	GUSD	Gemini Dollar	600
37	LDO	Lido DAO	1794	85	RUNE	THORChain	593
38	ALGO	Algorand	1767	86	SNX	Synthetix	583
39	QNT	Quant	1736	87	NEO	Neo	565
40	VET	VeChain	1690	88	IMX10603	ImmutableX	539
41	ICP	Internet Computer	1689	89	PAXG	PAX Gold	516
42	HBAR	Hedera	1647	90	OP	Optimism	512
43	MANA	Decentraland	1414	91	GMX11857	GMX	490
44	FTM	Fantom	1282	92	OSMO	Osmosis	490
45	BTCB	Bitcoin BEP2	1230	93	GT	GateToken	478
46	BIT11221	BitDAO	1169	94	XAUT	Tether Gold	470
47	AAVE	Aave	1168	95	NEXO	Nexo	460
48	WBNB	Wrapped BNB	1170	96	LRC	Loopring	452

Nr.	Tickers	Full name	Market value in millions of US dollars	Nr.	Tickers	Full name	Market value in millions of US dollars
97	CVX	Convex Finance	442	145	IOTX	IoTeX	270
98	ENJ	Enjin Coin	440	146	FLUX	Flux	269
99	ZIL	Zilliqa	436	147	XYM	Symbol	266
100	LUNA20314	Terra	425	148	AUDIO	Audius	262
101	FEI	Fei USD	423	149	GLMR	Moonbeam	256
102	1INCH	1inch Network	406	150	ANKR	Ankr	251
103	ETHW	EthereumPoW	404	151	JASMY	JasmyCoin	244
104	RPL	Rocket Pool	396	152	BNX	BinaryX	244
105	KAVA	Kava	391	153	XCN18679	Chain	240
106	GALA	Gala	391	154	GLM	Golem	236
107	COMP5692	Compound	387	155	CHSB	SwissBorg	232
108	HNT	Helium	385	156	JST	JUST	230
109	CSPR	Casper	381	157	LUSD	Liquity USD	227
110	BAT	Basic Attention Token	380	158	USDN	Neutrino USD	223
111	STX4847	Stacks	375	159	ASTR	Astar	222
112	XDC	XDC Network	366	160	OCEAN	Ocean Protocol	221
113	HOT2682	Holo	364	161	FET	Fetch.ai	220
114	T	Threshold	362	162	BONE11865	Bone ShibaSwap	216
115	DYDX	dYdX	355	163	USTC	TerraClassicUSD	213
116	CELO	Celo	353	164	EDGT	Edgecoin	210
117	RVN	Ravencoin	353	165	AGIX	SingularityNET	208
118	AR	Arweave	344	166	FLOKI	FLOKI	204
119	DCR	Decred	337	167	OMG	OMG Network	200
120	XEM	NEM	336	168	MASK8536	Mask Network	200
121	GMT18069	STEPN	336	169	ICX	ICON	197
122	NXM	NXM	330	170	AMP	Amp	196
123	BAL	Balancer	317	171	WEMIX	WEMIX	193
124	TFUEL	Theta Fuel	314	172	LPT	Livepeer	191
125	ROSE	Oasis Network	315	173	ELON	Dogelon Mars	188
126	MV	GensoKishi Metaverse	313	174	BICO	Biconomy	187
127	DFI	DeFiChain	309	175	INJ	Injective	187
128	ENS	Ethereum Name Service	306	176	ZRX	0x	186
129	USDJ	USDJ	302	177	ONT	Ontology	186
130	BGB	Bitget Token	301	178	HIVE	Hive	186
131	RNDR	Render Token	299	179	RSR	Reserve Rights	183
132	KSM	Kusama	296	180	IOST	IOST	181
133	WOO	WOO Network	295	181	KEEP	Keep Network	178
134	BTG	Bitcoin Gold	293	182	POLY	Polymath	178
135	XCH	Chia	290	183	BORA	BORA	171
136	MAGIC14783	MAGIC	288	184	ANY	Anyswap	170
137	GNO	Gnosis	285	185	LOCUS	Locus Chain	170
138	ONE3945	Harmony	283	186	DGB	DigiByte	168
139	SUSHI	SushiSwap	280	187	SSV	ssv.network	166
140	WAVES	Waves	278	188	BABYDOGE	Baby Doge Coin	166
141	LN	LINK	278	189	SC	Siacoin	163
142	QTUM	Qtum	278	190	BDX	Beldex	161
143	KDA	Kadena	275	191	SXP	SXP	159
144	YFI	yearn.finance	272	192	WAXP	WAX	158

Nr.	Tickers	Full name	Market value in millions of US dollars
193	HOOK	Hooked Protocol	155
194	SFP	SafePal	154
195	SKL	SKALE	154
196	STORJ	Storj	151
197	TEL	Telcoin	151
198	DAO	DAO Maker	150
199	METIS	MetisDAO	150
200	CEL	Celsius	145
201	BTRST	Braintrust	144
202	EVER	Everscale	142
203	UMA	UMA	140
204	ILV	Illuvium	140
205	LYXE	LUKSO	139
206	ZEN	Horizen	138
207	RLC	iExec RLC	138
208	PEOPLE	ConstitutionDAO	136
209	BRISE	Bitgert	136
210	EURS	STASIS EURO	135
211	SYS	Syscoin	134
212	VVS	VVS Finance	134
213	CELR	Celer Network	132
214	SLP	Smooth Love Potion	131
215	MC	Merit Circle	130
216	ALI16876	Artificial Liquid Intelligence	130
217	NFT9816	APENFT	129
218	KNC	Kyber Network Crystal v2	129
219	RBN	Ribbon Finance	127
220	SCRT	Secret	126
221	CFX	Conflux	124
222	CKB	Nervos Network	124
223	PLA7461	PlayDapp	123
224	CTC	Creditcoin	122
225	LSK	Lisk	119
226	PUNDIX	Pundi X (New)	118
227	ANT	Aragon	117
228	NU	NuCypher	117
229	CHR	Chromia	116
230	XNO	Nano	116
231	VGX	Voyager Token	116
232	TRIBE	Tribe	114
233	COTI	COTI	113
234	GAL11877	Galxe	112
235	SYN12147	Synapse	112
236	API3	API3	112
237	MED	MediBloc	110
238	GTC10052	Gitcoin	110
239	REQ	Request	109
240	WEVER	Wrapped Everscale	109

Nr.	Tickers	Full name	Market value in millions of US dollars
241	ALPHA	Alpha Venture DAO	108
242	PYR	Vulcan Forged PYR	107
243	CVC	Civic	106
244	ERG	Ergo	104
245	VUSDC	Venus USDC	104
246	CEEK	CEEK VR	103
247	POLYX	Polymesh	102
248	BAND	Band Protocol	102
249	SRM	Serum	102
250	SNT	Status	100

Note: Not all these cryptocurrencies are utilised in the study.

A.4 Spillover tables

A.4.1 Static spillover tables

The tables illustrate return and volatility spillovers among the 48 cryptocurrencies under investigation for static full sample period. The tables illustrate the 10-day-ahead generalised forecast error variance decomposition of the Vector Autoregressive (VAR) model with an lag-order of 1 for the returns, and 4 for the latent volatility components. The selection of this order is based on the Hannan-Quinn information criterion. The off-diagonal column and row sums, which represent the contribution from and to other variables, are displayed in the far-right column and bottom row, respectively. The latter is accompanied by “contribution to self and others”, along with “net spillovers”. Net spillovers are quantified as the disparity between transmitted shocks and received shocks. At the bottom right of each table we see the spillover index $Sg(H)$ which can be interpreted as the average spillover among cryptocurrencies.

Static spillover table of returns

Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	6.1	1.6	2.3	2.3	1.8	2.4	1.6	1.7	2.1	1.8	2.3	1.2	1.6	2.5	0.3	2.5	2.9	1.8	1.4	2.3	1.5	2.0	1.9	2.1	2.6	1.4	2.7	2.6	2.5	2.6	1.2	1.7	2.1	3.0	1.6	1.3	2.0	1.1	1.6	2.2	3.4	2.4	1.7	2.5	1.8	2.3	1.8	2.0	93.9
ANT	2.0	7.8	2.4	2.1	2.0	2.5	1.4	1.8	2.2	1.8	2.2	1.0	1.9	2.2	0.3	2.0	2.9	1.8	1.6	2.3	1.5	2.1	1.9	2.3	2.5	1.8	2.4	2.6	2.4	2.5	1.3	1.9	2.4	2.0	1.9	1.6	1.6	1.1	2.0	1.9	2.2	2.3	1.7	1.9	1.7	2.3	2.1	2.3	92.2
BAT	2.2	1.8	5.8	2.1	2.0	2.3	1.5	2.0	2.2	1.9	2.1	1.0	2.1	2.3	0.3	2.2	2.7	2.2	1.6	2.2	1.8	2.0	1.9	2.3	2.5	2.1	2.6	2.7	2.6	2.4	1.4	1.8	2.4	2.1	1.8	1.5	1.8	1.0	1.9	2.2	2.4	2.3	1.9	1.9	1.8	2.3	1.8	2.7	94.2
BCH	2.1	1.5	2.0	5.6	1.9	2.8	2.7	1.6	3.1	1.9	2.0	1.2	1.4	3.1	0.3	2.9	3.3	1.7	1.6	1.8	1.6	1.8	1.7	2.2	3.2	1.3	2.5	3.0	2.5	2.8	1.1	1.5	2.3	1.8	1.5	1.4	1.8	1.0	1.7	1.9	2.2	2.8	1.7	2.1	1.6	2.8	2.0	1.9	94.4
BNB	1.9	1.7	2.2	2.2	6.4	2.9	1.8	1.8	2.3	1.9	2.1	0.9	1.8	2.4	0.4	2.1	2.9	2.0	1.9	2.3	2.5	2.0	2.0	2.4	2.8	1.5	2.3	2.7	2.3	2.6	1.4	1.7	2.3	1.9	1.6	1.6	1.7	1.1	1.8	1.8	2.0	2.6	1.8	1.7	1.9	2.4	1.7	2.1	93.6
BTC	2.1	1.7	2.1	2.8	2.5	5.4	2.0	1.6	2.5	2.5	2.2	1.3	1.8	2.5	0.4	2.4	3.5	1.8	2.0	2.0	1.7	1.8	1.6	2.2	3.2	1.5	2.4	2.7	2.3	2.6	1.1	1.6	2.3	1.9	1.5	1.4	1.9	1.1	1.7	1.7	2.2	2.9	1.8	1.8	1.9	2.4	1.8	2.0	94.6
BTG	2.0	1.4	1.9	3.6	2.1	2.7	7.4	1.7	2.7	1.9	2.0	1.1	1.3	2.8	0.3	3.3	3.0	1.7	1.8	1.8	1.7	1.8	1.6	2.2	2.9	1.2	2.5	2.8	2.4	2.9	1.1	1.7	2.1	2.0	1.6	1.4	1.6	1.0	1.7	1.9	1.9	2.5	1.5	2.2	1.5	2.5	1.8	1.9	92.6
CVC	1.9	1.7	2.4	2.0	2.0	2.1	1.6	7.1	2.3	1.9	2.0	0.8	1.7	2.1	0.3	2.0	2.5	3.0	1.5	2.1	1.7	1.7	1.7	2.6	2.3	1.9	2.6	2.6	2.5	2.3	1.8	1.8	2.5	2.3	2.1	1.6	1.4	1.3	1.9	2.1	2.1	2.3	2.0	2.0	1.6	2.3	1.7	2.3	92.9
DASH	1.9	1.6	2.1	3.1	2.0	2.5	2.0	1.8	5.6	2.0	2.0	1.1	1.4	2.7	0.2	2.7	3.0	1.8	1.5	2.0	1.7	1.8	1.6	2.4	3.1	1.4	2.5	3.0	2.6	2.6	1.1	1.6	2.3	1.9	1.6	1.4	1.8	1.0	1.7	1.9	2.1	3.0	1.7	2.0	1.8	3.5	2.2	2.1	94.4
DCR	2.0	1.6	2.2	2.4	2.0	3.1	1.7	1.8	2.4	6.9	2.1	1.2	1.7	2.5	0.3	2.3	3.2	1.9	1.9	2.1	1.6	1.9	1.6	2.3	2.9	1.6	2.3	2.7	2.5	2.4	1.2	1.9	2.3	1.8	1.7	1.6	1.6	1.1	1.8	2.0	2.1	2.5	1.9	1.8	1.6	2.4	1.9	2.1	93.1
DGB	2.4	1.8	2.2	2.3	2.1	2.6	1.7	1.9	2.3	2.0	6.3	1.3	1.9	2.4	0.3	2.1	2.8	1.8	1.7	2.1	1.5	2.0	1.8	2.2	2.5	1.5	2.4	2.7	2.4	2.3	1.2	1.8	3.0	2.0	1.7	1.6	1.8	1.1	1.7	2.0	2.3	2.4	2.0	1.9	1.6	2.4	2.1	2.2	93.7
DOGE	2.2	1.4	1.9	2.4	1.6	2.7	1.7	1.4	2.3	1.9	2.4	11.2	1.5	2.3	0.3	2.8	2.5	1.6	1.6	1.8	1.5	1.7	1.4	2.1	2.7	1.4	2.1	2.5	2.2	2.4	1.1	1.6	3.6	1.9	1.4	1.4	1.8	0.8	1.4	1.8	2.5	2.3	1.7	2.0	1.5	2.1	2.0	1.8	88.8
ENJ	2.0	1.8	2.8	2.0	2.2	2.5	1.4	1.8	1.9	1.9	2.3	1.0	7.6	2.3	0.3	2.0	2.6	1.8	1.7	2.6	1.4	2.1	1.9	2.2	2.2	2.7	2.2	2.4	2.4	2.3	1.4	2.1	2.5	1.8	1.8	1.6	2.2	1.1	1.9	1.5	2.0	2.3	1.7	1.7	1.8	2.1	1.9	2.4	92.4
EOS	2.3	1.6	2.1	3.1	2.0	2.5	2.0	1.6	2.6	1.9	2.0	1.1	1.5	5.4	0.3	2.8	3.0	1.7	1.5	2.0	1.7	1.9	1.7	2.2	3.0	1.4	2.5	2.9	2.6	3.1	1.1	1.7	2.0	2.1	1.5	1.4	2.2	0.9	1.7	2.0	2.5	2.4	1.7	2.4	1.8	2.4	1.9	2.2	94.6
ERG	1.6	1.0	1.6	1.3	1.6	2.0	1.0	1.3	1.3	1.4	1.4	0.8	1.2	1.8	33.7	1.5	1.0	1.0	1.4	1.4	1.2	1.4	1.3	1.4	2.1	1.2	1.7	1.7	1.8	2.0	0.9	1.6	1.5	1.3	1.2	1.3	0.9	0.6	1.8	1.9	1.5	1.5	1.5	1.1	1.3	1.3	1.4	1.7	66.3
ETC	2.4	1.5	2.1	3.0	1.9	2.5	2.5	1.6	2.8	1.9	1.9	1.4	1.4	2.9	0.3	5.7	3.2	1.7	1.8	2.0	1.4	1.8	1.7	2.3	3.0	1.4	2.6	2.9	2.7	3.0	1.0	1.7	2.1	2.0	1.6	1.4	1.8	0.9	1.7	1.9	2.4	2.5	1.7	2.1	1.8	2.7	1.9	1.8	94.3
ETH	2.2	1.8	2.2	2.8	2.2	3.0	1.9	1.7	2.5	2.2	2.1	1.0	1.6	2.6	0.3	2.6	4.7	1.8	2.4	2.1	1.7	2.1	2.0	2.2	3.2	1.4	2.3	2.9	2.6	2.6	1.2	1.7	2.1	1.9	1.6	1.4	1.8	1.1	1.8	1.9	2.2	2.6	1.8	2.1	1.9	2.5	1.9	2.1	95.3
GLM	2.1	1.6	2.6	2.1	2.2	2.3	1.6	3.0	2.2	1.9	1.9	0.9	1.6	2.1	0.2	2.0	2.7	7.0	1.7	2.2	1.8	1.7	1.8	2.5	2.3	1.7	2.4	2.4	2.6	2.2	1.7	1.7	2.6	2.4	2.3	1.7	1.5	1.1	1.9	2.2	2.1	2.2	1.9	1.8	1.5	2.1	1.7	2.4	93.1
GNO	1.8	1.6	2.2	2.2	2.3	2.9	1.9	1.7	2.2	2.1	2.1	1.1	1.7	2.2	0.4	2.6	3.9	1.9	7.9	2.2	1.7	1.9	2.2	2.2	2.8	1.5	2.2	2.4	2.3	2.4	1.3	1.8	2.1	1.6	1.7	1.4	1.6	1.0	1.9	1.8	2.1	2.3	1.8	1.7	1.5	2.2	1.8	2.1	92.1
ICX	2.4	1.9	2.4	2.0	2.2	2.3	1.5	1.9	2.3	1.9	2.1	1.0	2.1	2.3	0.3	2.2	2.7	2.0	1.7	6.2	1.6	2.1	2.0	2.4	2.4	1.7	2.6	2.8	2.6	2.5	1.3	1.8	2.4	2.1	1.8	1.5	1.8	1.1	1.8	1.9	2.3	2.4	1.9	1.8	1.9	2.3	1.8	2.4	93.8
KCS	2.0	1.5	2.4	2.3	3.0	2.5	1.9	1.9	2.3	1.8	1.8	1.0	1.5	2.5	0.3	2.0	2.8	2.0	1.7	2.1	7.8	1.8	1.8	2.3	2.6	1.4	2.3	2.8	2.3	2.6	1.2	1.6	2.1	2.1	1.5	1.6	1.6	1.1	1.8	2.1	2.2	2.3	1.8	2.1	1.6	2.4	1.7	2.2	92.2
LINK	2.2	1.8	2.3	2.3	2.1	2.3	1.6	1.7	2.3	1.9	2.1	1.0	1.9	2.4	0.3	2.2	3.0	1.7	1.7	2.4	1.6	6.8	2.0	2.3	2.4	1.6	2.4	2.6	2.4	2.5	1.3	2.2	2.1	1.8	1.7	1.6	1.8	1.1	1.8	1.9	2.2	2.2	1.8	1.8	2.1	2.3	2.0	2.3	93.2
LRC	2.3	1.7	2.3	2.2	2.3	2.2	1.6	1.7	2.1	1.7	2.1	0.9	1.8	2.2	0.3	2.2	3.0	1.8	2.0	2.4	1.6	2.1	7.2	2.4	2.5	1.6	2.3	2.8	2.6	2.4	1.4	1.9	2.4	2.0	1.8	1.6	1.6	1.2	1.8	1.9	2.1	2.2	1.8	1.7	1.7	2.2	1.9	2.6	92.9
LSK	1.9	1.7	2.3	2.3	2.1	2.4	1.7	2.1	2.4	1.9	2.0	1.1	1.6	2.4	0.3	2.4	2.7	2.1	1.6	2.3	1.7	1.9	1.9	5.8	2.6	1.6	2.5	2.7	2.7	2.7	1.3	1.9	2.4	2.0	2.0	1.6	1.6	1.1	2.0	2.1	2.0	2.4	1.8	1.9	1.7	2.5	2.0	2.3	94.2
LTC	2.2	1.7	2.2	2.9	2.2	3.0	2.0	1.7	2.8	2.1	2.0	1.2	1.4	2.8	0.4	2.7	3.4	1.7	1.8	2.0	1.7	1.8	1.7	2.3	5.1	1.3	2.5	2.7	2.6	2.8	1.1	1.7	2.2	1.9	1.6	1.5	1.7	0.9	1.8	2.0	2.2	2.6	1.8	2.2	1.8	2.7	1.9	1.9	94.9
MANA	1.9	1.9	2.9	1.9	2.0	2.4	1.4	2.3	2.0	1.9	2.0	1.0	3.0	2.2	0.3	2.0	2.4	2.0	1.5	2.2	1.5	2.0	1.8	2.3	2.1	8.3	2.4	2.4	2.2	2.2	1.4	1.7	2.3	1.8	1.8	1.8	2.0	1.1	1.7	1.6	2.1	2.3	2.1	1.8	1.6	2.2	1.8	2.5	91.7
MIOTA	2.4	1.7	2.4	2.5	2.0	2.4	1.9	2.0	2.5	1.8	2.1	1.0	1.6	2.5	0.3	2.5	2.7	1.9	1.5	2.3	1.6	1.9	1.7	2.4	2.7	1.6	5.5	2.7	2.5	2.7	1.2	1.7	2.3	2.3	1.8	1.5	1.7	1.1	1.8	2.2	2.6	2.5	1.9	2.2	1.7	2.5	1.9	2.2	94.5
NEO	2.2	1.7	2.3	2.7	2.1	2.5	1.9	1.9	2.6	2.0	2.1	1.1	1.5	2.7	0.3	2.6	3.0	1.8	1.5	2.2	1.8	1.9	2.0	2.4	2.7	1.4	2.5	5.0	2.8	3.0	1.2	1.7	2.3	2.1	1.7	1.5	1.7	1.0	1.7	2.1	2.3	2.6	1.8	2.1	1.8	2.6	2.0	2.2	95.0
OMG	2.2	1.6	2.4	2.5	1.9	2.3	1.7	1.9	2.5	2.0	2.0	1.0	1.7	2.6	0.3	2.5	2.9	2.0	1.6	2.3	1.6	1.9	2.0	2.5	2.7	1.4	2.4	3.0	5.4	3.0	1.2	1.7	2.3	2.1	1.9	1.6	1.8	1.0	1.8	2.0	2.2	2.3	1.7	2.0	2.0	2.4	2.1	2.4	94.6
QTUM	2.3	1.7	2.2	2.6	2.2	2.5	2.0	1.7	2.4	1.9	1.9	1.1	1.6	3.0	0.4	2.8	2.9	1.7	1.6	2.1	1.8	1.9	1.7	2.4	2.8	1.4	2.5	3.2	2.9	5.3	1.1	1.7	2.2	2.1	1.7	1.4	1.9	0.9	1.7	2.1	2.3	2.3	1.7	2.2	1.8	2.4	1.9	2.1	94.8
REQ	2.1	1.6	2.5	1.9	2.2	2.1	1.5	2.6	1.9	1.7	1.9	0.9	1.8	2.0	0.3	1.9	2.6	2.4	1.7	2.1	1.5	2.0	1.9	2.2	2.2	1.7	2.1	2.4	2.3	2.1	10.1	2.0	2.7	1.9	1.9	1.7	1.9	1.3	1.7	1.6	2.0	2.1	2.1	1.6	1.6	2.1	1.6	2.3	89.9
RLC	2.1	1.8	2.4	2.1	2.0	2.3	1.7	1.9	2.1	2.0	2.1	1.0	2.0	2.3	0.4	2.3	2.7	1.8	1.7	2.2	1.5	2.4	2.0	2.5	2.5	1.5	2.3	2.6	2.3	2.4	1.5	7.4	2.1	1.9	1.8	1.8	1.7	1.0	2.0	1.9	2.3	2.3	1.9	1.9	1.6	2.2	1.9	2.2	92.6
SC	2.0	1.8	2.4	2.4	2.1	2.5	1.7	2.0	2.4	2.0	2.8	1.8	1.9	2.2	0.3	2.2	2.6	2.2	1.6	2.2	1.5	1.8	1.9	2.5	2.5	1.6	2.4	2.7	2.4	2.4	1.5	1.7	5.8	2.2	2.1	1.6	1.9	1.2	1.7	2.1	2.2	2.3	1.9	1.9	1.5	2.3	1.9	2.2	94.3
SNT	3.2	1.6	2.3	2.1	1.9	2.2	1.7	2.1	2.2	1.7	2.1	1.1	1.5	2.5	0.3	2.3	2.6	2.2	1.3	2.1	1.7	1.7	1.8	2.2	2.4	1.4	2.6	2.7	2.5	2.6	1.2	1.6	2.4	6.4	1.9	1.5	1.8	1.1	1.6	2.5	3.3	2.3	1.6	2.4	1.9	2.2	1.7	2.1	93.6
STORJ	2.0	1.9	2.4	2.0	1.9	2.1	1.7	2.3	2.2	1.9	2.1	0.9	1.7	2.1	0.3	2.1	2.5	2.5	1.7	2.2	1.4	1.9	1.9	2.6	2.3	1.7	2.5	2.5	2.7	2.4	1.4	1.8	2.7	2.2	7.6	1.7	1.3	1.0	2.0	2.0	2.1	2.3	1.6	1.8	1.7	2.2	2.1	2.4	92.4
SYS	1.9	1.7	2.2	2.1	2.1	2.2	1.6	2.0	2.2	1.9	2.1	1.0	1.7	2.3	0.4	2.1	2.6	2.1	1.5	2.0	1.7	2.0	1.9	2.3	2.5	1.8	2.3	2.6	2.6	2.3	1.4	2.0	2.3	2.0	1.9	8.5	1.7	1.3	2.0	1.9	2.1	2.3	1.8	1.9	1.5	2.1	2.0	2.0	91.5
TRX	2.4	1.5	2.2	2.4	2.0	2.6	1.7	1.5	2.3	1.8	2.2	1.2	2.2	3.0	0.2	2.4	2.8	1.6	1.6	2.1	1.5	1.9	1.7	2.1	2.5	1.8	2.2	2.6	2.5	2.7	1.4	1.7	2.4	2.1	1.3	1.5	7.4	1.0	1.5	1.8	2.2	2.4	2.1	2.4	1.7	2.3	1.7	2.1	92.6
VGX	2.1	1.7	2.0	2.0	1.9	2.3	1.6	2.1	2.1	1.9	2.1	0.8	1.6	2.0	0.2	1.9	2.7	1.9	1.5	2.1	1.7	1.9	2.0	2.3	2.2	1.6	2.3	2.5	2.2	2.1	1.4	1.7	2.3	2.0	1.6	1.8	1.6	11.6	1.8	2.0	2.1	2.1	1.8	2.0	1.5	2.0	1.6	2.0	88.5
WAVES	2.0	1.9	2.3	2.2	2.1	2.4	1.8	2.0	2.3	1.9	1.9	0.9	1.8	2.3	0.5	2.3	2.8	2.0	1.8	2.1	1.7	2.0	1.8	2.5	2.6	1.5	2.4	2.5	2.5	2.3	1.2	2.0	2.1	1.9	1.9	1.7	1.5	1.1	7.4	1.8	2.2	2.3	1.7	1.9	1.9	2.2	2.0	2.2	92.6
XEM	2.5	1.6	2.5	2.3	1.8	2.0	1.7	2.0	2.2	1.9	2.1	1.0	1.3	2.5	0.4	2.3	2.7	2.1	1.5	2.1	1.8	1.9	1.8	2.5	2.6	1.3	2.7	2.8	2.4	2.6	1.1	1.7	2.5	2.6	1.8	1.6	1.7	1.2	1.6	6.8	2.7	2.2	1.7	2.4	1.5	2.3	1.8	2.1	93.2
XLM	3.3	1.6	2.4	2.3	1.8	2.3	1.5	1.7	2.2	1.7	2.1	1.3	1.5	2.7	0.3	2.5	2.7	1.8	1.5	2.2	1.6	1.9	1.7	2.0	2.6	1.5	2.7	2.7	2.4	2.6	1.2	1.8	2.2	3.0	1.6	1.5	1.7	1.1	1.7	2.4	5.8	2.4	1.8	3.0	1.9	2.4	1.8	2.1	94.2
XMR	2.1	1.7	2.2	2.8	2.2	3.0	1.9	1.8	3.0	2.0	2.1	1.1	1.6	2.4	0.3	2.4	3.0	1.8	1.6	2.2	1.7	1.8	1.7	2.3	2.8	1.5	2.5	2.9	2.4	2.4	1.2	1.7	2.2	2.0	1.6	1.5	1.8	1.0	1.8	1.8	2.3	5.6	1.7	1.9	1.7	3.1	2.1	2.2	94.4
XNO	2.0	1.5	2.4	2.2	2.0	2.4	1.5	2.0	2.1	2.0	2.2	1.1	1.6	2.3	0.4	2.2	2.8	1.9	1.7	2.2	1.7	1.8	1.8	2.2	2.5	1.8	2.5	2.6	2.3	2.4	1.5	1.9	2.4	1.9	1.6	1.5	2.1	1.2	1.7	1.8	2.3	2.3	7.2	2.3	1.5	2.4	1.9	2.3	92.8
XRP	2.7	1.6	2.1	2.5	1.7	2.2	1.9	1.8	2.3	1.7	2.0	1.1	1.4	2.9	0.2	2.5	2.8	1.8	1.4	1.9	1.7	1.8	1.6	2.2	2.8	1.4	2.6	2.7	2.4	2.7	1.0	1.6	2.1	2.5	1.5	1.5	2.1	1.1	1.6	2.3	3.4	2.2	2.1	6.5	1.7	2.5	1.9	1.9	93.5
XTZ	2.2	1.7	2.3	2.2	2.2	2.6	1.5	1.7	2.4	1.8	1.9	1.0	1.7	2.4	0.3	2.4	3.0	1.7	1.5	2.3	1.5	2.4	1.7	2.3	2.7	1.5	2.4	2.7	2.7	2.6	1.2	1.6	2.0	2.2	1.7	1.4	1.7	0.9	2.0	1.8	2.5	2.3	1.6	2.0	7.5	2.3	1.9	2.3	92.5
ZEC	2.1	1.6	2.2	2.8	2.0	2.5	1.8	1.8	3.5	1.9	2.1	1.0	1.5	2.5	0.3	2.6	3.0	1.7	1.6	2.1	1.7	1.9	1.7	2.4	2.9	1.5	2.5	2.9	2.5	2.6	1.1	1.6	2.2	1.9	1.6	1.4	1.7	0.9	1.6	1.9	2.3	3.1	1.9	2.2	1.7	5.6	2.3	2.1	94.4
ZEN	2.0	1.8	2.2	2.4	1.9	2.3	1.7	1.7	2.7	1.9	2.2	1.2	1.7	2.5	0.3	2.4	2.7	1.7	1.6	2.1	1.4	2.1	1.8	2.4	2.6	1.5	2.4	2.8	2.6	2.5	1.1	1.7	2.3	1.8	1.9	1.7	1.6	1.0	1.8	1.9	2.1	2.6	1.9	2.0	1.8	2.9	6.9	2.3	93.1
ZRX	2.0	1.8	2.8	2.1	2.0	2.2	1.6	2.0	2.3	1.9	2.2	1.0	1.9	2.5	0.3	2.0	2.8	2.1	1.7	2.4	1.7	2.1	2.2	2.4	2.3	1.8	2.4	2.7	2.7	2.4	1.4	1.8	2.4	2.0	1.9	1.5	1.7	1.0	1.8	1.9	2.2	2.4	1.9	1.8	1.8	2.3	2.0	6.1	94.0
Contribution to self and others	107.5	85.6	112.7	115.9	102.2	120.5	88.6	94.0	115.9	96.0	103.5	61.2	86.8	119.9	48.3	114.8	138.3	95.9	84.9	106.3	84.6	96.7	91.7	113.5	127.9	81.1	118.6	130.6	121.3	123.3	68.6	89.5	114.3	102.3	88.2	80.5	88.8	60.8	90.3	98.5	112.7	117.6	91.9	100.2	87.5	116.9	95.7	108.1	**Total spillover index**
Contribution to others	101.5	77.8	106.9	110.3	95.8	115.1	81.2	86.8	110.3	89.2	97.2	50.0	79.2	114.5	14.6	109.1	133.6	88.9	77.1	100.1	76.8	89.9	84.5	107.8	122.8	72.8	113.1	125.6	116.0	118.0	58.5	82.1	108.6	95.9	80.6	72.0	81.4	49.2	82.9	91.7	107.0	112.0	84.7	93.6	79.9	111.4	88.8	102.1	**92.7 %**
Net spillovers	7.6	-14.4	12.7	15.9	2.2	20.5	-11.4	-6.1	15.9	-4.0	3.5	-38.8	-13.2	20.0	-51.7	14.8	38.3	-4.1	-15.0	6.3	-15.4	-3.3	-8.4	13.5	27.9	-18.9	18.6	30.6	21.3	23.3	-31.4	-10.5	14.3	2.3	-11.8	-19.5	-11.2	-39.2	-9.8	-1.5	12.8	17.6	-8.1	0.2	-12.6	17.0	-4.3	8.1	

Static spillover table of Volatility

Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	11.0	0.8	2.3	3.5	2.4	2.0	1.3	0.4	2.8	0.8	2.3	0.2	0.9	3.9	0.0	2.1	3.6	1.4	2.5	3.2	1.8	1.8	1.7	2.4	3.3	1.2	2.7	1.8	3.0	2.6	0.5	1.8	2.2	1.3	0.4	1.7	2.1	0.5	1.3	2.3	4.0	1.5	1.1	3.5	2.2	1.3	1.2	1.8	89.0
ANT	2.7	10.0	3.3	1.9	3.1	1.7	0.5	0.8	3.4	0.9	1.7	0.1	1.7	2.5	0.0	1.4	3.7	1.9	2.0	2.8	2.0	3.2	1.4	3.7	1.9	1.5	1.8	1.4	3.7	2.7	0.9	2.5	2.3	1.1	1.4	2.6	2.0	1.2	2.0	1.4	1.7	1.4	0.7	2.1	3.3	1.2	0.7	2.2	89.9
BAT	2.6	0.5	10.5	2.5	2.9	1.4	1.0	1.0	3.2	0.8	1.7	0.1	2.2	3.1	0.0	1.7	3.7	1.8	2.1	3.0	3.0	2.5	1.5	2.6	2.4	2.3	2.6	1.9	3.7	2.8	1.1	1.6	2.5	1.0	1.1	1.7	1.7	0.6	1.3	1.3	2.2	1.4	0.8	2.3	2.6	1.3	1.0	3.8	89.6
BCH	2.8	0.7	2.8	11.0	2.1	2.8	2.4	0.6	4.4	0.8	1.6	0.1	0.8	3.9	0.0	3.2	2.9	1.0	1.7	2.2	1.9	1.8	1.2	2.8	4.2	0.6	2.7	2.3	3.0	3.0	0.3	1.5	1.7	0.9	0.6	1.2	2.0	0.7	2.0	1.5	2.7	2.4	0.9	3.4	2.3	2.0	1.3	1.6	89.0
BNB	2.4	1.2	3.0	2.4	9.3	2.0	1.2	0.9	3.6	0.6	2.5	0.1	1.4	2.7	0.0	1.6	3.6	1.6	2.6	3.1	3.1	2.5	1.4	3.1	2.9	1.2	2.1	1.6	3.1	2.7	0.5	2.1	2.2	0.8	1.2	1.7	2.9	1.2	1.3	1.4	2.0	1.7	1.0	2.6	2.9	1.4	1.3	2.4	90.7
BTC	2.6	0.7	2.4	3.9	2.9	10.0	1.2	0.7	3.2	1.1	2.6	0.1	1.0	3.0	0.0	1.8	3.5	1.5	2.2	2.9	1.9	2.7	1.1	2.7	3.5	1.1	2.6	2.1	3.1	2.7	0.5	1.9	2.5	0.7	0.9	1.5	1.8	1.1	1.4	1.3	2.4	2.8	0.8	2.2	2.7	1.6	1.7	1.4	90.0
BTG	2.0	0.5	2.4	5.0	2.3	1.5	16.7	0.7	5.1	0.5	1.1	0.0	0.6	3.6	0.0	4.5	2.2	0.6	1.6	2.0	1.8	1.9	0.8	2.9	2.7	0.8	2.2	2.5	2.6	3.3	0.2	1.4	1.4	1.0	1.1	0.9	1.9	0.9	1.2	1.2	2.4	1.3	0.5	3.4	2.2	1.7	1.2	1.9	83.3
CVC	2.0	0.7	2.2	1.8	2.0	1.2	0.6	20.7	3.1	0.7	1.4	0.2	0.8	2.3	0.0	1.6	2.7	2.5	1.6	2.6	1.8	1.5	1.2	2.6	2.1	1.2	4.6	1.6	2.6	2.3	0.7	1.9	2.8	1.7	1.1	1.3	1.3	0.6	0.9	1.6	2.4	1.0	0.9	2.6	1.9	1.3	1.1	2.8	79.3
DASH	2.4	0.8	2.9	4.0	3.1	1.6	2.1	1.0	9.0	0.8	1.7	0.1	0.9	3.6	0.0	3.1	3.1	1.1	1.9	2.5	2.3	2.0	1.3	3.7	3.3	0.9	2.9	2.2	3.3	2.9	0.3	1.7	2.1	0.7	0.8	1.5	1.4	1.0	1.9	1.3	2.2	2.1	1.0	2.9	2.1	3.0	1.6	2.2	91.1
DCR	1.9	0.8	2.7	3.1	2.1	2.5	1.2	1.0	3.0	19.8	1.8	0.0	1.0	2.6	0.0	2.1	3.4	1.3	2.1	2.4	1.3	2.2	1.3	2.6	2.9	0.7	1.7	2.3	3.1	2.5	0.6	1.7	1.8	0.7	0.8	1.4	1.0	0.7	1.2	1.5	1.5	1.7	0.7	2.1	2.2	1.5	1.7	2.3	80.2
DGB	3.5	0.8	2.7	2.8	2.8	2.2	1.0	1.0	3.2	0.6	12.0	0.3	1.2	2.7	0.0	1.8	2.7	1.5	2.1	2.8	1.5	2.3	1.1	2.2	2.9	1.2	3.2	2.1	2.5	2.5	0.4	1.6	4.0	1.6	0.8	1.4	2.2	0.6	1.2	1.5	2.6	1.6	1.2	2.7	2.5	1.6	0.9	2.7	88.0
DOGE	0.8	0.8	0.5	1.0	0.4	0.9	0.2	0.2	0.7	0.1	1.0	64.0	0.5	0.7	0.0	0.9	1.1	0.3	0.4	0.5	0.4	0.8	0.4	0.6	0.8	0.5	0.4	0.7	0.7	1.5	0.1	0.5	4.7	0.6	0.3	0.4	0.6	0.1	0.4	0.5	2.5	0.4	1.3	0.9	0.6	0.4	3.1	1.0	36.0
ENJ	3.1	0.7	4.2	1.8	3.4	1.7	1.1	0.9	2.9	0.6	2.1	0.0	11.5	3.2	0.0	1.3	3.9	1.2	1.9	3.7	2.9	2.3	1.5	2.5	2.6	2.0	1.9	2.1	3.3	2.6	0.4	2.5	2.2	1.6	1.5	1.6	1.9	0.4	1.3	1.6	2.1	1.5	1.0	1.9	1.8	1.1	0.9	2.0	88.5
EOS	2.9	0.4	2.6	4.5	2.2	1.8	1.9	0.6	3.5	0.6	1.6	0.1	0.7	10.1	0.0	4.1	3.4	1.1	2.1	2.4	2.1	1.7	1.1	2.7	3.2	1.2	2.6	2.9	3.9	4.5	0.3	1.8	1.6	1.2	1.0	1.6	2.5	0.4	1.7	1.2	2.6	1.2	0.6	3.6	2.2	1.5	0.8	1.8	89.9
ERG	0.1	0.1	0.1	0.3	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	3.6	0.1	91.5	0.1	0.2	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.2	0.0	0.1	0.1	0.1	0.0	0.1	0.1	0.1	0.0	0.1	0.1	0.2	0.1	0.1	0.2	0.1	0.0	0.4	0.1	0.0	0.1	0.1	8.5
ETC	2.7	0.4	2.2	4.7	2.1	2.0	3.0	1.0	4.0	0.8	1.4	0.2	0.7	3.6	0.0	13.3	2.9	0.9	2.1	2.1	1.8	1.5	1.1	3.0	3.2	0.8	2.1	2.3	2.8	3.9	0.2	1.4	2.0	1.5	0.6	1.3	1.4	0.9	1.6	1.5	2.2	1.6	0.6	3.2	2.4	2.4	1.2	1.6	86.7
ETH	2.8	0.5	3.2	3.3	2.6	2.3	0.9	0.8	3.5	0.8	1.5	0.1	1.1	4.8	0.0	2.7	8.2	1.5	2.5	2.5	2.1	2.5	1.3	2.6	3.2	1.0	1.7	2.9	4.8	3.2	0.4	2.0	1.9	0.9	1.1	1.7	1.3	1.0	1.6	1.9	2.1	1.9	0.6	3.2	3.1	1.9	0.9	2.2	91.8
GLM	2.4	0.4	3.1	1.9	2.4	1.6	1.1	2.1	3.1	0.8	1.8	0.1	0.9	2.6	0.0	1.4	2.3	14.4	2.0	3.0	2.0	1.9	1.3	2.9	1.9	1.5	3.0	1.9	3.9	2.8	1.7	1.5	2.8	1.3	1.1	2.4	1.2	1.1	1.6	1.4	1.9	1.3	0.6	2.4	2.2	1.3	0.8	3.2	85.6
GNO	2.7	0.7	3.0	2.7	3.4	1.7	1.3	0.6	2.8	0.8	2.2	0.1	1.1	2.6	0.1	1.6	4.1	1.7	14.8	2.7	1.8	2.9	2.7	2.3	3.1	0.5	1.5	1.9	2.9	2.6	0.7	1.7	2.5	0.5	1.2	1.1	1.5	0.8	2.1	2.2	1.6	1.7	0.7	2.2	2.9	1.3	1.0	1.7	85.2
ICX	3.6	1.0	3.0	2.6	2.6	1.6	1.2	1.4	3.1	0.7	2.6	0.0	1.5	2.7	0.0	1.8	2.7	1.8	2.1	9.7	2.3	2.1	1.6	3.6	2.3	1.0	3.1	2.2	3.5	3.4	0.4	1.9	2.7	1.4	1.0	1.9	1.7	0.7	1.4	1.4	2.1	2.2	1.1	2.4	2.0	1.6	1.1	2.6	90.3
KCS	1.9	0.6	2.9	2.3	4.5	1.6	0.9	0.8	2.9	0.5	1.6	0.1	1.2	3.6	0.0	1.6	3.0	1.8	1.9	2.8	17.4	2.1	1.5	2.7	2.1	1.2	1.7	1.8	3.4	2.6	0.4	1.5	1.3	1.3	1.5	1.5	2.9	0.6	1.3	1.4	2.3	1.4	1.1	2.2	1.9	1.5	0.7	2.4	82.6
LINK	3.1	0.8	3.0	2.9	3.0	2.0	1.0	0.8	2.9	0.8	1.7	0.0	1.2	3.3	0.0	1.6	4.2	1.8	2.6	2.9	2.4	9.9	1.7	2.8	2.6	0.9	2.1	2.0	3.7	2.9	0.6	2.4	2.0	0.7	1.1	1.8	2.0	0.7	1.6	1.3	2.3	2.1	0.8	2.6	3.3	1.6	0.9	2.0	90.1
LRC	3.4	0.7	2.7	2.3	2.7	1.4	0.8	1.0	2.7	0.6	2.1	0.3	1.0	2.2	0.0	1.8	2.5	0.9	2.8	2.9	2.7	2.1	16.7	1.9	2.4	2.0	1.7	1.9	3.0	2.5	0.4	1.4	3.3	1.2	0.6	1.6	2.4	1.1	1.4	1.3	2.4	2.1	1.8	1.9	1.4	1.3	0.7	2.0	83.3
LSK	2.7	0.9	3.2	2.5	3.1	1.7	1.2	1.1	4.0	0.7	2.0	0.1	1.4	3.0	0.0	2.2	2.9	1.4	1.8	3.5	2.0	2.3	1.1	9.3	2.7	1.3	2.6	1.9	3.6	3.4	0.4	2.1	2.9	1.3	1.3	1.9	1.8	0.9	1.9	1.5	1.8	1.3	0.7	2.2	2.9	1.6	1.1	2.9	90.7
LTC	2.1	0.8	2.8	4.3	2.7	3.6	1.2	0.8	4.1	0.9	1.6	0.1	0.9	3.6	0.0	2.7	3.6	1.1	2.5	2.5	1.9	2.1	1.4	3.2	8.8	1.0	2.5	1.8	3.6	2.7	0.3	1.8	1.6	0.7	1.0	1.6	1.4	0.6	1.7	3.1	2.3	2.4	0.8	3.0	2.2	1.8	1.7	1.5	91.2
MANA	2.7	0.6	4.4	1.5	2.5	1.6	0.6	0.8	2.3	0.6	1.5	0.1	2.3	2.5	0.0	1.3	2.8	1.5	1.3	3.0	2.9	2.3	1.7	2.2	1.7	15.5	3.2	1.8	2.8	2.2	0.3	1.8	2.1	1.9	0.9	2.8	2.1	0.8	1.2	2.2	2.5	2.0	0.9	1.6	2.6	1.2	0.6	2.6	84.5
MIOTA	3.9	0.8	2.8	2.9	3.1	2.0	1.4	1.0	3.5	0.7	2.3	0.1	0.7	4.1	0.0	2.0	2.9	1.7	2.2	3.3	1.6	2.2	1.4	3.1	2.4	1.0	9.2	1.9	3.3	3.1	0.6	1.5	2.6	1.4	1.0	2.1	1.2	0.7	1.7	1.1	2.4	1.4	0.8	3.4	2.2	1.4	1.2	2.8	90.7
NEO	2.9	0.6	2.5	3.5	2.5	2.3	1.1	0.8	3.5	0.9	2.5	0.1	0.6	3.6	0.0	2.4	2.5	1.1	1.6	2.8	2.6	2.0	1.4	3.0	3.0	0.9	2.8	8.8	3.8	3.7	0.3	1.7	1.9	1.5	1.0	1.4	1.9	0.5	1.6	1.7	2.5	2.2	1.1	2.9	2.1	1.5	1.5	2.8	91.2
OMG	2.4	0.9	3.4	2.9	2.3	1.8	0.8	1.0	3.6	0.7	2.1	0.1	1.1	3.6	0.0	2.5	3.5	1.6	2.3	3.3	1.9	2.1	1.8	3.4	2.8	1.3	2.6	2.9	9.1	4.2	0.4	1.9	2.1	1.2	1.0	1.6	1.6	0.5	1.7	1.3	2.0	1.2	0.8	2.9	2.8	1.7	0.9	2.7	91.0
QTUM	2.7	0.5	2.9	2.6	2.8	2.0	1.1	0.9	2.8	0.6	1.9	0.0	1.1	3.8	0.0	3.1	2.9	1.4	1.7	2.5	2.4	2.1	1.3	3.3	2.4	1.4	2.6	3.3	4.1	9.5	0.7	1.8	2.3	1.6	1.0	1.9	2.6	0.5	1.4	1.6	2.7	1.1	0.9	3.2	2.6	1.7	0.8	2.0	90.5
REQ	1.6	0.3	2.9	1.5	2.6	1.3	0.4	1.3	2.0	0.8	1.4	0.0	1.2	1.8	0.0	0.5	2.6	3.9	1.2	2.0	1.3	2.0	1.2	2.0	1.7	1.0	2.3	0.8	2.3	2.5	29.9	1.6	3.9	0.5	1.0	2.6	1.6	1.2	0.7	0.5	1.1	1.3	0.7	1.9	2.2	1.4	0.6	1.2	70.1
RLC	2.9	0.8	3.1	2.0	2.9	1.8	0.6	1.0	2.3	0.8	1.7	0.0	1.6	2.7	0.0	1.9	3.3	1.2	1.7	3.1	1.4	2.7	1.8	3.2	1.9	1.2	1.6	2.2	3.3	3.1	0.6	14.8	2.0	1.2	1.3	2.2	1.9	1.1	1.9	1.4	2.3	1.2	1.2	2.3	2.9	1.3	1.0	2.0	85.2
SC	3.0	0.9	3.0	2.3	2.2	1.5	0.8	1.2	3.0	0.5	3.1	1.2	1.7	2.5	0.0	2.0	2.6	2.0	1.7	2.9	2.0	2.0	1.4	2.4	2.0	1.6	2.3	1.8	2.9	2.9	1.2	1.7	10.4	2.5	1.0	1.4	3.0	0.7	1.2	2.0	3.5	1.2	1.3	3.2	1.9	1.3	1.1	2.4	89.6
SNT	3.9	0.8	2.0	2.3	1.8	1.7	1.5	1.3	2.1	0.6	2.1	0.3	1.1	2.5	0.0	2.0	2.4	1.6	2.2	2.8	2.1	1.4	1.6	2.6	2.5	1.4	2.7	1.5	2.7	2.6	0.6	1.6	2.7	15.9	0.9	1.2	2.5	0.6	1.6	2.0	4.1	0.8	1.0	3.5	1.7	1.1	1.0	1.5	84.1
STORJ	1.7	0.6	3.7	1.2	3.1	1.1	1.0	1.2	2.3	0.5	1.4	0.1	1.4	2.5	0.0	1.0	3.2	2.1	3.3	2.3	1.7	2.2	1.2	3.2	2.2	1.5	1.7	1.4	3.6	2.5	0.7	2.0	2.7	1.4	20.3	1.5	1.2	0.9	2.2	1.7	1.3	1.1	0.6	1.9	1.9	1.0	0.8	2.0	79.7
SYS	2.4	0.4	3.3	1.6	2.8	1.3	0.7	2.2	2.3	0.6	1.4	0.0	1.0	3.0	0.0	1.4	3.2	2.4	2.0	2.5	1.7	2.2	1.6	2.8	1.9	2.0	2.4	1.9	3.4	4.2	1.6	2.2	2.1	1.2	1.1	15.4	1.0	0.7	1.7	1.6	1.8	1.1	0.5	2.3	3.3	1.3	0.8	2.2	84.6
TRX	2.7	1.5	2.6	2.9	2.2	1.9	1.3	0.5	2.6	0.5	2.3	0.2	1.3	2.8	0.0	1.5	2.1	0.8	1.9	3.0	2.4	2.0	1.1	2.4	2.6	2.3	2.8	1.8	3.0	2.4	0.8	1.8	2.1	2.2	0.7	1.0	14.2	0.6	1.2	2.1	4.0	1.4	1.7	3.2	2.4	1.2	0.5	1.5	85.9
VGX	2.4	0.6	2.9	1.2	2.8	1.8	0.4	0.7	2.4	0.7	1.5	0.9	1.0	2.0	0.0	1.1	3.6	1.6	1.6	2.6	1.7	2.1	1.9	2.1	1.4	1.6	1.7	1.2	2.8	2.2	0.7	2.5	2.0	1.3	0.8	2.1	1.4	22.5	1.7	1.0	2.1	0.9	1.1	1.6	3.4	1.1	1.6	1.8	77.5
WAVES	2.1	1.7	2.7	2.3	2.2	1.6	0.7	0.7	3.2	0.6	1.6	0.0	1.2	2.5	0.0	1.7	2.7	1.9	2.0	3.0	1.9	2.5	1.5	3.6	2.7	0.8	2.2	2.0	2.8	2.3	0.4	2.2	1.9	1.1	1.1	1.3	0.8	0.4	18.4	1.2	1.5	2.3	0.4	2.7	2.2	1.8	1.5	2.6	81.6
XEM	2.5	0.5	2.5	2.2	2.1	2.9	0.9	1.1	2.1	0.8	1.6	0.3	1.2	2.6	0.0	2.0	2.2	2.1	1.8	3.1	3.1	1.7	0.8	2.1	2.2	2.3	3.5	2.0	3.3	2.7	0.3	1.7	2.6	1.8	1.1	1.2	1.8	0.3	1.0	15.1	3.4	1.8	0.6	2.9	1.4	1.1	1.4	2.2	84.9
XLM	4.2	0.7	2.4	3.6	1.7	1.9	1.4	0.6	2.6	0.7	2.2	0.6	0.7	3.2	0.0	1.9	2.6	1.3	1.8	3.0	2.1	1.7	1.6	1.8	2.6	0.7	2.9	2.0	2.9	2.9	0.5	1.7	2.6	2.1	0.8	1.4	2.1	0.4	1.3	2.1	11.5	1.5	1.4	5.6	1.9	1.5	1.7	1.5	88.5
XMR	3.3	0.6	2.9	3.8	2.5	2.6	1.2	0.8	4.0	0.9	2.1	0.1	0.7	2.9	0.0	2.1	2.6	1.3	1.6	3.2	2.4	2.0	1.2	3.1	3.2	0.6	3.5	2.4	2.7	2.3	0.5	1.6	2.1	0.6	0.9	1.5	1.2	0.7	1.9	1.3	1.9	11.4	1.0	2.2	2.3	2.5	1.5	2.6	88.6
XNO	2.6	0.6	2.1	2.9	2.0	1.7	0.7	0.7	2.8	1.0	2.5	0.6	0.6	2.4	0.0	2.0	2.1	1.2	1.5	3.5	2.0	1.9	2.4	2.1	3.2	0.9	2.5	1.6	2.8	2.2	0.5	2.3	2.9	1.2	0.5	1.0	1.6	0.5	1.0	1.2	2.7	1.6	18.9	3.1	1.6	1.2	1.9	1.5	81.1
XRP	2.4	0.6	2.4	3.3	2.1	1.7	1.5	0.8	3.2	0.5	1.4	1.9	0.9	3.9	0.0	2.3	3.2	1.3	1.4	2.5	2.0	1.8	0.8	2.4	3.5	0.7	2.4	1.8	3.3	3.4	0.5	1.5	2.2	1.5	0.8	1.6	2.2	0.5	1.7	2.9	4.9	1.4	1.2	11.8	1.9	1.8	1.5	1.1	88.2
XTZ	3.1	0.7	3.6	2.4	3.0	2.0	1.0	0.9	2.4	0.8	1.9	0.1	1.4	3.2	0.0	2.1	3.4	1.7	1.7	2.4	2.0	2.5	1.2	3.2	2.2	1.7	2.2	2.1	3.9	3.7	0.9	2.6	1.8	1.3	0.8	1.9	2.5	1.1	1.3	0.9	2.2	1.2	1.0	2.3	12.0	1.2	0.5	2.2	88.0
ZEC	2.3	0.6	2.6	3.6	2.5	1.9	1.6	1.1	5.7	0.7	1.8	0.1	1.0	3.1	0.0	2.6	2.7	1.3	2.0	2.3	2.8	2.1	1.2	3.1	3.3	1.0	2.5	1.7	2.9	2.8	0.2	1.4	2.1	0.7	0.7	1.5	1.7	0.9	1.7	1.6	2.6	2.7	0.8	3.0	1.6	10.0	2.0	2.0	90.0
ZEN	2.2	0.7	3.1	2.9	2.6	2.0	0.7	1.5	4.2	1.1	1.3	0.4	0.8	3.1	0.0	2.2	2.9	0.9	1.8	2.0	2.2	2.2	1.2	2.8	3.2	0.8	2.4	1.9	3.1	2.5	0.3	1.7	1.9	1.0	1.0	1.8	1.1	0.8	2.1	1.6	2.6	1.8	1.0	2.9	2.0	2.8	12.4	2.7	87.6
ZRX	2.3	1.1	3.9	1.9	1.9	1.0	0.7	1.3	3.2	0.6	2.2	0.3	1.3	3.2	0.0	1.4	3.1	1.6	1.5	2.9	2.3	2.3	1.6	2.9	2.2	1.6	2.7	2.2	3.8	2.4	0.5	1.4	3.0	1.2	1.2	1.3	1.5	0.7	1.7	1.4	2.3	2.0	0.6	2.4	2.2	1.5	1.1	14.9	85.1
Contribution to self and others	132.0	43.3	141.0	136.1	126.1	94.4	67.4	64.3	151.9	52.1	97.2	73.7	65.5	147.2	92.1	104.6	145.1	83.4	103.6	134.4	112.4	106.5	80.3	134.2	127.9	71.4	120.4	99.0	155.1	140.6	55.1	97.0	118.9	71.9	64.4	89.0	95.3	55.8	87.4	85.7	122.2	84.1	60.4	134.4	116.9	79.4	66.4	112.9	**Total spillover index**
Contribution to others	120.9	33.3	130.5	125.1	116.7	84.4	50.7	43.6	143.0	32.4	85.2	9.8	54.0	137.1	0.6	91.3	137.0	69.0	88.7	124.7	94.9	96.5	63.5	124.9	119.1	55.9	111.2	90.2	146.0	131.1	25.1	82.2	108.5	56.0	44.0	73.6	81.2	33.3	68.9	70.6	110.7	72.7	41.5	122.5	104.9	69.4	54.0	98.0	**83.9 %**
Net spillover	31.9	-56.7	41.0	36.1	26.1	-5.6	-32.6	-35.8	51.9	-47.9	-2.8	-26.3	-34.5	47.3	-7.9	4.6	45.1	-16.6	3.6	34.4	12.4	6.4	-19.7	34.2	27.9	-28.6	20.4	-1.0	55.0	40.6	-45.0	-3.0	18.9	-28.1	-35.7	-11.0	-4.7	-44.2	-12.6	-14.3	22.2	-15.9	-39.6	34.4	16.9	-20.6	-33.6	12.9	

A.4.2 Temporal spillover tables

The tables illustrate temporal return and volatility spillovers among the 48 cryptocurrencies under investigation for the yearly sub-sample periods. Each table illustrate the 10-day-ahead generalised forecast error variance decomposition of the Vector Autoregressive (VAR) model. The selection of this order is based on the Hannan-Quinn information criterion. The off-diagonal column and row sums, which represent the contribution from and to other variables, are displayed in the far-right column and bottom row, respectively. The latter is accompanied by “contribution to self and others”, along with “net spillovers”. Net spillovers are quantified as the disparity between transmitted shocks and received shocks. At the bottom right of each table we see the spillover index $Sg(H)$ which can be interpreted as the average spillover among cryptocurrencies.

Return spillover table 2018

Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK
ADA	3.4	3.4	3.0	2.2	1.0	2.3	2.3	1.7	2.8	1.9	2.0	2.9	2.3	1.5	1.0	2.3	3.3	0.6	1.0	2.6	2.8	1.2	1.4	2.0
ANT	3.1	4.4	2.8	2.1	0.7	1.9	2.4	2.0	2.0	2.7	2.3	2.5	2.9	1.8	1.3	1.8	3.0	1.3	1.7	2.7	2.3	1.8	2.2	1.9
BAT	3.2	3.6	4.0	2.5	1.0	2.6	1.4	2.1	2.9	2.3	2.2	4.1	1.1	1.7	1.6	1.5	2.4	0.7	1.0	2.7	2.1	1.3	1.5	2.5
BCH	2.6	4.0	3.4	4.2	1.3	2.1	1.9	0.9	3.3	2.1	2.0	2.8	1.8	2.6	1.7	1.1	2.3	0.7	1.9	1.9	1.3	1.6	1.4	1.8
BNB	2.9	3.5	2.7	1.9	2.8	2.4	2.1	2.1	1.7	2.1	2.8	2.1	2.2	2.3	1.2	2.3	2.0	1.0	1.9	1.5	3.3	1.6	2.0	1.7
BTC	2.3	3.2	3.2	2.2	1.4	2.9	1.7	2.1	3.0	2.3	2.3	3.5	1.2	1.3	1.1	1.2	2.8	0.9	1.0	2.6	2.1	2.2	0.9	2.2
BTG	3.6	3.2	3.1	1.9	1.1	2.1	4.3	1.5	2.4	2.6	2.1	2.3	2.0	1.4	0.8	1.8	2.9	0.7	1.2	1.6	1.8	1.4	1.8	2.3
CVC	1.7	3.0	1.9	1.4	2.2	2.3	1.5	4.2	2.7	2.5	2.0	3.6	0.9	1.2	2.3	1.0	2.8	1.9	1.4	2.4	2.1	2.8	1.2	2.7
DASH	2.3	3.4	2.9	1.4	1.4	2.1	1.4	1.5	4.5	2.2	2.6	4.5	1.1	1.6	2.1	1.6	3.2	0.7	2.1	2.2	1.8	2.0	1.3	1.8
DCR	2.6	3.6	2.6	1.0	1.5	2.6	1.5	1.8	2.5	4.0	3.3	2.9	0.9	2.2	1.3	1.6	2.2	2.1	1.4	2.4	1.7	2.7	1.7	2.7
DGB	2.3	4.1	2.8	1.4	1.0	2.2	1.5	2.2	2.1	2.9	3.9	2.8	0.8	2.7	1.4	1.0	2.7	1.7	1.3	2.2	2.6	2.2	2.1	2.6
DOGE	2.0	3.5	2.4	1.2	1.1	1.8	1.0	2.1	3.5	2.7	1.7	5.0	1.1	1.6	0.8	1.4	2.2	1.3	1.7	3.1	1.1	1.8	1.6	2.9
ENJ	2.9	3.5	2.7	1.6	1.9	2.2	2.6	1.7	2.2	2.3	2.1	2.9	4.1	1.3	1.4	2.3	2.6	1.0	2.5	1.6	2.0	2.0	1.5	1.4
EOS	2.5	3.8	2.7	1.8	1.3	2.0	1.8	1.5	2.0	2.2	3.5	2.0	1.4	5.1	1.2	1.3	1.9	1.5	1.2	1.5	2.9	1.7	2.9	1.8
ERG	1.6	1.5	1.7	2.4	2.8	0.9	1.0	3.8	1.9	1.3	1.3	1.3	2.4	1.7	7.9	3.2	1.8	1.8	2.2	2.5	3.4	1.1	1.7	2.5
ETC	2.8	3.3	3.0	1.9	2.3	2.1	2.2	1.7	2.4	2.1	2.3	3.0	1.8	1.8	1.8	3.4	2.4	1.1	1.4	1.6	2.0	1.9	1.9	1.5
ETH	2.4	3.8	2.8	2.2	1.3	2.4	1.9	1.8	3.2	2.5	3.1	3.8	1.5	1.8	2.2	2.0	3.3	0.8	1.9	1.5	2.2	1.5	1.4	1.8
GLM	2.2	4.0	2.1	1.5	0.9	2.1	1.8	2.0	2.6	2.9	3.6	2.5	1.2	2.2	1.9	1.2	2.4	2.9	1.0	2.3	3.4	2.0	1.9	2.0
GNO	2.3	3.6	2.6	1.6	1.2	1.8	1.6	2.3	2.2	2.6	2.3	2.4	2.3	2.3	1.3	1.6	2.5	1.6	3.1	2.3	2.2	2.3	2.5	2.0
ICX	2.8	3.0	2.3	1.4	2.1	2.2	2.2	2.3	2.3	2.6	2.0	2.4	1.7	1.5	1.4	1.7	2.7	1.3	1.3	3.3	2.5	2.2	1.8	1.8
KCS	2.3	3.1	2.7	1.3	1.4	2.3	1.8	2.7	2.7	2.0	2.4	3.6	1.0	1.5	1.2	1.6	2.3	1.5	1.1	2.4	4.2	1.5	1.8	2.2
LINK	2.1	2.5	1.5	0.6	2.9	2.7	0.8	2.9	1.4	4.4	2.2	1.9	0.6	2.0	1.3	1.3	2.0	2.2	2.1	2.1	1.3	6.5	3.0	2.1
LRC	2.5	3.6	2.2	1.6	1.7	1.8	1.7	2.0	2.2	2.5	2.4	2.7	1.5	2.5	1.0	1.5	2.5	2.1	1.9	2.0	2.7	2.4	3.7	1.6
LSK	2.6	3.2	2.9	1.6	1.9	2.4	1.6	2.8	2.4	2.8	2.8	3.5	1.0	1.1	1.2	1.5	2.3	0.8	1.8	2.2	1.7	1.7	1.6	3.7
LTC	2.1	4.1	3.0	2.2	1.6	2.2	1.2	2.5	3.5	1.9	2.7	4.7	1.3	2.3	2.1	1.0	2.5	1.0	1.1	1.9	1.6	1.7	1.1	2.1
MANA	2.5	3.6	2.8	2.2	1.0	2.0	2.6	1.2	2.2	2.0	2.2	2.8	1.1	2.4	1.2	1.1	3.1	1.8	1.7	2.1	2.8	1.2	1.2	1.9
MIOTA	2.2	2.7	2.5	2.3	2.1	1.8	1.7	2.6	3.1	1.1	1.5	3.3	1.3	1.5	1.7	2.1	2.8	0.9	2.1	2.5	2.5	1.2	0.9	1.6
NEO	2.3	3.1	2.6	1.6	1.8	2.7	2.1	2.6	2.6	2.1	2.2	2.9	1.2	1.7	1.5	1.6	3.3	1.0	1.5	1.9	2.6	1.9	1.3	1.7
OMG	2.8	3.2	2.7	2.0	1.6	2.0	1.4	2.3	2.6	2.0	2.3	3.0	1.4	2.1	1.0	1.8	3.0	1.4	1.5	2.5	2.6	1.9	1.7	1.8
QTUM	2.3	3.5	2.8	2.2	1.0	1.9	2.3	2.3	2.5	1.6	1.9	2.8	1.1	1.6	0.9	1.1	2.9	1.2	1.0	3.0	2.3	1.6	1.6	1.9
REQ	2.3	3.4	2.2	0.8	2.1	2.2	1.6	3.1	2.1	2.4	2.1	3.0	1.4	1.2	1.0	1.7	2.4	1.8	2.2	2.6	2.8	2.1	2.0	2.0
RLC	3.2	3.5	2.6	2.6	1.1	2.1	2.0	2.0	2.5	3.0	2.2	3.2	2.2	1.4	1.3	1.5	2.5	1.6	1.3	1.6	1.5	2.4	1.7	2.0
SC	2.5	4.0	2.4	1.4	1.9	2.5	1.9	2.9	2.1	2.9	2.6	2.7	1.0	1.4	1.2	1.6	3.0	1.4	1.6	2.3	2.7	2.2	1.7	2.4
SNT	3.7	2.7	3.1	2.5	1.6	2.5	2.3	1.1	2.1	1.9	2.0	1.9	2.5	1.6	1.1	2.4	2.7	1.0	1.3	2.0	2.9	1.7	1.6	1.6
STORJ	2.4	2.8	2.8	1.6	1.6	2.3	2.0	2.1	2.1	1.8	2.2	2.1	1.7	2.3	1.2	2.0	2.6	1.3	1.3	2.8	3.3	2.5	2.0	1.6
SYS	2.2	3.3	2.4	2.6	1.0	2.3	1.6	2.8	2.3	2.7	1.4	2.2	1.6	2.0	1.0	1.3	3.2	1.6	1.6	2.3	2.0	2.5	1.1	2.5
TRX	2.4	3.0	2.5	1.7	2.2	1.5	1.8	3.4	2.0	1.8	1.2	2.4	1.7	1.8	1.7	1.7	2.1	1.2	2.3	1.6	2.0	1.7	1.9	2.0
VGX	2.4	3.1	1.9	1.5	2.8	2.1	2.0	2.3	2.2	1.6	1.4	2.3	3.0	1.2	1.9	1.7	2.7	0.8	2.4	2.6	3.4	1.6	1.3	1.5
WAVES	2.4	2.6	3.0	2.0	2.2	3.1	2.1	1.1	3.0	3.0	3.1	3.0	1.2	2.6	1.8	1.1	2.0	1.3	2.0	1.5	2.0	3.1	2.3	1.4
XEM	3.0	3.5	2.2	1.5	1.8	2.3	1.5	3.1	1.7	2.5	1.6	2.1	1.8	0.9	1.0	1.6	2.7	1.8	1.2	3.1	2.6	2.7	1.6	2.6
XLM	3.5	3.5	3.6	2.5	1.2	2.0	2.1	1.6	2.5	2.0	2.3	3.0	1.4	1.8	2.2	1.7	3.1	0.4	1.7	2.3	2.1	1.3	1.5	2.3
XMR	2.1	3.9	3.1	2.3	1.3	2.2	1.3	1.1	3.1	1.8	1.6	3.9	1.4	1.8	1.8	1.5	2.6	0.8	0.9	2.4	1.8	1.8	1.1	2.3
XNO	2.1	2.8	2.2	1.1	2.6	2.6	1.0	2.7	1.2	2.4	2.3	1.9	1.7	2.7	2.0	1.8	1.4	1.3	1.7	2.7	2.3	2.2	2.1	2.5
XRP	2.3	3.6	2.0	1.3	1.4	2.1	2.0	2.7	2.9	1.5	1.8	2.7	1.7	1.6	1.4	3.0	2.8	0.5	1.1	1.6	2.5	0.7	1.0	3.0
XTZ	3.1	5.1	2.5	0.7	1.0	1.2	1.8	0.9	1.8	2.0	1.6	3.5	2.1	2.1	2.4	1.1	1.8	1.8	2.3	2.9	1.8	1.3	1.9	1.5
ZEC	2.8	3.4	3.4	2.6	2.0	2.2	2.0	1.2	3.3	2.8	2.6	3.0	0.8	2.0	1.4	1.1	3.3	0.6	1.3	2.6	1.9	2.2	1.5	2.0
ZEN	2.4	3.1	3.2	1.7	1.6	2.9	0.9	1.8	1.6	2.8	2.4	2.1	1.2	1.8	1.7	1.9	2.1	0.9	0.9	2.0	2.6	2.9	2.0	1.8
ZRX	3.6	4.6	3.6	2.6	1.1	1.8	1.7	1.3	2.1	2.4	2.1	2.8	1.8	2.4	1.2	1.2	2.6	1.0	1.4	2.9	1.4	1.5	2.4	1.7
Contribution to self and others	123.5	163.4	128.8	88.1	77.3	104.9	86.5	102.2	117.5	112.2	108.1	138.0	76.1	90.9	75.8	79.6	123.4	60.4	76.0	108.9	111.5	95.0	83.0	98.8
Contribution to others	120.0	159.0	124.8	83.9	74.5	102.0	82.1	98.0	113.0	108.2	104.2	133.0	72.0	85.7	67.9	76.2	120.1	57.5	72.9	105.6	107.3	88.5	79.3	95.1
Net spillovers	23.5	63.4	28.8	-11.9	-22.7	4.9	-13.6	2.2	17.5	12.2	8.1	38.0	-23.9	-9.1	-24.2	-20.4	23.5	-39.6	-24.0	8.9	11.5	-5.0	-17.0	-1.2

Tickers	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	1.7	1.4	3.5	3.2	2.9	2.5	1.9	1.1	2.9	2.6	1.9	1.7	1.6	0.8	1.9	2.7	2.4	2.5	1.4	2.1	0.8	2.4	0.9	2.3	96.6
ANT	1.8	1.6	3.0	2.9	2.4	2.6	1.9	1.5	3.2	2.3	1.8	1.8	1.0	1.1	1.1	2.8	1.9	2.1	1.4	1.9	1.0	2.4	0.7	2.5	95.7
BAT	2.6	1.1	3.2	3.6	2.8	2.1	2.4	1.0	3.2	1.9	1.5	1.5	2.3	1.4	1.0	2.3	2.6	2.8	2.1	1.6	0.7	1.9	0.4	2.6	96.0
BCH	1.5	2.5	3.2	2.7	2.0	1.5	1.4	2.5	1.9	2.2	1.1	2.4	1.9	1.1	2.3	1.5	1.5	3.9	2.6	1.1	0.8	2.8	1.4	3.8	95.8
BNB	1.3	1.0	2.6	2.7	1.7	2.2	2.1	2.0	3.1	2.7	2.4	1.7	1.9	1.1	2.5	3.4	2.3	2.3	1.1	2.2	0.9	1.7	1.1	2.4	97.2
BTC	3.0	1.6	3.2	3.5	2.1	2.4	2.5	1.3	3.0	1.9	1.5	2.1	1.9	1.7	2.0	2.2	1.4	3.7	1.7	1.5	0.9	2.2	0.9	2.7	97.1
BTG	1.8	2.6	2.8	2.7	1.9	2.2	1.5	2.0	3.0	3.4	1.5	2.3	2.3	1.2	1.7	2.2	2.5	2.5	1.7	1.7	0.7	2.7	0.9	2.5	95.7
CVC	2.2	1.2	2.4	3.6	2.0	2.5	3.5	1.3	3.1	1.6	1.9	1.2	0.8	2.1	2.0	2.6	1.5	2.8	1.7	1.9	1.0	2.0	1.0	2.4	95.8
DASH	2.5	1.4	3.4	3.6	2.5	2.2	2.1	0.9	3.1	1.6	1.4	1.7	1.2	1.4	1.4	1.9	2.0	3.7	1.5	1.9	1.1	2.4	0.8	2.7	95.5
DCR	1.8	1.2	2.0	3.0	1.2	2.0	2.3	3.1	3.5	2.4	1.8	1.5	1.4	1.9	1.6	2.6	2.0	2.9	1.7	1.5	1.0	1.4	0.9	2.4	96.0
DGB	2.4	1.1	1.9	3.1	1.7	2.9	2.7	1.7	3.6	2.1	1.8	1.4	1.5	1.1	1.8	2.6	1.8	2.4	1.8	1.5	1.8	1.4	1.0	2.7	96.1
DOGE	2.3	1.9	3.0	3.2	2.6	2.5	2.7	2.1	2.9	1.6	1.6	1.3	1.7	1.3	1.3	2.7	2.4	2.8	1.8	2.0	1.2	2.2	1.8	2.9	95.0
ENJ	2.6	1.3	2.4	2.5	2.8	2.1	1.7	1.5	3.0	2.6	1.8	1.3	1.3	1.2	1.9	3.6	2.7	2.4	1.9	1.0	0.8	1.9	1.1	2.5	95.9
EOS	1.8	0.6	2.3	3.1	1.6	2.8	1.8	1.6	2.4	2.2	2.3	1.2	1.3	1.0	2.8	2.9	2.0	3.3	2.8	1.5	1.0	1.6	1.7	3.0	94.9
ERG	0.7	0.9	2.6	2.0	1.8	2.1	2.2	1.3	1.3	0.8	3.0	2.5	1.3	1.4	1.3	3.0	1.0	1.8	2.1	3.4	3.6	2.5	1.6	2.5	92.1
ETC	1.8	1.2	3.2	3.0	2.3	2.1	1.6	1.8	3.0	2.6	2.2	1.9	2.4	0.6	1.4	2.4	2.7	2.2	1.7	1.8	0.8	2.3	1.3	2.5	96.6
ETH	2.3	1.5	3.1	3.4	2.0	2.1	1.7	1.5	3.4	2.0	1.5	1.6	1.5	1.2	2.2	2.2	1.9	3.0	1.2	1.6	0.7	2.1	0.9	2.2	96.7
GLM	1.3	1.0	2.2	3.3	1.7	2.6	3.3	2.2	3.4	1.8	2.0	1.4	1.0	1.4	2.1	3.0	1.3	2.8	1.9	1.5	0.7	2.0	1.1	2.8	97.1
GNO	1.3	1.2	2.6	3.3	1.7	2.9	2.3	1.7	2.9	1.9	2.5	1.4	0.8	1.8	1.4	2.8	1.8	3.1	1.3	1.8	1.7	2.1	0.9	2.8	96.9
ICX	1.4	1.9	2.8	3.3	1.8	2.3	2.6	2.0	3.1	2.8	2.2	1.5	1.3	2.0	2.1	2.9	1.9	2.9	1.7	1.4	0.5	2.3	0.8	2.1	96.7
KCS	2.3	1.2	3.2	3.6	2.3	2.9	3.2	1.0	3.4	1.4	2.9	1.7	1.7	1.2	1.9	3.2	1.4	2.8	1.1	2.1	0.8	1.9	0.8	1.7	95.8
LINK	1.7	0.7	1.0	1.9	1.9	2.0	1.6	3.6	2.8	3.7	3.6	0.8	1.0	1.3	2.8	3.2	1.8	1.0	2.1	0.8	1.8	1.0	3.6	1.8	93.5
LRC	1.9	1.6	2.4	2.6	1.5	2.6	2.4	1.9	3.3	2.9	2.6	1.4	1.3	1.3	2.2	3.1	1.9	2.1	1.3	1.3	0.6	2.4	1.2	2.4	96.3
LSK	2.4	1.5	2.4	3.0	2.1	2.1	2.3	1.7	3.3	2.7	1.7	1.8	2.1	1.7	1.3	3.1	2.5	2.4	1.7	2.1	1.0	2.0	0.6	1.8	96.4
LTC	4.2	1.6	2.5	2.8	2.3	2.0	2.2	1.3	2.8	2.0	1.0	1.8	1.7	1.2	2.0	2.7	1.8	3.0	1.8	1.4	0.6	2.0	1.2	3.0	95.8
MANA	2.0	6.3	2.5	2.8	1.4	2.4	2.2	2.0	2.9	2.2	1.3	2.2	1.2	1.7	1.9	1.8	1.6	2.3	1.3	1.5	1.9	2.6	1.1	2.4	93.7
MIOTA	1.6	2.0	3.8	3.6	2.6	2.6	2.8	0.9	2.3	1.6	1.9	1.7	1.4	1.5	1.6	2.3	1.6	4.0	1.8	2.6	0.9	2.6	1.7	2.7	96.2
NEO	2.0	2.1	2.8	4.0	2.0	2.6	2.8	1.1	3.0	2.1	2.0	1.8	1.4	1.9	2.6	2.2	1.7	3.4	1.7	1.7	0.8	2.1	0.8	1.8	96.1
OMG	2.4	0.9	2.7	3.0	3.1	2.7	2.4	1.3	2.7	2.4	2.2	1.3	1.6	0.8	2.2	3.0	2.3	2.2	1.8	2.1	0.7	1.9	0.9	2.9	96.9
QTUM	1.9	1.0	3.1	3.5	1.8	3.5	2.5	2.2	2.4	2.7	2.3	1.7	2.1	1.5	2.3	2.4	1.7	3.1	1.7	2.3	1.2	2.6	0.8	2.7	96.5
REQ	1.8	1.2	2.2	3.5	1.8	2.6	3.7	1.3	3.4	2.0	2.7	1.7	1.1	2.4	1.9	2.8	1.9	2.4	1.6	1.8	1.2	1.6	1.1	1.9	96.3
RLC	2.1	1.6	2.5	2.7	2.0	1.7	2.2	3.3	2.9	3.7	1.3	1.8	1.5	1.7	1.1	3.0	2.8	2.2	1.2	1.3	1.1	2.2	1.2	2.1	96.7
SC	2.3	1.6	2.3	2.9	2.0	2.8	2.6	1.6	3.5	2.6	2.3	1.6	1.0	1.1	1.4	3.3	1.8	1.9	1.4	1.6	1.4	1.8	0.8	2.5	96.5
SNT	1.2	1.7	3.2	2.7	2.1	2.2	1.8	1.9	2.9	4.1	1.9	1.7	1.9	1.4	2.1	2.7	2.6	2.3	1.2	1.6	0.9	2.7	1.6	2.0	95.9
STORJ	1.1	0.7	3.0	3.9	2.2	3.4	3.1	1.4	2.7	1.8	3.4	1.6	1.1	1.5	2.2	2.4	1.5	2.7	1.8	2.0	0.7	1.7	1.4	2.7	96.5
SYS	2.4	2.9	2.4	3.0	1.8	2.5	2.3	1.7	2.2	2.2	1.5	3.9	1.1	0.9	1.6	1.5	1.1	3.1	2.5	2.0	3.0	1.8	1.0	2.7	96.1
TRX	2.7	1.8	2.3	2.4	2.1	2.3	1.9	1.4	2.1	2.9	2.0	2.0	3.3	1.0	2.3	2.9	2.6	3.2	2.3	2.4	1.7	2.0	0.9	2.4	96.7
VGX	1.9	2.7	2.7	3.0	2.2	2.6	2.6	1.0	2.3	2.6	2.7	1.4	1.2	2.5	2.2	2.4	1.7	2.1	1.8	1.5	1.8	2.1	1.6	2.3	97.5
WAVES	1.8	0.4	2.5	3.4	1.6	1.8	2.0	2.2	3.3	2.6	2.2	1.0	1.0	1.6	3.6	2.4	1.8	3.0	1.3	0.8	1.4	1.7	1.6	2.3	96.4
XEM	1.9	1.1	2.3	2.3	2.5	2.5	2.6	2.4	2.9	3.3	2.4	1.4	1.2	1.2	1.6	4.8	2.3	1.1	1.7	1.8	1.1	1.9	1.1	2.3	95.2
XLM	2.2	1.7	2.9	2.6	2.9	2.3	1.4	1.1	2.7	2.9	1.3	1.5	2.0	0.6	1.4	2.5	3.5	2.6	1.4	2.2	1.4	2.3	1.0	2.2	96.5
XMR	2.0	2.9	3.6	4.1	1.6	2.0	2.4	1.1	2.5	1.9	0.8	2.8	1.8	2.0	1.7	1.5	1.3	5.1	2.4	1.5	1.1	2.1	0.8	2.8	94.9
XNO	1.6	1.8	1.4	3.3	1.3	1.8	2.8	2.3	2.4	2.4	2.9	1.6	1.7	2.1	2.7	2.1	1.5	2.3	5.8	1.1	1.1	0.9	2.2	2.0	94.2
XRP	2.1	1.6	3.5	3.5	2.5	2.8	2.4	1.1	2.4	2.1	2.0	2.5	2.1	1.1	2.2	2.8	2.2	2.5	1.4	4.4	1.3	2.2	0.6	2.0	95.6
XTZ	1.1	2.3	2.1	2.8	1.4	2.2	1.8	2.5	2.2	2.9	1.1	1.9	2.6	1.5	1.2	3.2	2.3	2.8	3.0	1.8	2.7	1.6	2.1	3.0	97.3
ZEC	1.7	2.2	3.0	2.9	2.0	2.1	2.1	1.5	3.2	2.2	1.4	2.0	1.0	1.7	1.7	1.6	1.8	3.3	2.0	1.3	0.6	3.4	0.8	2.8	96.6
ZEN	2.1	2.2	2.1	2.7	2.2	2.0	2.5	2.0	2.9	2.3	2.8	1.8	2.0	1.2	2.3	2.6	2.1	2.1	2.2	0.8	0.3	1.2	4.5	3.2	95.5
ZRX	1.8	1.9	2.4	2.3	2.7	2.7	1.6	1.5	2.5	3.0	1.7	1.5	1.9	0.7	1.1	2.6	2.8	2.4	1.8	1.3	0.8	2.0	0.8	5.4	94.6
Contribution to self and others	94.3	79.0	128.0	146.1	99.4	114.2	109.8	82.5	136.8	113.7	95.2	83.1	75.1	66.6	90.6	126.4	95.3	128.7	88.1	83.7	55.1	98.2	59.0	121.6	**Total spillover index**
Contribution to others	90.1	72.7	124.2	142.1	96.3	110.6	106.1	79.3	133.2	109.6	91.8	79.2	71.8	64.1	87.0	121.6	91.8	123.6	82.3	79.4	52.4	94.8	54.5	116.2	**96.0 %**
Net spillovers	-5.7	-21.1	28.0	46.0	-0.6	14.2	9.8	-17.4	36.8	13.7	-4.8	-16.9	-24.9	-33.4	-9.4	26.4	-4.7	28.7	-11.9	-16.3	-44.9	-1.8	-41.0	21.6	

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Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	4.8	0.8	2.4	2.8	1.9	1.7	2.9	2.2	1.2	1.2	2.5	0.6	1.5	2.2	0.7	3.1	3.1	0.8	2.6	2.5	1.5	1.3	2.9	1.3	2.8	0.5	2.1	3.3	2.8	4.7	1.9	3.8	2.6	2.8	2.7	0.6	2.7	1.1	2.1	1.4	2.4	1.5	1.4	2.6	2.6	1.1	0.9	1.4	95.2
ANT	2.9	3.7	1.9	2.4	1.5	1.8	2.5	1.1	2.5	2.6	2.2	1.1	2.7	2.0	0.9	1.4	2.7	1.3	1.5	3.1	2.1	0.9	1.9	2.0	2.9	3.0	2.0	2.3	2.6	3.6	3.2	1.9	2.7	2.7	2.0	2.4	3.4	1.9	0.8	0.8	2.1	2.2	2.1	2.2	1.1	0.8	1.5	1.4	96.3
BAT	2.5	0.8	3.6	2.3	1.1	2.7	2.5	3.6	1.4	3.6	1.8	1.9	1.2	1.5	2.4	1.2	1.6	1.2	2.8	3.4	1.8	1.5	2.5	1.4	2.6	2.7	1.9	2.0	2.5	1.6	0.9	2.7	1.9	2.4	2.4	2.0	2.4	1.8	2.4	1.7	2.2	2.4	2.3	2.6	0.7	1.9	2.7	1.5	96.4
BCH	3.8	1.2	1.8	4.7	2.5	2.4	3.3	1.8	2.0	1.0	1.8	1.3	1.5	1.7	1.4	1.6	2.8	0.4	2.3	2.1	1.7	1.5	2.1	1.7	3.8	2.5	3.0	3.7	2.2	3.0	1.8	1.9	2.5	3.7	2.6	2.6	2.1	0.9	1.9	0.9	1.5	2.4	0.7	1.7	1.6	1.3	1.4	2.0	95.3
BNB	2.3	1.3	2.3	1.8	3.8	2.9	1.8	2.2	1.5	1.4	3.9	1.3	1.6	2.1	1.3	1.6	3.7	1.3	2.0	1.9	1.8	1.4	3.0	3.1	3.2	3.1	1.8	2.4	1.8	1.6	3.6	3.4	1.4	2.0	4.0	3.7	1.1	3.3	0.8	0.9	0.9	1.4	1.5	1.4	1.5	1.2	0.9	2.3	96.3
BTC	2.4	2.2	2.4	1.9	3.0	4.0	1.0	2.1	2.6	2.5	2.5	0.7	2.2	2.4	1.5	0.6	2.9	1.9	1.7	2.9	0.8	1.3	2.2	1.6	3.2	1.5	2.2	2.2	3.2	1.8	1.2	1.7	1.5	1.8	3.0	3.3	2.9	3.2	1.7	1.7	2.3	1.7	1.5	2.0	1.8	1.9	1.8	2.1	96.0
BTG	3.1	1.0	1.3	2.8	2.0	2.2	5.6	2.8	1.3	1.8	2.9	0.5	0.9	1.5	1.6	1.1	2.3	1.2	2.1	2.3	2.8	0.8	2.1	2.1	3.0	3.8	2.2	2.5	2.1	3.6	3.0	2.0	2.7	3.0	1.9	2.9	1.7	1.7	2.1	0.9	1.9	3.1	1.6	3.0	0.5	1.1	0.8	1.0	94.5
CVC	2.9	2.0	1.8	2.4	1.4	2.2	2.7	4.5	2.2	1.5	2.5	1.2	1.9	1.7	1.7	1.9	1.9	0.8	1.9	2.5	1.5	1.4	2.8	2.4	2.6	0.8	2.6	2.1	2.5	3.3	2.1	3.0	2.9	2.3	2.1	1.1	2.5	1.3	1.4	2.3	2.5	2.6	2.4	2.6	1.0	1.4	2.0	1.1	95.5
DASH	2.7	2.6	1.4	2.7	2.5	3.0	1.3	1.7	4.1	2.6	2.0	1.1	2.6	2.9	0.9	2.4	3.3	1.0	1.3	2.3	1.6	1.1	1.9	1.8	3.3	1.8	2.7	2.5	2.9	2.2	1.3	1.5	2.0	2.6	2.2	2.2	2.3	1.9	1.5	1.9	2.7	2.4	1.5	1.2	2.2	1.2	0.9	2.3	95.9
DCR	2.2	2.2	2.5	2.2	2.3	3.1	2.0	1.7	3.0	6.2	3.0	0.7	0.9	1.7	1.4	0.5	2.1	1.0	2.2	3.9	2.4	0.8	1.6	2.0	3.0	1.0	1.7	1.6	2.5	1.4	2.0	2.5	2.8	2.1	2.4	1.1	2.2	3.3	0.4	1.2	4.1	3.3	2.1	1.9	0.6	1.8	2.1	1.8	93.8
DGB	4.2	1.3	2.2	1.8	1.1	2.0	1.3	1.1	1.6	3.0	1.6	1.1	1.6	1.7	6.2	1.2	1.7	1.4	1.9	4.2	1.0	1.1	2.0	0.9	1.8	4.5	1.5	2.3	2.8	4.4	1.3	2.1	1.6	1.5	3.0	2.9	5.2	1.4	1.7	0.9	5.0	1.6	1.3	1.7	1.3	0.8	1.5	0.9	98.4
DOGE	3.5	2.8	1.8	3.4	0.9	1.1	3.3	0.6	2.6	1.4	0.5	5.0	3.4	1.5	0.9	4.6	2.1	3.1	1.1	0.8	1.7	1.0	0.7	0.8	2.4	3.9	2.4	2.0	0.9	3.8	1.1	0.5	1.8	5.0	0.5	2.6	1.0	1.8	4.2	1.9	1.5	2.6	2.5	0.7	2.0	3.6	1.4	1.4	95.0
ENJ	2.6	1.8	2.0	1.5	1.6	1.7	2.7	2.6	1.3	1.3	2.4	1.2	3.3	1.9	2.6	1.0	2.7	1.5	2.3	2.5	2.8	1.0	2.6	1.4	3.1	3.6	2.2	1.8	2.7	1.6	3.3	2.1	1.8	3.6	2.2	3.1	2.3	1.2	1.4	1.7	1.6	2.3	1.8	2.8	0.9	2.4	1.4	1.2	96.7
EOS	3.5	1.4	1.1	2.3	3.2	3.3	1.3	1.8	2.3	2.8	2.8	0.7	1.9	2.6	1.1	2.7	3.9	0.4	1.4	2.7	1.3	1.4	2.7	3.3	3.3	0.9	1.6	2.6	2.4	2.7	2.6	2.3	1.1	2.2	4.3	1.0	1.4	2.5	1.5	2.4	1.8	2.3	1.2	1.3	2.4	1.2	1.7	1.5	97.4
ERG	2.2	1.3	3.5	1.7	1.7	2.7	1.9	3.3	1.5	2.8	2.1	1.0	2.2	1.7	3.9	0.2	1.3	1.2	2.9	3.3	2.0	0.9	2.8	2.4	2.9	1.2	2.5	1.7	3.0	1.1	1.6	2.7	3.0	1.9	1.6	1.4	4.1	2.2	0.8	1.7	2.4	1.4	2.6	3.5	1.0	1.9	2.2	1.5	96.1
ETC	2.2	1.3	0.8	1.8	1.4	1.5	1.7	1.4	2.1	2.6	1.7	2.0	1.9	2.4	3.0	6.6	2.4	2.2	0.9	1.9	1.4	2.2	2.2	2.6	1.3	4.5	1.9	2.0	1.8	4.0	2.0	1.5	1.3	2.2	1.8	3.1	1.7	1.7	1.9	1.2	4.4	1.6	1.6	1.4	3.1	1.1	1.7	1.3	93.3
ETH	2.9	1.5	2.3	2.3	2.5	3.0	1.8	1.8	1.7	2.0	2.6	1.1	2.3	2.4	1.1	1.7	4.0	1.2	2.2	3.1	1.7	1.8	2.6	2.1	3.5	1.4	2.2	2.2	2.9	1.8	1.9	2.3	1.6	2.7	3.4	1.5	1.2	2.1	2.0	1.1	2.8	1.5	1.3	1.9	2.2	1.6	0.7	2.4	96.0
GLM	4.4	1.9	2.1	3.8	1.7	2.7	2.0	2.1	2.9	1.3	1.5	0.7	1.9	1.4	3.1	1.6	2.5	3.0	1.8	2.7	1.1	1.7	1.9	1.1	2.9	0.5	2.7	4.0	2.3	3.8	1.0	2.2	2.5	2.7	3.4	0.4	3.5	0.6	1.9	0.8	2.8	2.5	1.0	1.5	1.3	1.3	2.4	1.2	97.0
GNO	3.0	0.9	3.2	1.5	1.1	3.1	2.0	3.9	1.3	3.3	2.6	1.1	1.3	1.7	2.0	0.4	2.0	0.6	4.2	4.2	2.1	1.0	2.2	1.7	2.3	2.0	1.5	2.2	2.5	2.1	1.4	3.7	2.2	1.9	3.8	1.7	2.5	1.6	0.8	1.8	3.3	1.7	2.4	2.2	0.4	1.5	1.9	2.2	95.8
ICX	2.0	1.0	2.2	1.6	1.4	2.7	1.4	4.1	1.5	2.6	3.4	0.8	2.0	1.8	1.3	1.9	2.5	1.0	2.0	3.2	1.5	1.4	2.9	3.5	2.3	1.2	1.9	1.5	2.5	1.5	2.7	3.2	1.7	2.1	2.7	0.8	1.3	2.9	0.9	2.8	2.5	1.8	3.2	1.9	3.0	1.8	2.3	1.7	96.8
KCS	2.8	1.7	1.7	2.0	2.1	1.8	2.7	0.7	1.7	2.3	2.4	1.0	2.3	2.3	1.2	2.4	3.5	2.7	1.9	2.4	4.7	1.1	2.2	2.7	3.3	1.7	1.2	1.4	2.3	2.8	3.5	1.7	1.9	2.3	2.8	1.5	2.1	2.8	1.8	1.9	1.8	1.9	2.1	1.6	1.8	1.1	0.6	1.8	95.3
LINK	2.2	0.6	1.5	2.6	4.0	2.3	2.0	2.0	1.1	2.2	2.0	1.8	2.1	1.2	1.9	3.3	3.3	3.1	1.2	1.5	0.8	2.5	2.3	2.5	3.8	3.9	1.6	1.9	1.0	1.2	3.5	1.6	0.6	3.5	3.2	5.2	1.6	1.2	3.6	0.9	1.6	1.0	2.0	0.7	2.5	1.9	1.7	0.8	97.5
LRC	2.9	1.0	2.0	2.0	1.5	2.6	2.3	3.1	1.7	1.3	2.3	0.9	2.2	3.3	1.0	1.4	3.2	1.5	2.0	2.1	1.4	1.1	4.9	2.3	3.3	2.3	2.3	2.1	2.9	2.0	2.6	2.9	1.7	2.5	3.2	1.8	1.8	1.2	1.7	1.5	1.5	1.6	1.5	2.8	1.6	2.4	1.3	1.8	95.0
LSK	1.3	0.8	1.5	1.6	1.8	2.5	1.8	2.8	1.4	1.8	3.1	2.4	1.5	1.7	3.6	2.2	2.4	2.8	1.1	1.9	2.6	0.8	2.5	5.0	2.9	3.1	1.5	0.9	1.7	2.0	4.0	2.1	1.5	2.1	2.5	2.7	1.0	3.5	2.1	2.0	1.4	1.8	2.7	1.2	1.8	1.8	1.6	1.6	95.0
LTC	2.7	2.4	2.1	3.2	3.0	2.8	2.3	1.6	2.3	1.4	2.5	1.6	1.4	1.5	2.2	1.1	3.2	1.6	1.5	2.2	2.3	1.2	2.1	2.9	4.6	3.1	2.5	2.4	2.1	1.4	3.1	1.4	2.0	3.1	2.3	3.6	1.7	2.1	1.9	0.6	1.9	2.3	0.7	1.3	1.4	1.4	0.8	1.4	95.5
MANA	1.7	2.1	1.2	2.5	2.1	3.6	2.0	2.5	3.6	5.2	1.3	1.8	1.7	1.3	3.4	2.0	1.6	1.3	1.2	2.3	2.1	0.9	1.3	1.0	2.7	5.7	1.8	1.9	1.5	1.1	1.1	1.2	1.5	2.4	2.6	4.2	2.1	1.7	1.6	1.1	2.7	3.1	1.6	1.0	1.2	2.0	2.4	2.1	94.3
MIOTA	4.8	2.2	1.3	3.9	1.1	1.2	1.9	1.4	2.3	0.5	1.1	2.2	3.5	1.9	2.2	5.7	2.9	1.2	1.2	1.7	0.9	1.1	1.5	0.7	2.4	0.5	4.1	3.9	2.4	6.6	0.8	1.2	2.6	2.9	2.0	0.8	4.0	1.4	1.3	1.0	4.2	1.5	0.7	1.6	2.8	1.0	0.5	1.6	95.9
NEO	3.8	1.2	1.4	4.2	2.0	2.4	2.1	1.6	2.1	1.0	1.5	0.8	1.6	2.5	2.2	4.3	2.8	0.6	1.9	2.0	0.9	1.0	2.1	1.2	3.0	1.3	2.7	3.9	2.5	5.2	1.6	1.6	2.2	2.7	2.3	1.5	2.2	0.7	2.0	1.8	3.5	1.8	1.0	1.9	3.9	1.3	0.9	1.6	96.1
OMG	3.3	1.8	2.8	1.9	1.3	2.1	2.0	1.8	2.0	1.8	2.2	1.5	2.2	2.7	1.7	1.9	2.8	1.1	2.3	3.6	1.8	1.5	2.5	1.3	2.6	1.8	2.7	2.1	3.8	3.4	1.8	2.2	2.1	2.3	1.9	1.5	3.1	1.6	2.1	1.2	2.6	1.6	2.1	3.0	1.4	1.1	0.7	1.8	96.2
QTUM	3.4	0.7	1.6	2.3	1.3	1.7	2.9	3.7	1.5	0.7	2.1	0.5	2.2	2.1	1.1	2.9	2.1	1.3	2.0	1.9	1.3	1.8	2.9	2.0	1.8	2.0	2.1	3.1	2.3	5.1	2.2	3.1	2.1	2.6	2.9	1.6	2.1	0.9	1.3	3.4	1.4	2.9	2.3	2.6	1.8	0.9	2.7	1.1	95.0
REQ	2.4	1.8	1.6	1.6	1.7	1.7	2.6	2.1	1.2	1.8	3.1	1.3	2.5	1.5	0.9	2.3	3.0	2.3	1.9	2.3	3.1	0.9	2.2	2.7	3.0	1.3	1.5	1.4	2.1	2.4	4.7	2.4	2.0	2.9	2.6	1.2	1.6	2.5	2.0	3.6	1.8	2.3	1.8	1.9	1.9	1.2	2.2	1.4	95.3
RLC	3.6	1.3	2.2	1.6	1.6	1.7	2.4	3.9	1.5	1.6	2.6	0.2	1.9	2.3	1.6	0.7	2.3	1.4	3.4	2.4	1.3	0.8	3.5	1.5	2.4	1.6	2.2	2.8	2.6	2.7	2.2	4.5	2.4	2.9	2.4	1.5	2.0	1.0	0.8	2.8	1.7	2.3	2.0	3.3	0.6	1.7	2.8	1.6	95.5
SC	3.8	2.0	2.1	2.7	1.5	1.5	2.8	2.1	1.7	1.9	2.4	1.2	1.2	1.5	1.8	1.8	2.3	1.4	2.1	2.8	1.5	1.6	2.2	2.5	2.2	1.5	2.0	2.4	2.1	3.4	2.1	3.3	4.0	2.3	2.3	0.8	2.5	2.0	1.7	2.1	2.6	1.9	2.4	2.3	0.9	1.1	2.0	1.6	96.0
SNT	4.0	1.2	1.1	3.7	1.8	1.7	3.2	1.8	2.4	1.1	1.8	0.4	2.1	2.0	1.1	2.1	2.7	0.9	1.8	2.4	2.0	1.5	2.0	1.1	3.2	1.9	3.0	3.6	2.7	3.7	1.8	1.6	3.0	4.8	1.6	1.4	2.0	0.8	1.7	1.4	2.7	3.4	1.2	1.6	1.5	1.7	1.9	1.1	95.2
STORJ	2.4	1.8	2.2	1.8	1.8	3.3	1.7	3.0	1.8	1.8	3.0	1.1	2.7	2.3	1.2	0.8	3.1	1.1	2.7	1.9	1.4	1.3	3.4	2.3	3.2	1.2	1.6	2.5	2.2	1.5	2.7	3.4	1.7	2.3	5.3	1.8	2.0	2.2	1.0	1.9	1.5	1.7	1.5	1.8	1.4	1.9	1.5	2.5	94.7
SYS	1.0	2.1	1.2	1.1	2.4	2.8	1.6	2.8	3.0	2.5	1.4	0.7	2.4	2.8	2.7	1.4	1.9	4.9	1.4	1.0	1.5	0.7	2.0	1.2	1.9	5.4	1.9	2.0	1.6	1.0	2.3	1.6	0.7	1.6	3.4	6.6	4.0	1.7	1.6	2.7	1.7	1.7	1.2	0.8	1.3	2.1	2.2	2.9	93.4
TRX	2.3	2.1	2.9	1.4	0.7	1.6	2.7	2.7	1.6	1.9	1.7	0.8	2.1	2.0	2.4	1.0	2.4	2.0	2.8	2.3	1.8	0.9	2.3	1.6	2.3	1.8	1.8	1.9	2.7	2.2	2.1	2.3	3.0	1.7	2.1	1.1	4.8	1.6	0.8	3.9	1.9	1.7	2.1	3.4	1.4	2.6	2.6	2.5	95.2
VGX	1.4	3.5	1.3	1.4	2.0	2.0	1.9	1.5	2.5	2.8	2.7	0.6	3.1	2.1	3.4	1.3	1.6	4.1	1.4	1.9	1.9	0.9	1.8	2.8	1.7	3.1	1.9	2.2	1.7	1.4	3.3	1.6	1.9	1.5	2.2	3.3	4.2	4.2	1.1	1.1	3.7	1.4	1.9	1.1	1.5	1.3	1.7	1.4	95.8
WAVES	3.3	1.0	2.3	1.5	1.4	3.7	1.7	2.8	1.6	3.6	1.9	1.2	1.9	1.3	3.8	1.0	2.5	1.3	1.4	4.7	1.1	1.7	3.0	2.8	3.0	2.6	2.0	1.2	2.9	2.3	1.2	2.5	0.9	2.1	4.0	1.4	2.1	1.4	3.6	0.5	2.5	2.2	1.7	1.5	1.0	0.9	3.2	0.8	96.4
XEM	2.4	1.3	1.6	2.2	1.2	1.1	1.8	2.9	1.9	1.2	1.9	1.4	2.3	1.8	2.9	2.6	1.8	0.9	2.7	2.0	2.3	1.3	1.6	1.7	1.8	0.9	2.0	2.3	2.1	3.3	2.8	2.5	2.1	2.5	1.2	0.6	2.1	1.8	0.8	6.7	2.3	2.2	3.0	2.2	2.9	2.7	3.0	1.8	93.3
XLM	3.2	1.2	1.4	3.6	2.1	1.4	2.8	1.1	2.0	1.6	1.6	1.6	1.5	1.3	1.8	2.8	2.1	2.1	1.6	3.0	2.0	1.9	1.7	1.7	2.4	1.3	2.7	2.8	2.5	3.3	1.8	1.8	2.6	3.1	2.0	0.6	2.0	1.3	2.3	2.0	5.1	2.5	1.7	2.2	2.5	1.9	1.9	0.9	94.9
XMR	3.5	1.8	1.0	3.8	1.6	2.2	2.6	2.0	2.3	1.0	1.8	1.1	2.8	1.2	4.7	1.1	2.4	1.7	1.1	1.8	1.4	0.7	1.8	1.3	3.8	2.0	3.3	3.0	2.1	2.6	2.4	1.3	1.8	4.6	2.4	1.7	2.2	1.5	1.9	1.1	2.9	3.2	1.2	1.6	1.1	2.4	2.7	0.9	96.8
XNO	1.3	0.7	2.2	2.5	1.1	2.6	1.5	3.4	1.4	4.1	3.9	1.8	1.4	2.2	1.2	1.6	1.5	0.8	2.5	3.5	1.8	1.2	2.9	4.3	1.1	2.6	1.5	1.3	2.1	1.4	3.3	3.4	2.0	1.0	2.4	1.5	1.4	4.2	0.6	1.6	1.2	1.6	6.4	2.4	1.5	1.2	1.5	1.7	93.6
XRP	2.3	1.0	1.4	1.9	1.5	1.7	2.2	4.0	1.8	1.3	1.8	1.9	2.5	3.8	0.6	1.2	2.2	1.2	2.1	2.3	1.8	1.1	4.4	1.4	2.1	0.7	2.5	1.8	3.8	2.1	1.6	2.5	2.0	2.5	1.4	0.7	2.1	1.0	1.6	3.0	1.6	2.5	2.9	5.1	2.3	3.5	2.2	1.6	95.0
XTZ	2.1	0.9	1.4	1.6	1.5	3.2	2.1	1.9	2.1	1.6	1.3	0.8	1.9	2.1	4.5	2.2	2.1	5.4	1.0	2.2	3.5	1.1	2.7	1.4	2.5	1.2	2.8	2.6	2.7	1.9	3.1	1.4	0.8	2.1	4.5	1.5	1.7	1.5	3.1	1.9	2.3	1.7	0.8	1.9	3.7	1.1	1.3	1.6	96.3
ZEC	2.7	1.7	1.9	1.7	1.2	2.0	2.4	2.5	1.9	3.1	1.1	1.1	1.8	1.5	2.1	1.2	1.8	0.6	2.2	3.7	1.4	1.6	2.2	1.5	2.6	2.8	2.4	1.6	2.8	2.5	1.3	1.6	2.3	3.1	1.6	2.3	3.0	0.8	1.9	3.2	3.6	2.3	1.7	2.8	1.2	4.4	2.1	1.5	95.5
ZEN	2.4	2.1	1.4	1.4	2.5	1.9	1.6	2.6	2.2	2.1	2.9	0.9	1.2	1.7	4.2	1.3	1.9	1.4	1.7	2.3	1.2	1.1	2.2	2.3	1.4	1.8	1.4	1.7	2.2	3.7	1.9	3.1	1.6	2.0	1.7	3.2	1.8	3.3	1.7	1.8	1.7	2.6	2.5	2.6	0.6	1.5	6.5	1.4	93.5
ZRX	3.0	1.1	2.7	2.2	1.6	2.4	2.2	1.6	2.2	1.6	2.3	0.9	2.2	2.9	1.8	1.8	2.8	0.5	3.8	2.3	2.1	1.2	2.1	1.3	2.6	0.6	1.8	2.8	2.8	3.1	1.7	2.8	2.5	1.9	2.8	0.9	3.3	1.6	1.9	2.5	1.8	1.4	2.2	2.3	2.2	1.0	0.5	4.4	95.6
																																																	Total spillover index
Contribution to self and others	135.8	76.1	91.3	110.9	87.4	111.2	106.9	111.9	95.1	102.2	106.0	58.5	97.0	95.0	102.3	92.6	119.3	77.7	94.5	121.9	86.2	60.1	114.0	95.8	129.4	103.6	103.4	110.1	114.8	128.5	106.3	109.3	96.8	122.1	123.5	96.8	113.8	90.0	81.5	89.0	115.5	99.9	90.5	99.2	80.6	79.6	87.2	79.3	
Contribution to others	131.0	72.3	87.7	106.1	83.6	107.2	101.3	107.5	91.0	96.0	104.4	53.5	93.7	92.4	98.4	86.0	115.4	74.7	90.3	118.6	81.5	57.6	109.0	90.8	124.8	97.8	99.3	106.1	111.0	123.5	101.6	104.8	92.8	117.3	118.2	90.2	109.1	85.8	77.9	82.3	110.4	96.8	84.1	94.2	76.8	75.2	80.7	74.9	**95.5 %**
Net spillover	35.8	-24.0	-8.6	10.9	-12.6	11.2	6.9	11.9	-4.9	2.2	5.9	-41.5	-3.0	-5.0	2.3	-7.4	19.4	-22.3	-5.5	21.8	-13.8	-39.9	14.0	-4.2	29.3	3.6	3.3	10.1	14.8	28.5	6.3	9.3	-3.2	22.1	23.5	-3.3	13.9	-10.0	-18.5	-11.0	15.5	0.0	-9.5	-0.8	-19.5	-20.4	-12.8	-20.7	

Return spillover table 2019

Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	2.9	0.7	2.3	2.0	1.0	1.9	2.0	2.9	2.5	2.3	1.1	1.5	0.7	2.3	3.0	1.8	2.1	1.9	1.9	2.3	3.3	1.4	2.1	2.3	1.8	1.9	2.6	2.7	2.7	1.8	2.1	0.6	1.8	2.0	2.1	1.3	2.3	2.2	2.9	2.9	2.4	2.4	2.5	2.4	1.7	2.7	1.9	2.5	97.1
ANT	1.2	5.6	1.1	3.2	1.8	3.5	1.7	1.3	2.5	2.0	2.4	2.1	1.8	3.4	1.5	1.7	1.5	1.3	1.5	4.2	1.7	1.9	0.8	2.2	1.9	1.0	1.8	1.4	2.5	2.1	2.3	2.0	2.7	2.0	2.1	0.5	1.4	4.3	2.4	1.5	2.7	2.3	1.7	1.1	2.8	3.0	1.7	1.1	94.4
BAT	1.8	1.0	5.4	1.9	1.9	1.3	1.9	2.3	1.8	2.2	0.7	1.1	0.6	1.7	3.8	1.8	1.6	3.5	1.9	2.0	3.2	2.4	2.2	2.6	1.9	3.1	3.2	2.3	1.3	1.6	2.4	0.6	1.6	0.9	1.0	2.5	1.7	1.4	1.0	2.6	2.9	2.2	1.7	3.8	3.2	2.6	2.0	2.4	94.6
BCH	1.9	1.4	2.2	3.2	1.2	2.4	2.5	1.7	2.6	3.1	1.6	2.4	0.3	3.1	2.9	2.0	2.6	0.9	2.3	1.8	2.2	1.5	1.8	2.1	2.9	1.4	2.2	2.5	2.9	1.8	2.4	1.3	2.4	2.2	2.1	1.4	2.4	1.9	2.4	2.1	1.7	2.7	2.4	1.8	2.0	2.0	1.6	1.9	96.7
BNB	1.0	0.7	2.7	2.0	6.5	1.8	1.8	1.9	1.9	3.5	0.7	1.1	1.4	2.2	4.3	2.0	1.9	1.4	2.0	1.9	3.4	1.6	2.7	1.7	3.1	2.4	2.1	2.7	1.5	1.9	2.6	2.2	1.5	0.6	0.9	2.5	1.3	2.1	1.7	2.8	2.3	2.1	3.0	1.3	2.5	1.6	1.7	1.4	93.5
BTC	1.1	1.2	1.6	3.0	1.5	3.8	2.4	1.3	3.6	3.1	1.7	1.8	0.3	3.1	1.6	2.0	3.1	1.7	1.3	2.7	2.6	1.7	1.6	2.3	2.7	1.3	2.9	2.2	2.3	1.5	2.0	0.9	1.9	2.8	2.3	1.6	1.5	1.5	2.8	2.0	1.0	3.4	2.5	2.0	2.9	3.6	0.9	1.6	96.2
BTG	1.8	0.6	1.4	2.5	1.6	3.0	3.8	1.8	3.6	2.5	1.8	1.8	0.9	2.9	1.5	2.7	2.9	1.4	1.7	2.0	2.6	1.1	1.6	1.3	3.2	1.7	2.7	2.6	2.6	1.7	1.6	1.6	1.4	2.1	2.1	1.9	1.7	1.3	2.3	2.6	1.7	3.7	3.4	2.4	1.2	2.2	1.8	2.0	96.2
CVC	2.9	0.7	2.5	1.2	0.9	1.3	1.8	5.3	1.8	1.1	1.7	1.3	0.6	1.9	1.2	2.2	1.5	3.2	1.4	2.6	2.5	2.3	1.5	2.5	1.1	3.0	2.9	1.5	2.3	1.9	2.5	0.9	1.3	2.5	2.8	2.0	1.9	2.9	3.5	3.2	2.5	2.6	1.5	2.5	1.1	3.0	1.9	2.9	94.8
DASH	2.4	0.8	1.7	2.2	1.4	2.2	2.4	1.8	3.8	2.5	1.0	1.2	0.4	2.6	3.3	1.8	2.4	1.6	2.1	3.1	2.5	1.9	2.0	2.0	2.7	1.2	2.4	2.1	2.6	2.2	2.4	0.7	1.9	2.5	2.4	2.0	2.0	2.3	2.5	2.4	1.6	2.6	2.4	2.2	1.9	2.6	1.8	2.1	96.3
DCR	1.6	1.8	4.1	2.8	1.9	3.1	2.5	1.0	2.1	5.7	1.6	1.5	0.8	3.2	3.6	1.8	2.8	1.4	2.3	2.2	1.6	0.8	1.7	0.7	3.5	1.0	1.7	2.9	2.4	2.0	1.4	1.8	2.2	1.2	2.1	2.1	2.0	1.4	1.5	2.7	2.1	1.5	2.8	1.3	3.0	1.3	2.0	1.8	94.3
DGB	1.6	1.7	2.1	1.7	1.3	2.4	2.3	1.8	1.8	3.0	5.5	3.0	0.8	2.1	1.4	2.7	2.0	1.8	1.6	2.8	3.0	1.3	1.9	1.8	1.8	2.0	2.0	2.5	2.1	1.4	1.1	1.7	2.1	2.5	2.1	0.9	2.0	2.5	2.6	2.2	1.9	2.4	3.1	1.7	2.2	2.2	1.9	1.9	94.5
DOGE	1.2	0.7	2.4	2.4	1.7	2.7	2.3	1.3	2.1	3.2	2.4	4.3	2.1	3.1	4.2	3.1	2.0	1.1	1.3	1.7	3.0	1.6	1.7	2.1	2.6	2.6	1.8	2.1	2.5	1.2	1.2	1.5	2.0	2.5	2.3	1.9	1.6	1.2	2.5	1.4	1.3	2.9	2.9	1.4	1.3	1.8	2.4	1.7	95.7
ENJ	0.6	1.2	1.7	2.1	2.5	1.4	2.2	1.5	1.5	2.1	1.6	1.9	6.7	2.7	1.6	3.8	1.5	3.2	2.2	3.8	0.8	2.5	3.0	1.2	2.3	2.5	1.8	1.2	1.8	3.4	2.6	2.8	0.7	1.4	4.5	1.4	1.8	1.6	2.4	1.2	2.0	1.7	1.7	1.6	2.6	1.6	1.1	1.5	93.4
EOS	1.7	1.0	1.3	3.1	1.3	2.5	2.8	2.0	3.0	2.6	1.6	1.7	0.4	4.1	2.4	2.6	2.8	1.5	1.8	2.7	1.8	1.3	2.0	1.6	3.0	1.6	2.6	2.2	3.2	2.4	2.5	0.7	1.5	2.1	1.9	1.4	2.1	2.1	3.3	2.3	1.7	2.6	2.7	1.6	1.5	2.8	1.5	1.3	96.0
ERG	2.5	1.7	1.0	3.6	0.9	4.5	2.2	2.0	2.3	2.1	2.5	1.2	1.8	2.7	6.2	1.2	2.5	1.5	1.5	1.5	2.2	2.0	1.2	1.5	1.9	0.9	2.4	2.3	1.6	3.3	1.8	0.7	2.9	1.9	2.2	2.2	2.8	0.5	1.6	1.8	2.7	2.5	1.4	3.4	1.5	2.8	1.8	1.1	93.9
ETC	1.9	1.0	0.9	2.5	1.1	2.6	2.4	1.7	2.8	2.6	1.7	2.0	0.9	2.3	2.7	3.4	2.2	2.0	2.3	2.8	2.3	1.6	2.8	1.8	2.1	1.9	2.7	2.1	2.6	2.1	1.6	1.4	1.2	2.2	2.0	1.2	2.5	1.8	3.2	2.5	2.0	2.8	2.4	2.1	2.4	2.6	1.1	1.6	96.6
ETH	2.0	1.1	1.4	2.4	1.5	2.5	2.6	1.7	3.0	2.7	1.3	1.6	0.3	3.2	2.3	1.9	3.5	1.4	1.6	2.2	3.1	1.1	1.6	2.3	3.0	0.9	2.6	2.5	2.9	1.8	2.3	0.7	1.1	2.3	1.7	1.9	2.2	1.7	2.9	2.5	1.7	2.9	2.9	2.2	2.4	2.9	1.7	2.5	96.5
GLM	2.1	0.7	3.1	1.7	1.3	2.2	1.6	3.0	2.5	2.5	0.5	1.2	1.2	1.8	3.6	2.2	1.7	4.1	2.4	3.2	3.8	1.6	1.5	2.0	1.3	1.3	2.5	2.1	1.7	1.7	1.8	1.5	1.5	1.7	2.8	2.2	1.4	2.3	2.7	2.0	2.6	2.0	2.9	2.0	2.8	2.7	1.6	1.5	95.9
GNO	1.2	1.1	2.2	2.6	0.8	1.6	2.7	2.0	2.5	1.9	2.1	2.3	1.2	1.6	2.8	1.3	2.0	1.4	8.2	2.8	2.1	1.4	1.9	1.1	2.8	2.3	1.4	1.8	2.1	1.6	2.1	1.0	2.1	3.1	4.2	1.7	1.3	4.3	2.7	2.4	0.9	2.0	2.0	1.6	1.1	1.5	1.6	2.0	91.8
ICX	1.0	0.6	2.6	2.2	1.3	1.5	2.4	2.1	3.8	2.6	0.4	1.1	1.1	2.2	2.2	2.4	1.6	2.0	2.0	4.7	2.3	2.5	3.1	1.8	2.1	1.0	2.0	2.7	2.7	2.5	2.6	1.5	2.0	1.9	1.8	1.9	0.9	2.9	3.1	3.5	1.1	3.1	2.4	1.5	1.4	2.6	2.1	1.2	95.3
KCS	1.1	1.0	2.3	1.6	1.0	3.0	1.7	1.5	2.3	2.3	3.4	2.9	0.9	1.9	3.9	2.3	2.0	0.9	2.8	2.4	5.2	2.1	2.4	1.7	1.3	3.0	2.1	1.0	2.2	1.3	1.6	1.1	1.2	2.0	1.1	1.0	1.3	4.1	2.7	2.2	1.3	3.3	3.1	1.4	2.0	2.5	1.9	3.1	94.8
LINK	1.1	1.7	1.2	1.9	2.2	1.9	1.2	1.7	2.2	1.1	0.9	2.4	2.1	1.9	1.0	2.9	1.4	2.2	1.4	3.3	2.6	5.0	2.3	3.9	1.6	1.9	2.1	1.3	2.0	2.4	3.4	1.5	1.0	2.0	3.1	2.6	1.8	3.8	3.2	1.5	1.0	3.8	2.0	2.3	1.9	3.1	0.9	0.7	95.0
LRC	1.0	0.7	2.3	2.5	1.5	1.7	1.5	1.3	1.9	2.3	1.0	2.5	2.3	2.1	1.7	2.5	2.2	2.3	3.5	3.4	3.0	2.3	5.5	2.9	2.0	1.6	2.1	2.2	2.0	2.0	3.0	1.5	1.6	2.5	1.3	1.7	2.3	2.0	3.0	2.3	0.6	2.7	2.1	1.8	1.5	2.4	1.2	0.9	94.5
LSK	2.1	0.9	1.4	2.7	1.2	2.8	1.6	1.6	3.0	1.9	1.0	1.7	1.0	2.4	2.2	1.9	2.5	1.4	1.2	2.5	2.5	3.1	1.7	4.2	1.7	0.5	2.7	2.0	2.4	2.1	3.1	1.0	1.8	2.5	1.9	1.3	2.2	2.4	2.9	2.7	1.9	4.0	2.4	3.3	0.7	3.7	1.0	1.6	95.8
LTC	1.8	1.0	2.3	3.1	1.9	2.7	3.8	1.5	3.2	3.4	1.9	1.8	0.4	3.7	3.2	1.8	3.3	0.8	1.3	2.0	2.7	1.1	1.8	1.3	4.7	1.0	2.1	2.9	2.7	1.9	2.4	1.2	2.2	1.5	1.1	1.2	2.0	1.7	2.3	2.0	1.6	2.7	2.4	1.5	1.3	2.4	1.5	2.2	95.3
MANA	1.0	1.5	2.4	1.0	2.8	1.1	1.2	3.0	1.5	1.4	1.4	2.0	1.6	2.2	2.1	2.2	0.8	3.6	2.4	4.6	1.8	1.3	3.1	2.4	1.4	8.3	1.6	0.9	1.5	1.7	2.3	1.3	2.0	2.1	3.1	1.3	1.5	2.4	3.6	1.4	1.6	1.1	2.3	1.1	2.4	2.4	3.6	1.2	91.7
MIOTA	2.4	0.3	2.7	1.5	2.1	1.4	1.7	2.8	2.4	2.5	1.0	1.6	1.0	1.9	2.5	2.4	2.2	2.5	1.7	2.1	2.8	2.2	2.2	2.4	1.8	1.5	3.6	2.6	2.1	1.7	2.1	1.5	1.3	1.7	2.8	1.6	2.0	2.0	2.8	2.6	2.6	2.4	1.7	2.6	1.8	2.9	1.6	2.7	96.4
NEO	2.1	1.2	2.6	2.3	1.3	2.0	2.3	2.4	2.1	3.7	1.6	1.3	0.9	2.6	4.0	1.8	2.1	1.4	2.2	2.5	1.8	1.3	2.4	1.6	2.4	2.2	2.2	4.4	2.1	1.8	1.4	2.1	2.1	1.8	1.7	1.9	1.8	2.4	3.0	2.7	1.8	1.6	2.5	1.9	1.4	2.4	1.4	2.0	95.6
OMG	2.2	1.3	1.4	2.6	0.8	2.0	2.6	2.4	2.8	2.3	1.8	2.4	0.6	3.2	2.7	2.5	2.6	1.2	2.0	2.6	2.5	1.6	1.5	2.2	2.4	1.2	2.1	2.1	4.0	2.1	2.2	0.6	1.3	2.3	1.9	0.9	2.4	2.0	3.3	2.9	1.6	3.0	2.8	1.7	1.2	2.3	1.7	2.4	96.0
QTUM	1.4	1.0	1.7	2.7	1.1	2.0	2.6	1.7	3.2	2.8	1.3	1.3	1.2	3.1	2.7	2.3	2.1	1.3	3.6	3.0	2.2	2.4	1.8	2.0	2.4	1.0	1.9	2.6	2.8	3.3	2.9	1.0	1.5	2.1	2.0	1.4	1.9	2.6	2.5	2.3	1.2	2.8	2.6	1.6	1.7	2.8	1.3	1.7	96.7
REQ	1.6	0.8	1.2	2.7	1.5	2.2	1.9	2.4	2.6	1.5	0.6	2.2	0.6	3.1	1.0	2.5	2.5	2.4	1.9	3.7	2.2	2.7	2.8	3.3	2.3	2.0	2.5	1.6	2.5	2.7	4.3	0.8	1.4	1.8	1.8	1.2	2.2	2.3	3.0	2.7	0.9	3.0	1.8	2.1	1.8	3.0	1.5	1.0	95.7
RLC	1.1	0.8	1.4	1.2	2.3	1.3	2.3	0.8	1.8	2.2	0.7	2.7	1.5	1.6	3.9	2.9	1.8	2.0	1.8	3.5	3.0	2.1	3.5	1.8	2.0	1.8	3.1	1.7	1.5	0.9	1.4	6.1	1.3	0.7	3.8	1.7	1.4	2.0	2.2	1.8	1.7	2.3	2.0	2.1	5.4	1.9	1.2	2.4	93.9
SC	1.8	1.4	1.5	2.6	0.7	2.2	1.7	1.6	3.0	3.5	1.4	1.5	0.4	2.5	1.4	2.8	2.1	1.5	1.2	2.8	1.8	2.4	2.8	2.3	1.8	1.6	2.5	2.9	2.7	2.3	2.3	1.0	3.2	2.4	1.5	1.1	1.9	2.2	3.3	3.2	1.8	3.4	2.6	2.1	1.4	2.8	1.7	1.5	96.8
SNT	1.4	0.6	1.6	1.7	0.7	1.8	1.6	2.0	3.5	2.3	1.2	1.7	1.4	2.0	2.1	2.1	1.7	1.7	1.6	3.5	4.0	1.9	1.9	2.5	1.7	1.0	2.2	2.1	2.6	2.0	1.6	1.1	1.8	5.2	2.7	1.9	0.9	2.0	4.8	2.7	1.3	3.4	2.1	1.8	1.5	3.9	1.9	1.5	94.8
STORJ	2.2	0.6	1.2	1.1	1.1	1.5	1.8	3.6	2.7	0.8	1.8	2.1	1.9	1.8	1.7	2.7	1.0	3.4	3.5	4.5	2.9	2.7	2.1	1.6	2.1	1.3	2.4	0.7	1.9	2.0	2.1	1.1	0.9	3.7	8.8	0.8	1.2	2.8	3.9	1.3	1.0	2.1	0.9	1.8	1.5	2.4	1.1	1.9	91.2
SYS	2.1	1.7	2.2	1.5	1.4	1.5	2.7	2.3	2.5	1.5	1.7	1.5	1.0	1.6	1.9	2.2	1.9	2.4	1.8	2.2	3.4	2.2	2.4	2.7	1.8	1.5	1.9	2.2	2.3	2.0	2.2	1.5	1.5	1.9	2.3	5.0	2.0	1.1	2.2	2.5	2.3	3.2	2.2	2.8	1.6	2.1	2.6	1.2	95.0
TRX	1.9	1.7	1.7	3.1	1.0	2.2	2.9	1.7	2.7	3.1	2.0	2.1	0.6	2.9	1.9	3.0	2.5	1.6	2.1	2.1	2.7	1.4	2.0	1.7	2.5	1.4	2.3	2.7	3.0	2.0	2.2	1.4	1.7	2.3	2.3	1.0	3.4	1.0	2.7	2.2	2.0	2.8	2.9	1.8	1.4	2.0	1.0	1.6	96.7
VGX	1.5	1.1	2.9	2.0	1.3	1.1	1.1	1.8	2.4	3.0	1.3	1.8	1.3	2.1	2.2	2.4	1.4	1.6	3.0	2.8	1.9	3.8	2.2	3.6	1.5	1.6	2.6	1.9	2.3	1.8	3.1	1.4	1.8	2.6	2.3	0.2	1.8	4.6	2.8	2.5	2.5	2.3	1.7	2.0	1.2	2.3	2.2	1.7	95.4
WAVES	1.4	1.5	0.9	1.9	0.9	2.2	1.9	2.4	3.3	2.1	1.8	1.5	0.9	2.4	0.9	2.8	1.9	1.8	2.0	4.3	2.3	2.0	2.9	2.0	1.8	1.9	2.4	1.5	3.0	1.7	2.2	0.9	1.3	3.5	2.7	1.4	1.5	2.8	5.0	2.3	1.2	3.6	2.3	1.8	1.1	3.5	1.4	1.6	95.0
XEM	2.3	0.9	1.8	2.5	0.7	2.3	2.4	2.2	2.7	2.5	1.1	1.4	0.3	2.7	1.9	2.5	2.9	1.4	2.4	2.3	3.0	1.2	2.1	1.5	2.1	1.0	2.7	3.0	3.3	1.9	2.3	1.3	1.7	2.0	1.4	1.1	2.0	1.7	2.4	4.5	1.8	3.0	3.2	1.9	1.9	2.1	2.5	2.4	95.5
XLM	2.8	1.3	2.8	1.9	0.9	1.9	1.7	2.6	2.2	2.2	1.4	1.8	0.8	1.8	2.3	2.0	2.2	1.2	2.6	1.8	4.6	1.5	1.0	2.3	1.2	0.9	2.6	1.8	2.6	1.6	1.9	1.0	1.4	2.1	2.1	0.9	2.5	2.0	2.9	2.8	3.6	3.4	2.9	2.9	2.4	2.6	1.9	2.8	96.4
XMR	1.4	0.8	2.0	2.8	1.3	2.8	2.6	1.5	3.4	2.2	1.1	1.6	0.8	2.9	1.6	2.8	3.0	1.5	1.8	2.3	2.9	2.0	1.8	2.3	2.5	0.9	2.8	2.2	2.6	1.9	2.5	0.8	1.5	2.1	1.8	1.4	1.7	1.3	3.2	2.6	1.5	4.4	3.3	2.5	1.3	3.4	1.1	1.6	95.6
XNO	1.7	0.5	2.6	2.3	1.6	1.9	2.3	1.5	1.9	3.0	1.9	1.2	0.8	2.5	2.7	3.0	2.3	1.5	2.3	3.1	2.2	1.3	2.0	1.3	2.3	1.7	2.3	2.8	2.5	1.7	1.8	1.3	1.5	1.1	2.7	2.1	1.9	2.1	2.2	2.0	2.7	2.4	4.0	2.1	3.6	2.0	1.9	2.4	96.0
XRP	2.8	0.9	1.3	2.2	0.9	1.6	1.9	2.4	2.3	2.3	1.1	1.6	0.8	2.2	2.0	2.2	2.4	2.0	1.7	2.8	2.4	2.0	1.6	3.0	1.6	1.3	2.9	2.4	2.4	1.9	2.1	1.1	1.4	2.6	3.0	1.5	2.4	1.9	3.0	2.4	2.5	2.7	2.4	3.7	2.8	2.9	0.9	2.0	96.3
XTZ	1.4	1.7	1.4	2.5	1.8	1.8	1.8	1.0	2.7	3.2	1.1	1.9	2.3	1.9	1.8	2.7	2.1	1.7	1.1	2.5	1.4	3.7	2.8	2.6	2.2	1.7	1.9	1.7	2.8	2.2	2.1	2.5	2.0	2.4	2.8	1.5	2.6	1.3	2.2	1.7	1.0	3.4	1.8	2.1	3.6	2.0	1.7	2.1	96.4
ZEC	1.4	1.7	1.4	1.9	1.1	2.5	2.0	1.4	3.1	3.0	1.4	1.3	0.7	2.9	2.6	2.6	2.0	1.3	0.7	3.6	2.6	2.2	2.6	2.5	2.3	0.9	2.9	2.1	2.4	2.0	1.8	0.9	1.8	2.6	1.9	1.8	1.2	2.0	3.7	2.3	1.5	3.1	2.7	1.9	2.6	4.0	1.5	1.7	96.0
ZEN	2.6	0.8	2.3	0.6	0.8	1.1	2.4	3.2	2.2	2.1	2.6	1.1	1.2	2.2	1.9	2.7	1.6	1.6	0.9	1.3	0.9	0.8	1.8	1.6	1.8	3.7	3.0	2.2	3.8	2.2	0.9	1.1	2.2	2.5	2.4	2.2	1.5	0.9	3.4	2.8	3.7	1.9	1.3	1.9	1.1	2.9	7.4	4.0	92.6
ZRX	1.6	1.1	3.7	1.5	1.4	2.9	1.4	2.3	1.7	3.8	1.8	2.2	1.3	1.5	2.0	1.8	2.3	1.8	2.7	1.2	6.1	0.4	2.6	1.1	1.5	3.0	1.6	2.4	1.9	1.1	0.9	1.7	0.9	1.8	2.6	1.3	1.5	0.9	2.0	2.4	2.5	3.4	3.6	1.5	3.6	1.5	2.5	4.0	96.0
Contribution to self and others	83.5	55.2	97.8	106.2	70.6	103.5	102.6	96.7	122.5	121.1	74.8	86.6	54.6	117.7	117.4	112.0	103.0	88.1	100.4	131.4	127.1	91.9	103.9	100.8	104.3	86.1	113.3	104.1	115.8	94.1	103.0	65.7	79.9	104.0	113.9	77.1	89.3	102.2	134.1	113.5	89.4	131.3	115.8	97.4	96.7	122.3	85.7	92.0	**Total spillover**
Contribution to others	80.7	49.6	92.4	103.0	64.1	99.8	98.8	91.4	118.7	115.4	69.4	82.3	47.9	113.7	111.3	108.7	99.4	84.0	92.2	126.7	121.9	86.9	98.4	96.6	99.6	77.8	109.7	99.7	111.8	90.9	98.7	59.6	76.7	98.7	105.1	72.1	86.0	97.5	129.0	109.1	85.7	126.9	111.8	93.7	93.1	118.2	78.3	88.0	**index**
Net spillovers	-16.5	-44.8	-2.2	6.3	-29.4	3.6	2.6	-3.4	22.4	21.1	-25.2	-13.4	-45.4	17.7	17.4	12.1	2.9	-11.9	0.4	31.4	27.1	-8.1	3.9	0.8	4.3	-13.9	13.3	4.1	15.8	-5.9	3.0	-34.3	-20.1	3.9	13.9	-23.0	-10.7	2.1	34.0	13.6	-10.7	31.3	15.8	-2.6	-3.3	22.3	-14.3	-8.0	**95.2 %**

Volatility spillover table 2019

Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC
ADA	3.1	2.3	2.7	1.5	2.0	2.8	3.7	1.1	3.0	1.2	2.1	2.0	0.9	2.1	1.5	3.6	3.2	2.2	0.5	4.1	3.3	0.9	2.8	1.0	1.9
ANT	1.9	5.3	2.0	3.4	2.8	2.0	1.6	1.6	3.6	1.9	1.3	2.0	2.5	3.6	0.8	1.1	3.7	2.9	1.3	2.1	2.1	1.3	1.0	0.7	3.4
BAT	1.8	3.5	5.0	1.6	1.6	1.8	2.8	2.1	0.9	0.6	3.3	0.8	3.4	2.3	0.4	4.6	2.4	4.3	1.1	1.9	1.5	1.6	1.6	1.7	2.5
BCH	2.2	1.7	1.1	3.8	1.8	2.9	2.2	1.2	2.6	2.8	2.7	3.7	1.5	1.6	1.4	2.2	1.6	1.1	1.3	2.3	2.2	2.2	0.9	1.9	2.2
BNB	3.1	1.7	1.4	1.6	4.0	2.2	1.7	2.0	2.9	1.3	2.4	1.1	1.2	2.1	1.1	2.7	3.0	2.4	0.9	3.3	2.7	3.1	2.6	2.1	2.4
BTC	2.2	0.7	2.0	2.6	2.2	3.2	2.7	3.0	2.6	2.1	2.6	1.3	2.8	2.1	1.6	1.4	2.2	3.0	1.3	2.2	1.7	0.7	1.5	1.5	3.0
BTG	2.8	1.1	1.2	2.0	2.2	4.2	4.5	1.8	3.1	1.5	3.7	1.8	1.1	3.2	1.3	2.4	2.3	2.5	1.4	2.8	2.3	0.7	1.1	1.5	3.9
CVC	2.3	1.3	1.8	2.3	1.9	3.0	2.6	2.8	1.5	1.9	3.7	1.0	1.8	1.4	1.1	1.6	1.5	2.2	0.5	1.6	0.9	1.0	2.8	4.8	3.1
DASH	2.4	0.6	0.9	2.6	3.1	4.1	3.8	1.2	5.5	3.1	3.1	0.5	0.6	3.8	0.7	2.0	2.8	1.6	1.7	2.4	3.1	0.5	0.5	1.6	3.7
DCR	1.2	1.3	0.4	1.5	2.0	3.1	3.5	2.8	2.5	3.9	5.2	3.6	2.4	1.6	1.3	0.9	1.0	1.0	2.3	1.5	2.6	1.4	1.4	2.4	3.9
DGB	4.1	1.3	0.8	1.7	1.0	4.7	1.3	2.9	1.6	1.5	5.5	0.9	1.6	1.8	1.4	3.0	1.8	4.5	1.9	1.5	1.8	0.4	1.7	1.1	2.0
DOGE	2.1	3.4	0.7	1.0	1.5	1.4	1.1	2.4	1.9	4.1	1.6	7.8	3.0	1.2	1.8	1.7	1.8	1.0	2.6	3.3	1.4	1.2	0.7	1.7	2.4
ENJ	2.1	0.9	0.8	1.8	2.5	2.7	2.0	3.1	1.8	2.0	1.3	0.5	5.5	2.3	1.5	5.1	2.8	2.6	1.1	3.6	2.1	5.1	2.9	1.4	2.6
EOS	2.4	1.8	1.3	2.1	2.8	2.8	3.0	1.8	2.6	2.3	3.9	1.6	0.3	2.9	1.6	2.3	2.7	1.5	2.9	3.3	1.2	1.9	0.9	1.3	3.0
ERG	2.7	2.1	1.6	1.0	2.5	3.1	1.5	2.1	2.3	1.6	1.7	1.4	1.0	1.9	7.6	2.2	2.2	1.8	1.7	1.6	2.4	2.1	1.6	1.3	1.9
ETC	2.2	2.3	1.2	3.1	1.6	3.7	3.5	2.9	3.3	2.7	3.3	2.0	1.6	2.3	1.7	5.5	1.8	1.3	0.7	2.3	2.5	1.3	0.6	1.1	2.5
ETH	3.4	1.2	1.5	3.7	3.3	3.1	1.6	1.9	3.1	1.8	1.6	1.0	0.7	2.9	1.4	2.0	4.0	2.7	0.6	3.7	1.7	2.7	1.3	1.5	2.9
GLM	2.0	1.1	2.8	1.7	1.9	2.1	4.3	1.8	1.6	0.8	4.1	1.7	0.5	1.9	1.4	1.1	2.4	4.3	0.9	2.5	1.1	2.0	2.5	1.1	1.9
GNO	1.0	0.7	0.6	5.2	1.2	1.7	2.7	1.0	3.4	6.3	1.9	1.1	1.5	2.6	1.4	1.4	1.3	1.4	8.0	0.9	1.6	1.6	1.7	0.5	3.2
ICX	3.6	4.8	2.1	1.7	2.7	3.2	2.5	0.8	2.4	1.5	1.7	3.1	1.4	1.8	1.2	4.2	3.3	2.4	0.5	5.6	2.5	2.6	2.9	1.1	2.0
KCS	2.9	1.4	1.6	2.7	2.6	2.4	2.1	3.3	3.4	0.7	1.3	2.2	0.8	2.4	1.7	1.6	2.1	2.2	0.8	2.4	5.0	1.5	2.5	0.6	1.5
LINK	2.9	0.9	1.3	1.1	2.8	2.4	1.2	4.4	3.9	1.5	1.7	1.1	0.6	2.5	2.1	1.9	1.7	2.7	2.1	4.1	2.7	6.2	2.9	0.9	1.3
LRC	0.8	1.2	1.8	2.8	2.3	0.6	0.9	2.7	1.4	1.2	1.9	1.5	2.1	1.4	1.8	1.2	2.0	1.9	3.8	1.9	1.1	1.7	2.9	1.9	1.0
LSK	2.5	7.9	0.9	1.2	1.8	3.7	2.1	2.2	2.4	1.3	2.6	4.6	1.0	1.6	2.3	6.0	1.4	0.8	1.3	2.9	2.6	2.5	1.3	3.5	3.1
LTC	1.9	1.3	0.4	3.0	2.8	2.8	3.1	1.4	3.4	2.8	3.8	2.0	0.9	2.7	1.7	1.7	2.9	1.1	2.2	3.0	1.6	0.8	2.2	2.2	4.8
MANA	2.4	0.8	1.0	1.1	1.8	3.6	1.8	4.8	1.8	1.5	2.3	2.2	3.1	3.0	2.2	1.6	1.6	2.8	1.6	2.1	0.5	1.8	1.6	0.9	1.7
MIOTA	1.4	0.9	2.2	1.0	3.1	1.5	1.8	1.7	1.6	1.8	4.1	1.2	0.9	1.4	2.4	1.0	3.0	2.5	1.8	2.4	1.4	2.8	1.9	1.7	1.6
NEO	1.7	2.7	1.4	2.0	1.9	3.7	1.5	1.8	3.2	2.5	2.4	1.6	1.1	2.8	1.1	3.1	1.9	2.2	1.8	1.1	2.2	2.1	1.1	0.8	1.5
OMG	2.8	2.4	1.6	1.7	2.6	2.5	2.8	2.2	2.4	0.5	3.1	2.1	2.3	2.0	1.0	2.4	2.5	1.7	0.8	3.2	1.7	1.3	1.6	1.9	1.9
QTUM	2.9	0.7	2.4	1.6	3.0	3.1	2.4	2.8	3.2	1.0	2.2	1.1	1.7	1.8	2.6	1.2	2.4	2.9	2.0	2.3	2.6	1.1	1.9	0.6	2.3
REQ	2.0	2.0	1.8	1.4	2.0	3.9	1.9	1.7	3.4	1.8	2.1	1.7	1.0	3.5	0.6	3.9	2.6	1.8	0.8	1.6	2.7	2.2	1.0	1.5	1.3
RLC	1.6	1.6	1.1	1.5	2.8	2.6	2.5	3.5	2.0	1.5	2.5	1.1	3.1	3.0	4.0	0.6	1.8	1.6	2.4	1.5	1.9	2.2	1.2	1.1	2.4
SC	1.1	1.5	1.8	2.3	1.1	2.0	3.9	2.2	2.0	2.0	6.4	0.9	4.5	2.5	1.1	1.6	1.8	2.4	0.5	1.9	1.4	1.4	0.9	1.4	3.7
SNT	3.9	1.0	0.6	1.5	3.0	3.1	2.7	1.4	1.1	0.5	3.0	0.9	1.8	1.1	3.8	1.8	2.1	1.9	1.1	3.6	1.3	2.0	1.6	1.3	1.2
STORJ	2.3	2.3	1.8	0.8	2.1	1.9	2.4	2.3	2.4	1.1	3.2	3.2	1.9	2.8	1.2	1.2	2.2	1.4	3.8	3.4	1.9	1.9	2.2	2.4	2.7
SYS	2.4	0.4	2.0	1.5	2.4	3.1	2.1	1.8	1.7	1.6	3.3	0.6	1.4	4.1	1.0	1.9	4.2	3.2	2.5	2.2	1.7	1.2	1.4	1.7	2.2
TRX	1.3	1.0	1.8	2.4	2.6	1.7	3.0	2.1	2.4	2.2	2.2	1.0	1.6	2.0	1.3	2.0	2.1	1.1	2.8	2.4	2.1	2.9	2.2	1.5	1.5
VGX	1.4	2.9	1.1	3.3	0.7	2.4	2.2	2.5	1.8	2.1	2.6	1.8	2.6	1.1	2.6	4.2	1.6	1.6	1.3	2.6	1.9	4.5	1.9	1.8	0.7
WAVES	1.3	8.7	3.8	2.0	2.1	2.6	1.1	2.4	1.3	1.8	1.9	1.6	0.6	0.9	3.1	7.9	2.9	0.6	2.4	3.0	3.4	3.8	1.5	1.1	0.4
XEM	1.8	1.3	2.3	1.8	1.9	2.6	1.7	1.4	3.4	1.5	3.6	3.1	3.0	1.8	0.4	1.9	2.2	3.2	2.2	3.5	3.3	0.9	2.8	0.6	1.3
XLM	2.2	2.8	2.3	3.7	2.5	2.0	1.7	1.7	1.0	1.6	4.3	2.2	0.7	0.9	1.2	3.2	2.9	2.3	2.1	3.0	1.4	4.4	0.7	1.6	1.4
XMR	2.2	1.2	2.1	4.8	2.6	2.4	2.9	0.9	1.8	2.1	3.0	1.3	1.0	1.9	0.7	2.2	3.2	1.3	1.4	2.1	1.3	1.0	0.8	2.0	3.7
XNO	1.9	2.0	1.7	2.3	3.2	2.3	2.8	2.3	3.0	2.0	2.3	2.0	2.2	3.3	0.7	3.7	2.7	1.4	1.9	2.1	1.6	2.6	0.7	1.1	2.1
XRP	2.1	1.7	2.1	2.3	3.6	2.3	1.5	1.6	2.0	1.3	3.5	2.0	1.3	1.4	0.9	1.1	3.2	3.1	1.8	3.4	2.0	1.8	1.1	1.1	1.4
XTZ	1.3	2.9	1.6	2.0	2.0	2.3	1.9	2.0	2.7	1.8	2.2	4.7	2.2	2.3	1.0	2.3	2.3	2.7	2.3	2.4	1.6	1.7	1.4	0.8	1.5
ZEC	2.6	0.4	1.0	1.7	2.4	2.9	3.8	2.5	3.0	1.8	2.2	0.4	1.6	1.8	1.7	2.9	1.8	1.8	0.9	1.6	1.8	1.2	2.3	1.8	2.4
ZEN	1.1	1.2	1.0	2.3	2.4	2.1	1.1	4.3	2.7	1.9	2.2	2.9	2.3	3.3	1.4	1.0	1.0	1.3	0.4	0.9	2.4	0.6	0.9	2.2	3.4
ZRX	2.3	4.7	2.7	2.1	2.9	2.2	2.0	2.1	1.9	1.3	4.2	2.1	1.0	1.3	0.6	1.6	2.6	3.5	1.1	2.3	1.0	1.3	1.0	2.2	1.8
Contribution to self and others	105.2	98.4	78.7	103.5	111.2	128.3	113.0	106.0	118.4	89.6	136.6	91.7	83.3	105.5	78.5	117.5	112.6	103.5	83.0	120.9	96.3	93.6	78.6	73.6	109.8
Contribution to others	102.1	93.1	73.8	99.7	107.2	125.1	108.5	103.2	112.9	85.7	131.1	83.9	77.8	102.6	70.8	112.0	108.7	99.2	74.9	115.3	91.4	87.4	75.7	70.1	105.1
Net spillover	5.3	-1.6	-21.3	3.5	11.2	28.3	13.0	6.0	18.4	-10.4	36.6	-8.3	-16.7	5.5	-21.5	17.5	12.6	3.5	-17.0	20.9	-3.7	-6.4	-21.4	-26.5	9.8

Tickers	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	0.6	2.7	1.2	1.9	1.0	2.6	2.3	2.1	2.3	1.8	4.3	1.0	0.8	1.7	2.5	2.2	1.1	1.8	2.4	0.9	3.1	1.8	2.7	96.9
ANT	2.2	0.7	2.5	2.1	1.2	1.8	2.6	1.3	0.4	2.7	2.8	1.4	0.7	1.3	1.3	1.8	2.7	4.7	1.3	2.7	0.7	3.0	2.3	94.7
BAT	2.0	2.5	0.7	1.3	1.5	2.2	3.5	2.2	2.3	4.4	1.8	1.3	2.2	2.6	1.0	1.7	2.0	2.4	1.6	0.9	1.9	1.9	1.4	95.0
BCH	2.7	1.9	1.7	2.0	1.8	2.2	1.7	1.7	1.8	1.5	3.0	1.4	1.8	0.9	1.4	3.4	2.9	1.6	2.4	1.4	2.4	3.1	4.1	96.2
BNB	1.0	1.6	2.1	2.3	2.0	2.1	2.0	1.4	1.6	2.6	1.9	2.0	1.1	1.6	1.6	2.7	2.1	2.4	1.9	2.2	2.4	1.7	2.9	96.0
BTC	4.0	1.1	2.4	1.5	1.9	3.6	3.0	1.9	1.4	1.9	4.6	1.8	0.6	0.9	1.8	2.4	1.6	1.6	1.3	2.0	1.7	2.7	2.5	96.8
BTG	0.3	1.5	1.2	1.3	1.5	1.1	4.7	2.2	2.3	2.9	1.9	1.6	1.2	0.9	1.2	1.2	1.8	2.6	2.0	1.5	3.6	2.4	2.7	95.6
CVC	1.6	2.2	0.8	1.9	2.7	3.2	2.7	1.9	2.6	3.1	2.1	1.5	2.3	2.2	1.2	3.2	3.8	1.8	1.8	1.5	0.9	2.0	2.7	97.2
DASH	0.7	1.2	2.0	2.0	1.8	1.9	3.1	2.6	1.4	2.3	3.1	2.5	0.6	0.8	1.3	1.7	2.0	3.2	1.5	1.6	2.1	2.2	2.8	94.5
DCR	4.6	1.6	3.1	1.2	1.8	1.5	3.7	1.1	0.9	1.5	1.9	1.4	1.7	1.3	1.2	2.5	3.0	0.8	1.1	0.6	1.9	3.8	3.1	96.1
DGB	1.9	2.9	0.3	1.1	1.5	2.8	2.5	1.5	1.0	0.9	3.6	1.1	3.2	1.2	1.5	4.4	2.5	0.6	1.9	1.4	1.7	5.6	3.7	94.5
DOGE	4.4	2.2	1.2	2.4	1.0	1.5	2.5	0.6	2.5	3.2	2.8	1.0	2.9	0.7	2.4	1.2	1.6	1.6	2.3	2.4	3.5	1.4	2.2	92.2
ENJ	2.7	2.3	2.4	1.2	1.7	1.9	2.0	1.4	1.0	3.0	2.5	1.4	2.1	1.5	1.3	1.1	1.5	1.2	1.6	1.0	2.1	1.5	1.5	94.5
EOS	1.4	2.4	1.6	2.5	1.8	2.3	2.4	1.9	2.3	2.0	3.1	2.1	1.4	0.8	0.9	2.3	2.1	2.4	2.0	0.8	2.4	2.5	2.8	97.1
ERG	0.8	1.2	3.8	2.2	3.8	2.7	2.7	1.9	3.9	1.5	2.7	2.1	1.2	0.9	0.3	2.4	1.3	1.0	1.2	1.4	3.1	2.3	2.8	92.4
ETC	1.1	1.4	1.6	2.7	2.2	0.7	2.8	2.5	2.0	1.0	1.4	1.5	1.1	1.8	2.0	2.8	2.5	1.5	1.3	1.4	3.3	1.6	3.0	94.6
ETH	0.4	2.7	1.8	2.8	1.4	2.0	1.4	0.9	2.0	1.2	2.7	1.3	1.4	0.5	2.3	3.3	3.1	2.6	2.8	1.8	1.9	1.7	3.0	96.1
GLM	2.2	2.5	0.8	2.1	2.1	3.3	2.4	3.4	2.3	3.8	3.6	2.1	2.4	1.0	1.0	2.8	1.7	1.9	1.9	1.7	2.3	1.6	1.7	95.7
GNO	2.6	0.7	0.5	1.3	1.8	1.2	2.6	1.4	1.9	0.9	2.3	1.0	0.6	1.2	1.2	3.6	4.6	3.4	2.1	3.4	1.5	5.2	1.4	92.0
ICX	1.0	1.8	1.3	2.0	1.4	1.3	1.1	1.3	2.4	0.6	2.4	0.9	0.9	3.0	2.7	1.6	1.3	1.8	1.9	0.7	3.1	1.5	3.0	94.4
KCS	2.0	1.6	3.8	3.1	2.6	2.1	2.0	1.4	1.3	2.2	1.9	1.7	1.1	1.7	1.0	3.5	1.7	2.2	2.3	1.8	1.9	2.7	3.1	95.1
LINK	2.2	3.2	3.9	1.4	1.4	2.5	1.9	0.8	1.3	2.3	1.9	1.7	3.3	2.6	0.5	0.9	0.4	2.0	1.1	3.6	1.8	1.4	1.3	93.8
LRC	2.6	2.6	4.9	2.2	3.1	1.7	0.9	0.8	2.2	3.3	1.5	2.6	4.0	2.2	2.0	6.1	3.7	1.8	2.4	2.8	1.1	0.9	1.1	97.1
LSK	1.7	1.7	1.0	1.1	1.5	0.8	2.6	1.6	2.7	0.9	1.1	1.0	1.9	2.6	1.5	1.9	1.5	1.2	2.0	0.5	1.8	1.9	1.9	96.5
LTC	1.9	1.8	1.6	1.3	0.8	1.5	2.0	2.1	1.2	2.5	2.6	1.5	1.6	0.9	2.1	1.3	2.5	2.6	2.0	2.0	2.8	2.1	3.1	95.3
MANA	7.4	2.6	2.2	1.0	1.6	3.9	5.0	1.3	1.9	4.0	3.4	1.5	2.5	1.2	0.7	0.9	1.0	1.8	0.6	0.6	1.1	3.1	1.8	92.6
MIOTA	1.2	4.0	4.3	4.2	1.1	3.0	3.2	1.3	2.9	1.4	3.5	3.0	3.1	1.1	1.4	3.2	1.3	1.0	1.8	1.9	1.7	2.4	1.1	96.0
NEO	3.2	0.8	3.2	2.1	1.7	2.0	2.6	2.8	0.8	0.9	2.9	3.1	0.6	2.0	1.2	2.8	1.9	1.9	0.6	1.2	1.4	8.2	3.3	96.9
OMG	1.8	1.9	2.1	4.1	1.9	1.7	2.7	1.8	2.2	1.0	2.9	1.9	1.2	0.7	2.7	2.7	1.9	1.5	2.5	2.6	2.5	2.3	3.1	95.9
QTUM	1.0	1.1	3.5	3.4	5.8	2.4	1.3	1.6	3.0	1.2	2.7	2.0	0.3	2.0	0.9	3.1	1.3	2.3	2.2	1.6	1.9	1.6	2.2	94.2
REQ	1.0	3.3	0.4	1.8	1.0	5.7	2.7	0.9	1.3	2.7	4.4	0.5	2.1	2.9	0.9	2.6	1.7	3.1	1.6	1.3	2.6	3.4	2.3	94.3
RLC	2.7	1.1	4.1	1.5	2.5	2.2	6.3	1.3	2.6	2.8	1.7	2.8	1.6	1.5	0.5	2.0	2.0	2.7	0.7	1.0	1.7	2.7	0.8	93.8
SC	3.1	0.5	2.0	2.6	1.7	1.6	4.9	4.1	1.9	2.2	1.2	1.4	0.8	1.1	2.8	1.3	2.1	1.6	1.3	2.5	1.3	4.2	1.7	95.9
SNT	1.7	2.2	2.3	2.4	4.2	2.3	1.9	1.1	6.7	0.9	2.3	0.7	2.0	1.5	1.1	2.7	2.5	1.1	2.2	1.5	3.8	2.3	3.2	93.3
STORJ	1.3	0.9	1.6	1.7	1.8	1.1	2.6	2.4	1.6	6.1	1.6	1.9	1.9	1.2	2.0	1.3	1.7	2.2	1.7	1.8	2.6	2.4	2.1	93.9
SYS	0.4	3.4	0.7	2.4	1.2	4.2	3.5	1.3	0.9	2.0	7.3	0.9	1.1	1.6	0.8	2.0	2.0	2.5	1.4	0.9	2.1	3.1	2.6	92.6
TRX	0.7	1.5	2.2	2.5	1.5	2.2	2.3	2.5	2.3	1.5	3.3	6.0	1.1	1.2	2.4	2.0	2.0	2.3	0.8	1.4	1.0	4.9	3.4	94.0
VGX	2.1	2.8	1.9	1.2	0.9	2.9	1.6	0.9	1.3	1.8	1.3	0.5	3.7	2.9	2.0	3.7	2.5	2.1	2.4	1.1	1.9	4.0	1.6	96.3
WAVES	1.9	1.5	1.1	2.3	0.7	2.1	1.5	0.9	1.6	1.3	2.1	1.2	1.5	6.3	1.1	0.8	1.7	1.8	0.7	1.1	1.6	2.1	0.7	93.7
XEM	1.4	1.1	1.9	2.5	1.0	2.3	3.2	0.6	0.7	3.4	2.5	1.4	1.3	1.5	4.3	3.0	1.6	2.2	2.5	2.6	1.4	2.9	1.6	95.7
XLM	0.8	1.9	0.9	3.2	1.3	1.8	1.9	1.1	1.4	1.9	2.8	1.1	1.6	1.0	2.3	5.9	3.8	1.4	2.7	1.4	1.0	3.0	2.4	94.1
XMR	2.1	2.2	0.9	2.7	0.6	2.2	2.1	1.6	0.9	1.4	3.4	1.7	1.4	0.9	2.2	4.1	5.9	2.2	2.3	1.7	1.6	2.7	3.4	94.2
XNO	1.8	1.3	1.5	1.8	1.0	2.2	2.5	1.2	1.2	3.7	2.3	2.1	1.3	1.1	1.3	1.7	1.8	4.8	2.2	1.6	2.7	2.9	2.4	95.2
XRP	1.1	2.5	1.9	3.5	1.6	2.4	2.5	0.9	2.5	1.2	3.4	1.3	1.1	1.5	2.6	3.9	2.1	1.7	4.1	2.5	1.2	2.8	2.2	95.9
XTZ	1.1	1.9	1.5	1.2	2.0	2.6	3.2	1.3	2.6	1.7	3.4	1.0	1.1	1.3	2.7	2.3	1.6	2.4	1.6	5.3	1.5	3.9	1.5	94.7
ZEC	1.5	2.2	2.5	1.5	2.3	2.5	0.7	2.7	2.9	1.0	3.0	1.4	1.7	2.3	0.9	2.4	2.7	1.9	2.1	2.9	4.9	2.4	3.4	95.1
ZEN	3.4	1.3	1.7	0.6	0.8	1.9	3.4	0.9	1.5	2.5	3.5	1.5	1.4	1.8	1.6	0.9	2.5	2.5	0.9	0.8	0.9	11.7	5.5	88.3
ZRX	1.7	1.7	2.1	4.3	1.6	2.2	3.1	1.5	1.4	1.2	1.5	1.1	1.4	1.8	2.3	2.5	2.4	2.0	1.7	3.7	1.4	2.7	3.0	97.0
Contribution to self and others	92.4	91.3	94.7	101.2	84.8	107.5	125.6	77.9	92.9	101.7	130.0	78.9	77.4	76.8	78.0	119.5	104.8	99.3	86.8	85.0	98.7	140.0	117.6	**Total spillover index**
Contribution to others	85.0	87.3	91.5	97.1	79.0	101.8	119.4	73.8	86.1	95.6	122.6	72.9	73.7	70.6	73.7	113.7	99.0	94.5	82.7	79.7	93.8	128.3	114.6	**94.9 %**
Net spillover	-7.6	-8.7	-5.3	1.2	-15.2	7.5	25.6	-22.1	-7.1	1.7	30.0	-21.1	-22.6	-23.2	-22.1	19.6	4.8	-0.7	-13.2	-15.0	-1.3	40.1	17.7	

Return spillover table 2020

Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	3.5	1.7	2.5	2.4	2.3	2.2	3.3	1.4	2.1	1.5	1.3	2.1	1.5	1.9	1.8	2.4	2.0	1.8	1.2	2.3	2.9	2.5	2.1	1.4	1.7	1.7	2.4	2.4	1.6	2.3	2.2	1.3	1.8	1.8	1.5	1.7	3.3	1.8	1.1	3.7	2.0	1.5	1.4	2.4	2.3	2.1	4.0	2.1	96.5
ANT	2.0	3.2	2.3	1.9	1.9	3.1	1.6	1.8	1.9	1.6	1.2	0.7	2.5	1.4	2.0	1.8	2.0	2.3	1.3	2.9	1.8	2.0	1.5	1.7	2.2	2.6	2.2	2.1	1.7	2.4	2.4	3.2	1.9	1.9	2.6	1.5	2.4	2.7	1.7	2.6	2.1	2.0	2.1	2.7	2.7	1.7	2.3	2.3	96.8
BAT	3.1	1.8	3.3	2.3	2.8	2.5	1.8	1.2	1.7	2.2	1.8	1.5	2.1	1.9	1.3	1.9	2.6	2.4	1.4	1.7	3.1	2.7	1.3	1.4	2.0	2.4	2.3	2.3	1.4	2.5	1.8	1.5	2.0	1.1	2.1	1.6	3.3	2.6	0.6	2.9	2.1	1.7	2.0	2.2	2.7	2.6	2.6	2.6	96.7
BCH	2.6	1.4	2.6	3.7	2.3	2.7	2.5	1.8	2.1	2.3	1.8	1.7	1.4	2.8	1.3	2.5	2.3	1.6	1.3	1.8	2.7	2.0	2.0	1.7	2.7	1.4	2.0	2.1	2.5	2.6	2.0	1.4	2.0	1.9	1.4	2.1	3.2	2.2	0.9	2.2	2.6	2.3	1.7	2.0	2.0	2.1	2.3	2.0	96.3
BNB	2.9	2.1	3.4	2.1	3.4	3.4	2.4	2.1	1.3	2.2	1.4	1.4	2.2	2.0	1.5	1.7	3.2	2.1	1.0	2.2	2.9	2.6	1.7	1.2	2.0	2.1	2.2	2.7	1.2	2.9	1.6	1.5	1.8	1.9	1.3	1.2	3.1	1.8	1.1	2.5	1.6	1.8	1.5	2.2	2.5	2.5	2.6	2.1	96.6
BTC	2.5	1.5	2.6	1.6	2.0	3.9	1.9	2.2	1.8	2.2	2.1	1.7	1.9	1.6	1.4	1.6	3.1	2.4	1.5	2.3	2.1	2.6	1.9	1.8	1.9	2.0	1.7	2.2	1.6	2.6	2.3	2.0	2.4	2.2	2.4	1.9	3.1	2.0	0.9	1.9	2.1	2.2	1.5	2.2	2.2	1.9	2.1	3.1	96.1
BTG	3.1	1.8	1.6	2.6	2.3	2.2	5.6	2.2	2.8	1.1	1.1	1.9	2.6	2.1	2.6	2.9	1.9	2.3	1.0	1.3	2.8	1.9	1.4	1.2	2.0	1.8	2.8	2.5	1.7	3.1	1.3	1.1	1.7	2.7	3.1	2.0	2.3	1.5	1.2	2.2	1.8	2.3	0.6	1.5	1.8	2.2	2.1	2.6	94.3
CVC	1.8	1.2	1.6	2.7	2.0	3.0	1.9	5.2	1.3	1.3	1.7	2.3	2.1	2.6	1.2	2.3	2.3	3.8	0.6	1.9	1.1	1.8	2.0	1.4	2.8	1.7	1.8	1.6	3.0	3.0	2.3	1.5	1.1	4.5	2.7	1.7	2.5	2.3	0.8	2.6	2.3	1.6	1.8	1.5	2.0	1.4	1.5	2.9	94.8
DASH	2.2	1.9	2.7	1.9	1.8	2.1	4.1	1.1	4.6	2.1	1.5	1.8	2.6	2.0	1.5	2.9	2.1	1.9	1.5	1.0	3.2	1.8	1.4	1.5	2.1	2.0	3.3	2.8	1.5	2.3	1.2	0.7	2.7	2.3	2.5	1.3	2.8	2.2	1.2	1.0	2.5	1.4	0.8	2.7	1.9	3.4	1.7	2.3	95.4
DCR	2.8	1.0	2.0	2.8	1.6	3.4	2.0	2.4	1.8	3.1	2.7	2.6	0.8	2.3	1.1	2.1	2.4	1.9	2.3	1.4	2.9	2.3	1.7	1.1	2.2	0.9	1.3	1.7	2.0	2.6	2.5	1.5	2.2	2.4	2.1	1.5	3.1	2.3	1.9	2.5	2.7	2.2	1.7	1.9	1.7	1.8	2.2	2.8	96.9
DGB	2.0	1.2	1.7	2.2	1.2	3.0	1.7	2.1	2.5	2.3	6.4	2.3	3.0	2.5	1.0	2.4	2.9	1.6	2.5	1.6	1.8	2.1	0.8	1.7	2.1	1.7	3.0	1.6	1.9	2.8	2.2	1.2	2.1	1.9	2.2	1.0	1.8	1.0	0.5	2.2	3.4	2.3	1.4	3.5	2.4	1.7	2.0	2.0	93.6
DOGE	3.0	1.2	1.9	2.0	1.5	3.3	2.0	2.7	1.8	2.2	2.0	3.1	1.5	2.5	0.7	2.2	3.1	2.2	1.1	2.0	1.6	2.3	2.5	1.7	1.4	1.1	1.6	1.4	1.5	1.8	2.2	2.3	3.0	1.3	2.4	2.8	3.4	1.5	0.7	2.5	2.5	1.9	1.3	2.6	3.7	1.4	3.6	2.2	96.9
ENJ	2.0	2.6	1.6	1.9	1.8	2.4	1.9	2.3	2.4	0.8	3.4	1.4	5.2	1.6	2.5	2.0	1.7	2.0	1.3	3.3	2.6	2.8	1.1	1.4	1.9	2.8	2.6	1.6	2.0	2.5	1.7	2.0	1.3	2.4	3.1	0.7	1.2	1.3	0.9	1.9	1.9	2.7	1.4	2.5	2.2	2.4	2.9	2.6	94.8
EOS	2.4	1.3	2.3	3.6	2.4	3.0	2.1	2.0	2.2	2.8	2.4	2.2	1.8	3.7	1.0	2.8	2.6	2.0	1.7	1.3	2.5	1.8	1.3	1.4	2.8	1.2	2.1	1.8	2.4	2.8	1.7	1.5	1.8	1.4	1.6	1.8	2.9	1.8	0.6	1.7	2.6	2.8	1.7	2.1	1.9	2.3	2.0	2.1	96.3
ERG	2.8	1.5	1.7	1.4	1.2	1.7	2.5	2.8	2.0	1.1	3.0	2.6	2.9	1.2	6.9	2.0	1.8	2.1	1.8	1.6	3.1	1.3	1.5	1.8	2.5	1.9	2.4	2.4	2.8	2.8	1.1	0.8	1.6	2.9	1.9	1.4	2.4	1.3	1.1	4.0	1.7	0.6	2.3	3.2	1.3	1.1	1.7	2.9	93.1
ETC	2.3	1.7	1.9	2.7	1.4	2.7	2.9	1.7	2.9	2.2	2.3	2.3	2.5	2.7	1.4	3.6	2.3	2.1	1.3	1.8	2.2	1.6	1.8	1.4	2.7	1.5	2.0	1.5	2.1	2.3	1.8	1.8	2.4	1.5	2.4	2.0	2.8	2.4	1.0	2.5	2.2	2.8	1.4	1.9	1.7	1.8	1.7	2.0	96.4
ETH	2.8	1.6	2.8	2.0	2.4	3.8	2.0	2.2	1.7	2.5	2.7	1.9	1.9	2.1	1.5	1.9	3.6	2.1	1.2	1.9	3.0	2.4	1.3	1.2	1.9	1.8	1.7	2.1	1.3	2.9	1.9	1.5	2.3	1.6	2.1	1.3	3.0	1.9	1.1	2.3	2.0	2.3	1.2	2.3	2.8	2.1	2.1	2.4	96.4
GLM	2.3	1.6	2.3	2.4	2.2	2.5	1.6	2.8	0.9	1.4	1.9	1.9	2.6	2.3	1.6	2.0	2.1	3.9	1.1	2.2	1.1	2.4	1.7	2.0	2.6	2.0	1.9	1.5	2.3	2.6	1.7	2.0	1.2	1.9	2.5	2.1	2.9	2.4	1.4	3.7	1.5	2.5	2.1	1.6	2.6	1.6	2.2	2.7	96.2
GNO	1.7	2.4	2.0	1.9	2.1	3.6	1.7	2.1	1.4	2.6	1.8	1.5	1.6	1.6	1.1	1.9	2.6	1.5	5.6	2.2	3.0	2.8	1.9	0.5	2.3	1.1	1.4	1.6	2.8	2.2	3.8	2.0	1.5	2.0	2.1	0.8	2.6	2.2	3.1	2.0	2.0	1.3	1.4	2.5	2.2	1.7	2.1	2.5	94.4
ICX	1.8	2.6	1.9	1.0	1.4	2.8	2.1	2.5	2.0	1.0	2.1	1.2	4.9	0.9	1.7	1.6	2.2	2.4	0.9	5.0	2.0	2.9	2.4	1.0	1.1	2.8	2.0	1.8	1.1	2.1	2.3	2.5	1.9	3.4	2.7	1.9	2.3	2.6	1.2	1.9	1.5	2.4	1.3	1.9	2.8	1.8	1.8	2.9	95.1
KCS	2.0	1.6	2.9	1.8	2.8	3.1	2.0	2.0	2.1	2.0	2.9	1.2	1.7	1.8	1.3	1.7	2.7	2.3	1.2	0.8	4.4	2.1	1.4	2.1	2.5	2.2	1.7	2.2	1.9	2.7	2.6	1.1	2.1	1.0	2.8	2.3	2.5	1.9	1.0	2.1	1.8	1.6	2.6	2.4	2.7	2.3	1.7	2.5	95.6
LINK	2.4	2.9	2.8	1.4	2.3	3.0	2.0	1.1	1.1	1.9	1.6	1.4	1.8	1.6	2.3	1.3	3.2	2.6	1.5	2.0	2.6	4.2	1.9	2.0	1.3	2.0	1.8	1.6	1.6	1.9	1.8	2.0	2.7	1.2	2.8	1.5	2.6	2.3	1.8	2.1	1.9	1.5	1.4	2.6	3.7	2.5	3.4	1.4	95.7
LRC	2.3	2.6	1.6	2.3	1.5	2.5	1.5	0.9	1.5	2.2	2.0	1.8	3.2	1.1	1.5	1.4	1.8	1.9	2.1	2.4	3.1	2.4	5.3	1.2	1.7	2.3	2.1	1.3	2.1	2.2	1.4	1.8	2.8	1.2	2.4	3.6	3.1	3.3	1.1	3.2	1.2	2.4	1.3	1.3	2.3	1.1	2.8	2.2	94.8
LSK	2.0	2.1	3.4	1.7	2.1	3.0	2.2	1.7	1.4	2.4	1.5	1.6	2.2	1.5	0.9	1.8	2.7	2.1	1.5	1.3	2.0	1.5	2.1	4.0	2.0	2.9	2.0	2.4	1.4	2.2	1.8	1.6	2.4	2.0	1.0	3.4	3.9	3.8	0.8	1.8	1.7	1.5	1.9	2.0	2.5	1.7	2.9	2.0	96.0
LTC	2.3	1.6	2.5	2.9	1.9	3.0	2.1	1.9	2.1	2.6	2.0	1.4	1.5	2.3	1.0	2.3	2.3	2.0	1.3	1.9	2.5	2.1	1.6	1.7	2.8	1.7	2.2	1.9	2.9	2.7	2.2	1.2	2.3	1.9	1.8	1.6	3.2	2.3	0.9	2.4	2.7	2.1	1.7	2.9	2.1	1.9	2.0	2.4	97.3
MANA	2.6	1.7	2.7	2.0	2.3	2.6	1.7	2.2	1.4	2.1	1.2	1.5	3.0	1.6	2.1	1.8	2.3	2.6	1.1	3.0	1.8	2.7	1.5	2.2	2.2	3.5	2.2	1.7	1.9	2.6	1.6	1.9	2.0	2.7	2.4	2.2	2.5	2.1	0.4	1.7	2.0	2.1	2.2	1.8	2.2	2.1	2.1	2.4	96.6
MIOTA	2.4	2.2	2.6	1.7	2.1	2.6	2.8	1.6	2.3	0.8	1.9	1.1	2.5	1.8	1.4	2.2	2.1	3.1	1.1	2.0	1.8	2.7	0.6	1.0	2.1	2.3	3.5	2.3	1.7	2.7	1.7	2.2	1.9	1.5	4.0	1.2	2.3	1.0	0.8	1.9	2.2	2.4	2.3	2.9	3.2	2.7	2.3	2.9	96.5
NEO	3.2	2.1	3.4	2.6	3.2	2.4	2.4	1.8	2.5	1.2	1.0	1.3	1.9	2.0	1.0	1.7	2.4	2.3	0.5	1.7	2.3	2.0	1.4	1.2	2.1	2.6	3.1	3.9	1.4	3.1	1.2	1.2	1.8	1.9	2.0	1.3	2.9	1.6	0.8	2.4	2.4	1.7	2.3	2.4	2.2	3.2	1.9	3.1	96.1
OMG	2.0	1.3	1.8	3.0	1.7	2.7	1.7	1.6	1.8	3.5	2.3	1.9	2.5	2.4	1.9	2.0	1.9	2.2	2.3	2.1	4.0	2.5	1.9	1.3	2.6	1.8	1.8	1.5	3.6	2.5	1.6	1.3	1.9	1.7	2.0	1.9	2.7	3.0	1.0	2.3	2.0	1.7	1.8	2.4	1.5	1.7	1.3	2.5	96.5
QTUM	2.8	1.8	2.5	2.9	2.7	3.0	1.8	2.6	1.8	1.4	1.8	1.5	2.8	2.2	0.6	1.9	2.5	2.4	0.5	2.3	2.4	1.6	1.3	1.2	2.4	2.6	2.6	2.5	1.9	3.6	1.7	1.9	1.7	2.3	2.2	1.2	2.5	1.6	0.5	2.5	2.2	2.6	2.4	2.1	2.1	2.0	1.5	3.1	96.5
REQ	1.7	1.6	1.5	2.0	1.2	3.1	1.4	2.5	1.7	3.1	1.2	2.1	1.4	1.7	0.9	2.3	2.5	1.5	3.2	2.5	2.6	1.7	2.3	2.1	1.9	1.6	0.7	0.9	1.6	1.6	7.1	3.2	2.8	2.6	1.7	3.0	2.7	3.3	2.4	1.7	2.1	2.4	2.0	1.1	1.7	1.6	1.7	1.4	93.0
RLC	1.8	3.0	2.1	1.7	2.0	2.7	1.7	1.1	1.6	2.6	1.7	1.3	2.4	1.8	1.8	2.3	1.7	1.9	2.6	3.6	2.5	2.9	1.0	2.4	2.1	3.2	2.4	1.7	1.3	1.8	2.9	4.0	2.2	1.7	1.6	1.2	1.8	2.3	1.8	1.2	2.1	2.1	2.1	1.7	2.3	1.5	3.4	1.6	96.0
SC	3.0	1.4	2.5	1.6	2.0	3.5	1.4	1.4	2.0	2.4	1.6	2.5	2.3	1.4	1.7	1.6	3.1	1.7	1.9	2.9	2.0	2.3	2.3	1.9	1.2	2.0	0.9	1.7	0.6	1.7	3.2	2.2	4.9	1.9	1.8	3.1	3.1	2.2	1.4	3.1	1.3	1.7	1.7	1.4	2.5	1.7	2.2	2.2	95.1
SNT	3.1	1.5	1.1	3.3	1.5	2.6	2.9	3.7	1.9	1.2	1.8	2.8	2.2	2.1	1.1	2.4	1.1	2.2	1.1	1.7	1.1	0.7	2.4	1.8	1.9	2.0	2.1	2.0	1.3	2.3	2.8	1.9	2.1	5.7	2.3	3.2	2.8	1.6	0.7	3.9	2.0	2.0	2.0	1.1	1.0	1.2	1.7	3.2	94.3
STORJ	2.2	1.6	1.9	1.8	1.3	2.7	2.6	1.9	2.4	1.9	1.4	1.6	4.0	2.0	1.4	2.4	2.2	2.8	1.8	2.0	1.6	2.0	1.4	2.1	1.8	2.5	2.2	1.5	1.7	2.3	1.9	3.0	2.1	2.2	5.3	1.4	2.3	2.2	1.5	2.3	1.6	2.4	1.1	1.8	2.6	1.6	1.7	2.3	94.7
SYS	1.7	0.7	2.5	2.6	1.5	2.0	0.8	1.4	2.6	3.0	2.7	2.0	2.1	3.0	1.1	1.9	2.2	1.4	2.0	1.1	2.7	1.3	2.5	2.5	2.1	1.4	1.5	1.3	2.3	1.3	1.6	1.3	3.0	1.4	1.9	5.0	3.8	3.2	1.0	2.2	3.5	2.1	2.0	1.9	2.5	2.4	1.6	2.5	95.0
TRX	2.7	1.6	3.1	2.2	2.2	2.8	2.1	1.6	2.2	2.2	1.7	2.0	1.4	2.0	0.9	2.0	2.6	2.2	1.1	1.5	2.1	2.1	2.6	1.6	2.1	1.9	2.1	2.4	1.4	2.4	2.1	1.2	2.5	0.9	2.0	2.8	4.1	2.9	0.6	3.2	2.1	2.0	1.6	2.0	2.5	2.5	2.0	2.6	95.9
VGX	1.7	1.3	2.5	1.7	2.1	1.9	0.9	1.6	2.2	1.3	1.3	1.7	3.9	2.0	2.2	1.4	2.1	1.7	1.2	2.2	2.3	2.4	2.4	2.5	1.9	2.4	2.1	2.1	2.3	2.2	1.7	1.2	1.2	1.4	1.6	2.9	3.2	4.8	1.1	4.1	2.4	1.8	2.3	2.5	2.3	2.9	1.8	1.6	95.2
WAVES	3.1	3.3	2.1	1.5	1.9	2.6	1.6	1.6	1.5	1.9	1.7	1.5	1.7	1.1	2.0	1.1	2.1	1.5	3.3	2.6	2.6	3.5	2.2	1.3	1.5	1.8	1.3	1.9	1.1	1.6	3.0	1.8	1.3	1.8	1.4	1.6	3.1	3.5	5.1	3.5	1.6	1.4	1.5	1.7	2.1	2.4	2.2	2.8	94.9
XEM	3.0	1.3	2.2	2.6	2.1	1.8	2.2	1.7	2.1	2.0	2.5	2.3	1.5	1.6	1.7	1.8	2.0	1.7	1.5	1.3	3.1	1.8	3.1	1.3	2.0	1.3	1.8	2.0	2.0	2.0	1.7	0.5	1.7	2.8	1.0	2.6	4.6	4.4	0.5	6.4	2.7	0.7	1.6	2.4	2.1	1.4	2.3	1.8	93.6
XLM	2.3	1.7	2.1	2.9	1.9	2.7	1.6	1.9	2.6	2.0	2.9	1.9	1.6	2.9	0.5	2.1	2.2	1.6	1.6	1.4	1.9	2.0	1.6	1.1	2.3	1.3	2.5	2.3	2.3	2.5	1.9	1.7	1.6	1.4	1.9	1.6	2.8	2.3	1.1	3.1	4.1	2.6	2.1	2.6	2.3	2.2	2.0	2.6	95.9
XMR	2.4	1.5	2.7	1.6	1.8	3.1	2.6	1.3	2.3	1.8	2.9	1.7	2.3	1.5	2.2	2.0	2.4	2.3	0.8	2.6	2.6	2.2	1.7	1.8	1.9	2.5	2.1	1.9	1.2	2.5	1.8	2.1	2.8	1.9	2.9	1.4	2.5	1.5	0.5	1.7	1.6	3.8	1.6	2.1	3.0	2.1	1.9	3.1	96.2
XNO	2.2	1.8	2.6	2.1	2.6	3.0	1.5	2.0	2.1	1.9	2.1	1.1	2.5	2.1	1.0	1.5	2.4	2.3	1.9	1.8	1.4	1.5	1.1	1.6	2.3	2.3	3.1	2.3	1.6	3.1	2.7	2.3	1.5	2.5	2.3	1.6	2.5	2.0	1.0	1.8	2.5	2.5	3.1	2.5	2.6	1.9	1.6	2.7	96.9
XRP	1.4	2.9	2.7	2.1	2.1	2.3	1.2	1.2	2.5	2.0	2.3	1.0	2.4	2.4	0.7	2.0	2.6	1.4	1.0	1.6	2.1	2.5	1.7	1.4	2.4	1.7	3.1	2.4	2.1	2.5	1.4	1.7	2.4	0.9	1.9	1.6	2.6	1.8	1.2	2.4	2.9	2.0	2.6	4.9	3.4	2.7	2.7	1.4	95.1
XTZ	2.4	2.4	2.6	2.2	2.2	2.6	2.3	1.4	1.5	1.9	1.4	1.1	2.6	1.8	1.5	1.7	2.4	1.8	1.6	1.9	3.4	2.7	1.1	1.8	1.9	2.0	2.6	1.8	1.3	2.3	2.8	2.1	1.7	1.7	2.4	1.2	2.6	1.6	0.8	2.2	2.1	2.5	1.9	3.2	3.8	1.9	3.8	1.5	96.3
ZEC	2.3	2.2	3.4	1.9	2.7	2.1	2.5	0.8	3.4	1.8	0.9	1.5	2.3	2.3	1.4	2.8	2.4	2.4	1.0	0.9	3.3	2.6	1.0	2.0	2.4	2.2	3.4	2.9	1.8	2.6	0.7	1.0	2.1	1.3	2.0	1.4	2.9	2.3	1.0	1.3	2.8	1.3	1.5	3.1	2.3	4.0	2.0	2.4	96.1
ZEN	2.4	2.1	1.7	1.5	1.3	2.2	2.5	1.8	1.7	1.4	2.3	1.9	2.9	1.3	2.3	1.7	1.6	2.2	1.2	2.6	4.1	3.0	1.8	1.7	1.2	1.4	2.1	1.3	1.3	1.9	2.5	1.7	2.1	1.8	2.0	2.4	2.5	1.9	1.2	3.8	2.0	2.3	1.3	2.5	2.7	1.6	4.9	2.6	95.1
ZRX	3.4	1.2	3.1	2.5	2.2	2.5	1.6	1.7	1.7	1.3	2.3	1.3	1.7	1.7	1.0	1.4	2.1	2.8	0.5	1.9	1.2	1.7	1.6	1.7	1.7	2.6	2.3	2.6	1.6	2.7	1.4	2.0	2.5	1.8	2.4	2.4	3.2	2.5	0.6	3.6	2.8	2.4	2.5	1.4	2.8	1.9	1.7	4.8	95.2
																																																	Total spillover
Contribution to self and others	116.2	88.2	113.0	105.0	97.1	131.3	101.1	92.5	96.8	94.3	97.3	83.9	111.7	94.6	74.0	96.9	112.1	103.0	73.7	97.1	117.3	107.0	85.7	78.8	98.6	95.9	103.9	95.5	87.3	116.4	100.6	84.1	100.7	95.8	105.9	92.9	135.3	108.7	55.3	122.1	104.9	97.9	84.9	108.2	114.3	97.7	108.6	116.2	**index**
Contribution to others	112.7	85.0	109.7	101.3	93.7	127.4	95.5	87.2	92.2	91.2	90.9	80.7	106.5	90.9	67.1	93.3	108.5	99.1	68.1	92.1	112.9	102.8	80.4	74.9	95.9	92.5	100.4	91.6	83.8	112.8	93.5	80.2	95.8	90.2	100.6	87.9	131.3	103.9	50.2	115.7	100.8	94.0	81.8	103.3	110.5	93.7	103.6	111.4	**95.6 %**
Net spillovers	16.2	-11.9	13.0	4.9	-2.9	31.3	1.1	-7.5	-3.2	-5.7	-2.6	-16.2	11.7	-5.4	-26.0	-3.1	12.1	3.0	-26.3	-2.9	17.3	7.0	-14.3	-21.1	-1.4	-4.1	3.9	-4.5	-12.7	16.4	0.6	-15.8	0.7	-4.1	6.0	-7.1	35.3	8.7	-44.7	22.1	4.9	-2.2	-15.1	8.2	14.2	-2.3	8.6	16.2	

Volatility spillover table 2020

Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	3.4	1.4	2.4	2.1	2.8	2.8	1.8	2.4	1.8	2.8	1.0	2.4	3.1	2.2	0.6	2.4	2.6	1.9	1.7	2.9	2.5	2.0	3.5	1.9	2.3	1.8	2.1	1.6	2.2	2.5	1.7	1.8	2.3	2.0	1.9	2.2	2.2	2.8	1.3	1.0	1.7	2.7	1.9	1.5	2.5	0.6	1.4	1.9	96.6
ANT	2.1	2.7	2.5	2.4	2.6	1.9	1.7	1.1	2.5	2.4	1.6	2.4	2.3	2.5	1.5	2.2	2.5	2.2	1.7	2.6	2.4	2.5	2.8	2.5	2.1	2.3	2.1	1.2	2.3	2.5	2.1	2.2	2.1	1.2	2.2	2.1	2.2	2.6	2.0	0.3	1.5	2.2	2.4	2.1	2.7	0.7	1.5	1.8	97.3
BAT	2.3	1.9	2.7	2.2	2.5	2.2	1.4	1.4	2.4	2.5	1.7	2.5	2.3	2.5	1.4	2.4	2.5	2.0	1.7	2.4	2.2	2.3	2.3	2.3	2.3	2.1	2.3	1.6	2.6	2.6	2.1	2.3	2.1	1.5	2.1	2.0	2.3	2.2	1.7	0.8	2.1	1.9	2.3	2.1	2.6	0.7	1.6	2.0	97.3
BCH	2.4	2.2	2.4	2.8	2.7	2.4	1.8	1.1	2.3	2.2	1.5	2.6	2.4	2.6	0.8	2.5	2.5	2.1	2.0	2.7	2.3	2.3	2.7	2.2	2.3	2.0	2.0	1.6	2.2	2.7	2.3	2.2	2.0	1.4	2.0	2.1	2.6	2.7	1.4	0.5	1.7	2.3	2.3	1.8	2.7	0.7	1.5	1.7	97.2
BNB	2.6	1.8	2.4	2.3	2.8	2.2	1.8	1.8	2.0	2.7	1.1	2.4	2.5	2.4	1.0	2.5	2.6	2.0	2.0	2.8	2.1	2.1	3.0	2.2	2.2	2.3	2.2	1.5	2.3	2.6	1.9	2.0	2.0	1.7	1.9	2.4	2.4	2.7	1.5	0.5	1.8	2.5	2.1	1.8	2.7	0.7	1.7	1.8	97.2
BTC	3.4	1.5	2.6	2.5	2.9	3.5	2.0	2.3	1.7	2.8	0.9	2.7	2.9	2.1	0.4	2.4	2.5	2.0	1.7	3.3	2.2	1.9	3.6	2.0	2.2	1.8	2.3	1.5	2.4	2.9	2.1	1.5	2.3	1.8	1.4	2.1	2.3	2.8	1.0	0.2	1.2	2.5	1.8	1.0	2.5	0.9	1.4	2.5	96.5
BTG	1.7	2.5	2.7	3.2	2.3	1.7	5.6	1.1	3.0	2.0	1.7	2.0	1.7	2.6	0.8	3.0	2.2	1.9	1.6	3.1	2.0	1.7	2.1	2.2	1.8	2.3	1.8	1.3	2.2	2.4	2.1	1.9	1.3	1.3	1.9	2.5	2.8	3.1	1.7	1.0	1.0	2.4	1.8	2.0	2.7	1.0	2.4	1.3	94.4
CVC	2.4	1.9	2.2	1.9	2.1	2.1	1.3	5.7	2.1	2.5	2.4	1.9	2.0	2.1	2.5	2.5	2.2	1.3	1.7	2.0	1.3	1.5	1.7	2.5	2.1	2.2	2.4	2.2	2.0	2.0	2.2	1.6	1.7	4.1	1.5	3.1	2.2	1.6	1.9	0.6	1.8	2.2	2.1	1.9	2.0	2.2	1.7	1.3	94.3
DASH	1.9	2.5	2.7	2.8	2.6	2.2	3.2	1.1	3.0	2.2	1.8	2.3	2.2	2.7	0.8	2.5	2.5	2.1	1.9	3.0	2.2	1.9	2.5	2.3	1.9	2.5	1.9	0.8	2.4	2.6	2.4	1.9	1.9	1.2	2.2	2.3	2.4	3.1	2.0	0.4	1.5	1.8	1.9	2.0	2.9	0.5	1.6	1.1	97.0
DCR	2.7	1.6	2.4	2.1	2.7	2.3	1.3	2.3	1.9	3.0	1.3	2.3	2.7	2.3	1.4	2.4	2.7	1.8	1.9	2.6	1.9	2.2	3.0	2.4	2.2	2.3	2.0	1.9	2.3	2.5	1.8	2.1	2.0	2.0	2.0	2.7	2.3	2.0	1.8	0.5	1.8	2.6	2.3	1.8	2.6	0.7	1.4	1.8	97.0
DGB	1.4	2.9	2.8	2.5	2.3	1.6	1.2	0.8	3.2	1.8	5.1	2.0	2.5	2.4	1.9	1.5	1.9	3.0	1.5	3.0	1.8	2.0	1.9	2.7	1.9	1.8	2.1	1.2	2.1	2.5	2.4	2.3	2.0	1.2	2.8	1.7	2.0	2.3	3.3	0.5	1.6	1.1	2.7	2.3	2.7	0.7	2.1	1.4	94.9
DOGE	2.2	2.3	2.4	2.3	2.7	2.1	1.0	1.2	2.4	2.3	1.7	2.7	2.5	2.5	1.5	2.3	2.6	2.3	2.0	2.4	2.0	2.5	2.1	2.5	2.5	2.2	2.4	1.4	2.4	2.7	2.6	2.3	2.1	1.2	2.4	1.7	2.5	2.2	1.8	0.5	1.8	2.0	2.6	2.3	2.6	0.6	1.2	1.8	97.3
ENJ	2.8	1.7	2.7	2.2	2.8	2.3	1.8	2.2	1.8	2.9	1.1	2.4	3.1	2.2	0.6	2.3	2.6	2.2	1.7	3.2	2.5	1.8	3.5	2.2	2.2	1.9	2.4	1.6	2.1	2.6	1.9	1.7	2.1	1.5	2.0	2.3	2.2	2.3	1.5	0.5	1.5	2.7	2.1	1.4	2.6	0.6	1.8	2.1	97.0
EOS	2.4	1.9	2.2	2.5	2.6	2.2	1.6	1.4	2.4	2.3	1.4	2.4	2.3	2.7	1.1	2.7	2.5	2.0	2.2	2.2	2.0	2.5	2.4	2.2	2.3	2.4	1.9	1.6	2.5	2.5	2.1	2.3	2.0	2.0	2.1	2.3	2.5	2.3	1.8	0.7	2.1	2.1	2.2	2.3	2.7	0.7	1.3	1.6	97.3
ERG	2.1	1.6	2.6	1.8	2.4	2.2	1.4	2.5	1.7	3.1	1.4	2.0	2.2	2.1	4.4	2.2	2.6	1.9	1.6	2.2	1.6	1.9	2.2	2.6	1.8	2.6	2.0	2.0	2.1	2.2	2.0	2.0	1.4	2.2	2.4	3.0	2.2	2.0	2.2	0.5	2.1	2.3	2.2	2.5	2.4	0.8	1.7	1.7	95.7
ETC	2.4	1.7	2.5	2.5	2.6	2.2	1.8	1.7	2.4	2.4	1.3	2.5	2.2	2.7	0.8	3.0	2.6	2.0	2.0	2.3	2.0	2.3	2.4	2.2	2.2	2.4	2.1	1.7	2.6	2.6	2.0	2.3	2.0	1.7	2.0	2.4	2.7	2.2	1.5	0.5	1.9	2.3	2.1	2.1	2.7	0.6	1.5	1.7	97.0
ETH	2.3	1.8	2.3	2.1	2.5	2.2	1.6	1.7	2.4	2.6	1.3	2.5	2.2	2.5	1.9	2.5	2.7	1.8	2.2	2.2	2.0	2.3	2.5	2.4	2.3	2.6	2.2	1.3	2.5	2.4	2.2	2.1	2.2	1.8	2.0	2.2	2.3	2.2	1.7	0.7	2.0	2.0	2.2	2.4	2.6	0.8	1.4	1.5	97.3
GLM	2.2	2.4	2.3	2.3	2.5	1.8	1.9	1.1	2.5	2.1	1.6	2.3	2.3	2.4	2.3	2.2	2.2	3.2	2.1	2.5	1.9	2.3	2.1	2.4	2.2	2.0	2.2	1.6	2.5	2.6	2.0	2.1	1.7	0.8	2.9	1.4	2.4	1.8	2.1	0.7	1.9	1.9	2.4	2.9	2.5	0.7	1.7	2.4	96.8
GNO	2.5	1.3	1.8	2.1	2.6	2.5	1.4	1.9	2.7	2.1	1.2	2.6	2.4	2.4	1.0	2.5	2.4	1.8	4.2	1.7	1.7	2.4	2.5	1.9	2.8	2.6	1.5	1.3	2.5	2.2	2.2	2.4	2.4	2.8	2.2	1.8	2.2	1.8	2.3	1.7	2.6	1.7	1.6	2.4	2.5	1.3	0.5	1.3	95.8
ICX	2.6	1.7	2.3	2.3	2.5	2.4	1.9	2.2	2.1	2.6	2.0	2.3	2.6	2.3	0.9	2.6	2.5	1.9	1.9	2.7	1.9	2.1	2.9	2.1	2.1	2.0	1.9	1.8	2.3	2.6	1.9	2.1	1.9	2.3	2.0	2.8	2.4	2.2	1.8	0.4	1.7	2.5	2.2	1.7	2.7	0.8	1.2	1.7	97.3
KCS	2.4	2.1	2.6	2.4	2.7	2.4	1.8	1.6	2.0	2.6	1.2	2.7	2.4	2.5	0.9	2.5	2.9	1.9	1.6	2.7	3.1	2.0	2.7	2.1	2.3	2.3	2.3	1.3	2.2	2.6	2.4	1.8	1.8	1.5	1.9	1.8	2.3	3.7	1.0	0.9	1.4	2.4	2.1	1.6	2.6	0.8	1.3	1.9	96.9
LINK	2.6	2.0	2.5	2.2	2.7	2.3	2.1	1.3	2.2	2.6	1.3	2.5	2.4	2.4	1.2	2.3	2.6	2.1	1.8	2.9	2.6	2.4	3.1	2.3	2.0	2.5	2.0	1.1	2.4	2.6	2.0	1.8	2.3	1.6	1.9	1.8	2.2	3.1	1.8	0.6	1.3	2.2	2.1	1.7	2.6	0.8	1.1	2.2	97.6
LRC	2.3	2.3	2.3	2.1	2.4	2.0	1.3	1.7	2.3	2.2	2.3	2.3	2.4	2.3	2.5	2.0	2.3	2.2	2.1	2.4	1.7	2.5	2.9	2.4	2.0	1.8	1.8	1.7	2.2	2.4	1.9	2.5	2.0	1.8	2.4	1.9	2.2	1.8	2.3	0.8	1.8	2.1	2.4	2.2	2.6	1.1	1.5	1.7	97.1
LSK	2.0	2.0	2.6	2.2	2.5	1.9	2.2	1.6	2.2	2.7	1.6	2.3	2.3	2.3	1.4	2.4	2.5	2.0	1.8	2.8	1.8	2.1	2.8	2.6	2.0	2.4	2.2	1.6	2.3	2.5	2.0	2.1	2.0	1.7	1.9	2.8	2.3	2.2	2.0	0.6	1.6	2.2	2.2	1.9	2.6	0.8	1.9	1.7	97.4
LTC	3.0	1.6	2.4	2.3	2.9	2.6	1.4	2.0	2.0	2.8	1.0	2.6	2.9	2.2	1.1	2.3	2.6	2.2	2.2	2.7	2.2	1.9	3.4	2.3	2.5	2.1	2.2	1.5	2.3	2.6	2.1	1.8	2.3	1.7	1.8	2.1	2.3	2.2	1.4	0.4	1.5	2.5	1.8	1.6	2.5	0.9	1.5	1.9	97.5
MANA	1.9	2.0	2.2	2.1	2.5	1.8	1.7	2.0	2.6	2.5	1.7	2.2	1.8	2.6	2.4	2.5	2.6	1.7	2.4	1.9	1.7	2.5	2.4	2.6	2.1	3.2	1.9	1.3	2.5	2.2	2.2	2.1	2.1	2.0	1.9	2.6	2.3	2.1	2.3	0.4	1.9	1.9	2.1	2.7	2.5	1.1	1.5	1.2	96.9
MIOTA	2.4	2.0	3.1	2.2	2.8	2.3	2.8	2.3	1.6	3.2	0.7	2.4	2.7	2.1	0.7	2.5	2.7	2.1	1.0	3.7	2.5	1.5	3.2	2.5	1.9	2.1	2.9	1.3	2.2	2.7	2.0	1.3	1.9	1.2	1.8	2.5	2.3	2.8	1.0	0.4	1.0	3.0	2.2	1.1	2.6	0.3	2.3	2.3	97.1
NEO	2.7	1.3	2.4	2.4	2.5	2.5	2.3	1.8	1.6	2.7	1.0	2.2	2.4	2.4	0.6	2.8	2.7	1.8	1.8	3.1	1.9	2.0	3.1	2.1	1.9	2.0	1.8	2.8	2.3	2.6	1.6	2.1	1.7	1.8	1.8	2.8	2.6	3.0	1.4	1.1	1.5	2.8	2.0	1.4	2.8	0.6	2.0	1.8	97.2
OMG	2.2	1.6	2.4	2.3	2.5	2.1	2.0	1.7	2.4	2.5	1.4	2.4	2.0	2.5	0.9	2.8	2.4	2.4	2.2	2.1	1.8	2.4	2.5	2.4	2.1	2.6	2.1	1.7	3.2	2.6	1.8	2.3	2.5	2.0	2.0	2.3	2.3	1.7	1.8	0.4	1.7	1.8	2.0	2.2	2.6	0.6	1.4	2.3	96.8
QTUM	2.3	2.0	2.3	2.4	2.7	2.1	1.3	1.3	2.5	2.3	1.7	2.5	2.4	2.6	1.2	2.4	2.5	2.4	2.1	2.4	1.9	2.4	2.2	2.4	2.4	2.2	2.3	1.6	2.5	2.7	2.2	2.3	2.1	1.2	2.4	1.9	2.5	2.0	2.0	0.5	1.9	2.1	2.4	2.4	2.7	0.6	1.3	1.9	97.4
REQ	1.9	2.5	2.2	2.2	2.5	2.4	0.9	1.3	2.8	2.1	1.9	2.9	2.3	2.5	1.5	2.0	2.7	1.9	2.5	2.4	2.0	2.7	1.9	2.5	2.5	2.6	2.3	1.0	2.3	2.6	3.4	2.0	2.5	1.2	2.0	1.5	2.3	2.8	2.0	0.6	1.9	1.5	2.4	2.2	2.6	1.0	1.0	1.4	96.6
RLC	2.7	1.8	2.2	2.4	2.5	2.2	1.0	1.4	2.2	2.3	1.9	2.5	2.5	2.5	1.2	2.4	2.5	1.9	2.1	2.2	2.0	2.4	2.9	2.1	2.4	1.8	1.8	2.0	2.2	2.5	1.9	2.8	2.1	1.9	2.1	2.2	2.4	2.1	1.7	0.7	2.3	2.3	2.1	2.1	2.6	1.3	1.4	1.6	97.2
SC	2.4	1.7	2.2	1.8	2.4	2.5	1.1	1.9	2.4	2.3	1.8	2.6	2.3	2.3	1.1	2.1	2.4	2.0	2.3	1.9	1.8	2.5	2.1	2.3	2.5	2.4	2.5	1.7	2.8	2.5	2.4	2.2	3.2	2.0	1.7	1.7	2.0	2.2	1.7	1.5	3.0	1.4	2.3	2.2	2.3	0.7	1.4	2.1	96.8
SNT	2.6	2.1	2.3	2.3	2.8	2.6	1.3	2.1	2.2	2.5	1.2	2.6	2.6	2.5	1.0	2.5	2.7	1.9	2.1	2.5	2.2	2.4	2.5	2.2	2.4	2.4	2.1	1.4	2.2	2.6	2.5	1.8	2.0	2.4	2.1	2.1	2.5	2.5	1.6	0.4	1.8	2.3	2.2	1.8	2.7	0.4	0.9	1.6	97.6
STORJ	2.3	2.0	2.2	2.2	2.6	2.1	1.5	1.7	2.4	2.3	1.6	2.2	2.6	2.4	1.5	2.3	2.4	2.4	2.4	2.5	1.9	2.2	2.5	2.2	2.3	2.1	1.8	1.4	2.2	2.4	2.0	2.2	1.7	1.8	2.7	2.1	2.4	1.9	2.3	1.1	2.1	2.2	2.2	2.3	2.6	1.1	1.0	1.6	97.3
SYS	2.7	1.6	2.1	2.2	2.2	2.5	2.9	3.0	2.0	2.8	1.6	1.8	2.1	2.2	2.7	2.8	2.3	1.3	2.0	2.1	1.2	1.5	3.2	2.3	1.8	2.3	1.9	1.6	2.1	2.0	1.9	2.0	1.6	4.1	1.5	4.3	2.2	1.6	1.9	0.4	1.9	2.5	1.9	1.8	2.3	0.8	2.0	0.9	95.7
TRX	2.4	2.0	2.3	2.5	2.6	2.2	1.6	1.4	2.3	2.3	1.6	2.4	2.3	2.5	1.1	2.6	2.5	2.1	2.1	2.5	1.9	2.4	2.3	2.3	2.4	2.2	2.1	1.7	2.3	2.6	2.2	2.3	1.8	1.5	2.3	2.1	2.7	2.3	1.8	0.9	1.9	2.3	2.3	2.3	2.7	0.7	1.4	1.6	97.3
VGX	2.6	2.0	2.4	2.3	2.6	2.6	2.0	1.5	2.3	2.5	1.2	2.4	2.4	2.5	1.2	2.3	2.6	1.7	2.1	2.9	2.3	2.3	3.3	2.1	2.0	2.5	1.8	1.0	2.3	2.5	2.2	1.8	2.2	1.5	1.9	2.3	2.3	3.5	1.6	0.3	1.7	2.2	2.1	1.9	2.7	0.7	1.2	1.5	96.5
WAVES	1.8	2.1	2.2	2.0	2.3	1.7	3.9	1.6	2.5	2.5	2.0	1.8	2.3	2.2	2.3	2.3	2.1	2.2	2.1	2.5	1.8	2.3	2.6	2.4	2.0	2.5	1.7	1.2	2.1	2.1	1.8	2.1	1.7	1.3	2.8	3.3	2.1	1.8	3.4	0.9	1.5	2.2	2.3	2.3	2.5	0.7	1.1	1.4	96.6
XEM	2.0	1.9	1.2	1.7	1.9	2.2	1.3	2.2	2.0	2.0	1.0	2.1	1.3	2.1	2.2	2.8	2.4	1.4	3.5	1.2	1.0	2.6	2.0	1.8	1.9	3.6	1.3	1.3	2.6	1.8	2.0	2.0	2.2	3.5	1.7	3.1	2.1	1.8	2.0	4.7	2.4	2.2	1.5	2.2	2.0	2.2	3.3	1.0	95.3
XLM	2.5	1.7	2.1	2.2	2.4	2.7	1.3	1.4	2.5	2.2	2.0	2.4	2.5	2.5	0.9	2.3	2.5	1.9	2.1	2.4	1.7	2.3	2.1	2.1	2.3	2.2	2.0	1.5	2.2	2.4	2.6	2.3	2.1	2.0	2.2	2.1	2.4	2.5	1.9	1.1	2.9	2.0	2.2	2.4	2.6	0.9	1.6	1.2	97.1
XMR	3.0	1.5	2.6	2.3	2.8	2.2	3.3	2.2	1.5	2.9	0.8	2.2	2.6	2.1	0.9	2.9	2.5	2.1	1.6	3.3	1.9	1.5	3.8	2.0	1.9	1.9	2.2	1.5	2.1	2.5	1.4	1.6	1.6	1.6	1.9	2.6	2.5	2.4	1.1	0.8	1.4	3.7	1.9	1.4	2.5	0.9	2.2	2.0	96.3
XNO	2.3	2.2	2.4	2.2	2.6	2.2	1.3	1.4	2.2	2.4	1.8	2.4	2.6	2.4	1.5	2.1	2.4	2.2	1.9	2.6	2.0	2.5	2.4	2.4	2.3	2.1	2.3	1.5	2.2	2.6	2.2	2.1	2.1	1.5	2.4	2.0	2.4	2.2	2.0	0.7	2.0	2.1	2.7	2.1	2.6	0.4	1.4	2.0	97.3
XRP	2.5	1.7	1.9	2.5	2.5	2.2	1.7	1.4	2.3	2.2	1.5	2.1	2.1	2.6	1.3	2.6	2.4	2.1	2.4	2.1	1.7	2.4	2.5	2.1	2.2	2.3	1.7	1.7	2.5	2.4	1.8	2.5	1.8	1.9	2.3	2.4	2.7	2.1	1.8	0.9	2.4	2.4	2.0	2.9	2.6	0.8	1.8	1.3	97.1
XTZ	2.1	2.2	2.3	2.3	2.6	1.9	1.3	1.1	2.6	2.3	1.8	2.4	2.4	2.6	1.5	2.3	2.5	2.3	2.2	2.4	2.0	2.5	2.2	2.5	2.4	2.4	2.1	1.4	2.4	2.6	2.3	2.3	2.1	1.2	2.6	1.9	2.5	2.1	2.3	0.5	1.9	2.0	2.5	2.5	2.7	0.6	1.2	1.5	97.3
ZEC	2.2	2.1	2.2	2.7	2.4	2.6	4.2	1.3	2.7	1.9	2.2	2.4	2.1	2.3	0.9	2.2	2.2	2.4	2.6	2.8	1.8	2.1	2.4	1.9	1.9	2.0	1.8	1.1	2.4	2.6	2.5	1.7	2.1	1.5	2.0	1.7	2.3	3.3	1.9	0.7	1.4	1.5	2.0	1.7	2.6	1.7	1.3	1.8	98.3
ZEN	2.3	2.0	2.9	2.4	2.6	2.2	3.0	1.8	2.3	2.6	1.5	2.1	2.7	2.2	0.9	2.3	2.3	2.0	1.4	3.2	2.1	1.4	3.1	2.3	2.0	1.8	2.5	1.5	2.0	2.4	1.7	1.8	2.0	1.2	2.1	2.7	2.3	2.2	1.8	0.5	1.5	2.7	2.1	1.4	2.5	0.3	4.1	1.5	95.9
ZRX	2.5	1.7	2.3	2.1	2.5	2.6	2.4	2.1	1.6	2.9	1.0	2.4	1.9	2.1	1.0	2.7	2.5	2.3	1.5	2.5	2.0	2.6	2.6	2.4	1.9	2.8	2.2	1.8	2.9	2.7	2.0	1.6	2.2	2.1	1.7	2.4	2.3	2.6	1.3	0.9	1.3	2.1	2.2	1.7	2.4	0.5	1.1	3.4	96.6
																																																	Total spillover
Contribution to self and others	114.3	92.4	113.6	109.7	122.5	108.2	92.3	85.0	108.4	118.0	75.3	112.9	113.4	114.5	65.2	116.4	118.9	97.8	97.0	122.2	94.3	104.4	126.2	109.1	103.7	108.7	99.1	72.6	112.5	119.2	100.9	98.3	96.8	86.4	99.6	109.6	112.4	113.0	87.0	35.7	86.1	106.4	103.2	96.2	123.5	39.5	75.5	82.5	**index**
Contribution to others	111.0	89.7	110.9	106.8	119.8	104.7	86.7	79.3	105.4	115.0	70.2	110.1	110.4	111.8	60.9	113.5	116.1	94.6	92.9	119.4	91.2	101.9	123.3	106.5	101.3	105.5	96.2	69.8	109.3	116.5	97.5	95.5	93.6	84.0	96.9	105.3	109.7	109.5	83.6	31.0	83.2	102.7	100.4	93.3	120.8	37.8	71.5	79.1	**96.8 %**
Net spillover	14.3	-7.7	13.6	9.7	22.5	8.2	-7.7	-15.0	8.4	18.0	-24.7	12.9	13.4	14.5	-34.8	16.5	18.8	-2.2	-3.0	22.2	-5.7	4.3	26.2	9.1	3.8	8.6	-0.9	-27.4	12.5	19.2	0.9	-1.8	-3.2	-13.6	-0.4	9.6	12.4	13.0	-13.0	-64.3	-13.9	6.4	3.2	-3.9	23.5	-60.5	-24.5	-17.6	

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Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	3.7	1.1	2.2	2.9	2.3	1.8	1.8	2.5	2.3	1.6	2.3	1.9	2.3	2.9	1.6	2.1	2.4	1.8	1.4	1.6	2.2	3.0	2.5	2.2	3.0	2.6	2.3	2.3	2.2	2.6	1.4	2.4	2.0	1.6	0.3	1.7	1.6	1.1	1.3	1.6	2.7	2.3	2.4	2.8	1.3	2.1	1.6	2.7	96.4
ANT	2.1	5.9	1.7	1.8	2.0	1.9	2.4	2.7	3.1	4.1	2.8	1.3	2.5	2.0	1.8	1.7	1.4	1.5	1.5	2.1	2.4	1.7	1.0	1.7	2.6	1.2	2.4	2.1	2.9	2.2	2.0	2.0	1.9	1.4	0.9	1.6	2.6	1.5	1.4	1.5	2.0	2.7	2.6	2.5	1.6	1.8	2.2	1.8	94.1
BAT	1.5	1.7	3.7	2.1	1.8	1.3	2.0	1.9	2.9	2.1	1.6	1.8	2.1	2.2	3.1	3.1	1.7	1.3	2.6	2.1	1.7	2.6	1.8	1.4	2.5	2.2	1.9	2.1	2.8	3.0	0.9	1.8	2.0	1.7	0.6	1.8	1.5	2.0	2.3	2.3	2.6	1.8	1.2	2.5	2.4	2.0	2.3	3.3	96.3
BCH	1.3	0.8	1.4	3.4	2.0	1.5	2.4	2.3	2.7	1.4	2.5	1.7	1.8	2.8	1.6	3.0	2.9	1.5	1.7	1.5	2.0	2.7	1.9	2.1	3.3	1.6	1.8	2.8	3.4	2.8	1.3	1.4	1.7	1.8	0.6	1.5	1.7	1.6	1.7	1.6	2.7	2.6	2.4	2.8	2.5	3.1	2.2	2.5	96.6
BNB	1.4	1.3	1.7	2.7	3.1	1.8	2.5	2.1	2.9	1.7	2.5	1.4	1.9	2.5	2.1	2.8	2.8	1.7	1.3	2.3	2.2	2.5	1.3	2.3	3.0	2.1	2.1	2.5	2.4	2.7	0.9	2.0	1.9	1.9	1.3	1.1	2.0	0.9	1.4	2.1	2.1	2.9	2.0	2.8	1.9	2.5	2.4	2.5	96.9
BTC	2.1	1.0	1.5	2.5	1.9	3.5	3.0	1.7	2.0	1.4	2.3	1.1	2.5	2.7	1.6	2.5	2.8	1.2	1.4	1.9	2.4	2.8	2.0	1.8	2.9	1.3	2.1	3.4	2.6	2.3	1.0	1.5	2.4	1.6	0.6	1.0	1.9	1.3	1.8	2.1	3.0	2.4	2.8	2.7	3.4	2.1	2.6	2.1	96.5
BTG	1.7	1.2	1.3	2.6	1.9	2.1	3.5	1.8	2.9	1.4	2.1	1.1	2.1	2.7	2.7	2.8	2.7	1.2	1.4	1.9	2.6	2.7	2.1	1.8	3.1	1.7	2.2	2.6	2.2	2.7	1.5	1.8	1.9	1.9	0.8	1.0	2.3	1.3	1.3	1.9	2.6	2.9	2.0	3.1	2.9	2.0	2.0	2.1	96.5
CVC	2.0	1.3	2.6	2.5	2.7	1.9	2.5	2.9	2.4	1.4	2.7	1.0	2.4	2.5	1.2	2.1	2.8	2.1	1.1	2.3	2.6	2.6	1.2	2.6	2.6	2.6	1.8	2.8	2.0	2.1	1.0	2.3	2.6	1.7	0.5	1.6	2.0	1.3	1.0	2.4	2.8	2.4	2.6	2.3	1.9	1.7	1.7	2.8	97.1
DASH	1.4	1.7	1.7	3.0	2.1	1.6	2.9	1.9	3.2	2.4	2.7	1.7	1.7	3.0	1.5	3.1	2.2	1.5	1.0	1.7	2.3	2.5	1.9	2.4	3.2	1.6	1.8	2.7	3.0	3.4	0.6	1.7	1.8	2.0	0.7	0.9	1.7	1.0	1.3	1.9	2.4	2.8	1.6	3.0	2.3	3.2	1.8	2.5	96.8
DCR	1.5	3.2	1.5	2.1	1.6	2.0	2.7	1.9	2.6	3.5	2.6	2.5	2.6	1.9	2.8	2.6	2.0	1.5	2.2	1.2	1.6	1.8	1.4	2.2	2.6	1.2	2.1	2.2	2.4	2.5	1.5	1.6	2.3	1.3	1.2	1.8	1.5	1.8	2.2	1.6	1.8	2.7	1.9	2.6	2.8	2.5	2.7	2.0	96.5
DGB	1.1	1.3	1.0	2.9	2.5	2.0	2.9	1.5	2.7	1.8	3.7	1.1	2.7	2.3	2.2	2.5	2.6	1.0	1.0	1.6	2.3	2.2	1.6	2.6	3.4	1.0	1.8	3.0	3.0	2.6	1.2	1.7	1.8	1.9	0.7	1.4	1.7	0.8	1.7	1.3	2.2	3.5	3.1	2.8	2.8	3.0	2.5	1.9	96.3
DOGE	1.3	0.6	1.3	3.2	2.5	1.5	2.7	2.2	2.8	2.9	2.9	3.7	1.5	2.9	1.5	2.5	2.4	0.9	1.6	1.0	1.9	2.6	3.0	2.0	3.4	1.9	1.5	2.7	3.1	2.5	1.7	2.2	1.6	1.3	0.6	1.0	1.3	2.0	1.8	1.3	1.7	3.2	2.9	2.3	2.6	2.9	1.5	1.8	96.4
ENJ	1.6	1.7	1.4	2.6	1.6	2.0	2.3	1.6	2.9	2.3	3.1	1.1	3.8	2.0	2.3	3.2	2.3	1.0	2.1	2.0	1.9	2.2	1.7	1.6	3.0	1.6	1.7	2.3	2.8	2.5	0.4	1.9	2.5	2.2	1.3	2.7	1.2	0.9	1.2	1.5	2.3	3.1	2.6	2.4	2.2	2.8	2.4	2.3	96.2
EOS	1.6	1.1	1.3	3.5	2.0	1.7	2.8	1.5	2.7	2.1	2.5	1.6	1.9	3.6	1.4	2.6	2.3	1.2	1.0	1.5	2.6	3.1	2.2	2.0	3.9	1.5	1.6	3.0	3.3	3.1	0.6	1.5	1.4	1.8	0.6	1.5	1.7	1.1	1.4	1.8	2.8	2.6	2.2	3.8	2.4	2.7	1.8	2.3	96.4
ERG	2.2	2.0	2.2	2.5	1.7	1.1	1.8	1.5	2.9	1.8	2.2	0.5	2.4	2.4	5.1	2.9	2.6	1.4	2.2	1.5	1.2	2.9	1.3	2.0	3.3	1.8	2.7	1.9	3.0	3.0	0.6	2.9	2.1	1.9	0.9	1.6	0.7	0.6	1.3	2.1	2.5	2.8	1.3	2.5	2.4	2.7	2.8	2.8	94.9
ETC	1.6	1.0	1.8	2.8	1.9	1.7	2.8	1.7	3.0	2.0	2.7	1.8	1.8	2.7	2.1	3.4	2.9	1.0	1.8	1.3	2.3	2.7	1.7	1.9	3.2	1.5	1.7	2.6	3.3	3.2	0.6	1.7	1.8	1.5	0.9	1.5	1.5	1.5	1.3	1.8	2.0	2.6	2.0	3.0	2.5	3.0	2.5	2.6	96.6
ETH	1.9	1.2	1.0	3.4	2.0	2.3	3.0	1.6	2.8	1.3	2.8	0.9	2.1	3.0	1.9	2.8	3.5	1.5	1.1	1.1	2.2	2.9	1.7	2.1	3.7	1.3	2.4	2.9	2.8	2.4	1.1	1.4	1.5	1.4	0.6	1.5	2.0	1.4	1.1	1.5	2.2	3.2	2.3	3.4	2.3	2.9	2.6	2.1	96.5
GLM	2.1	1.2	1.9	2.7	1.8	1.9	2.3	2.5	3.1	0.8	1.8	1.2	2.0	2.8	2.0	2.9	1.9	3.9	0.9	1.8	1.6	2.0	1.7	2.8	2.7	2.2	3.8	2.3	2.3	3.0	0.9	1.3	1.4	2.8	1.7	1.2	2.0	1.3	1.3	2.2	2.5	2.8	1.2	2.7	1.8	3.0	1.8	2.3	96.1
GNO	1.7	0.9	2.3	3.0	1.9	2.0	1.7	1.9	1.9	1.8	1.9	2.6	1.7	2.7	2.9	3.6	2.3	1.1	5.0	1.9	1.4	2.5	3.3	1.7	2.3	1.3	2.4	2.0	2.1	2.5	0.6	1.1	1.9	2.4	1.4	1.2	1.6	1.8	1.3	2.1	2.1	1.9	1.9	2.2	1.2	3.5	3.1	3.1	95.0
ICX	1.5	1.1	1.9	2.9	2.6	2.1	2.8	1.6	2.2	1.4	2.2	1.0	2.4	2.9	1.3	2.8	2.5	1.4	1.9	2.9	2.9	3.0	2.2	2.2	3.0	1.2	1.4	2.9	2.1	2.6	0.4	2.0	2.0	2.0	1.0	1.6	2.3	1.0	1.2	2.2	3.3	2.1	2.3	3.0	2.1	2.3	2.2	2.6	97.1
KCS	2.1	1.9	2.0	2.5	2.5	2.2	3.0	1.4	2.3	1.6	2.3	0.9	1.8	2.5	2.3	2.3	3.1	1.4	1.3	2.3	3.7	2.7	1.6	1.8	3.0	1.4	2.0	2.7	2.4	2.3	1.0	2.1	1.8	1.8	0.8	0.8	2.3	1.3	1.4	2.0	2.4	2.5	2.0	3.2	2.3	2.2	2.5	2.4	96.3
LINK	2.0	1.4	1.6	3.0	1.9	2.0	2.6	1.2	2.4	1.3	2.2	1.5	2.3	2.9	2.3	3.0	2.7	0.8	1.6	1.7	2.1	3.2	2.4	1.6	3.3	1.1	2.0	2.6	3.2	2.9	0.9	1.9	1.8	1.6	0.4	1.6	1.7	1.7	1.2	1.8	2.8	2.6	2.5	3.0	2.6	2.6	2.3	2.3	96.8
LRC	1.4	1.2	2.6	2.6	1.9	1.3	1.6	1.1	1.8	2.1	1.9	3.1	1.9	2.6	2.0	3.2	2.2	1.1	2.5	1.7	2.2	2.8	4.7	1.3	2.7	1.6	1.3	2.6	3.9	2.8	0.8	1.5	1.8	1.9	0.5	1.7	1.7	2.0	1.1	2.0	3.0	1.8	3.1	2.6	2.1	2.8	1.9	2.4	95.3
LSK	1.1	1.3	1.3	2.7	1.9	1.5	2.5	1.8	3.0	2.2	2.7	1.6	1.8	2.4	2.4	3.3	1.9	1.7	1.5	1.3	1.7	2.0	1.9	2.9	2.9	1.6	2.5	2.5	3.4	3.6	1.0	1.8	1.6	2.3	0.9	1.5	1.3	0.7	1.7	1.6	2.3	2.9	1.7	2.7	2.6	3.6	2.3	2.5	97.1
LTC	1.7	1.3	1.4	3.2	2.0	1.7	2.3	1.6	2.4	1.6	2.6	0.9	2.4	2.8	1.9	2.5	2.8	1.4	1.6	1.7	1.9	3.1	1.8	2.2	3.8	1.2	1.6	3.0	3.5	2.5	1.3	2.0	1.7	1.7	0.8	1.6	1.6	0.9	1.7	1.6	3.0	2.7	2.8	3.1	2.8	2.5	2.0	2.4	96.2
MANA	1.6	1.8	2.4	2.4	1.6	1.4	2.3	2.4	3.5	2.7	2.2	2.3	1.8	2.3	2.4	3.5	2.1	1.7	1.9	1.4	1.8	2.2	1.7	1.8	2.4	3.2	2.2	2.2	3.2	2.9	1.1	1.5	2.2	1.8	0.9	1.8	0.9	1.1	1.7	2.1	2.0	2.6	1.4	2.1	2.0	2.5	2.2	3.2	96.8
MIOTA	2.0	1.9	2.1	2.8	2.0	1.5	1.9	2.2	2.8	2.0	2.5	1.2	2.0	2.8	2.1	2.6	2.2	2.1	1.9	1.5	2.1	2.2	1.7	2.4	2.8	1.9	3.2	2.3	2.6	2.6	0.9	1.4	1.6	2.3	1.1	2.2	1.2	0.8	1.1	1.8	2.6	2.6	2.0	2.8	1.5	2.9	2.5	2.8	96.8
NEO	1.4	0.7	1.6	2.5	2.4	1.8	2.6	2.1	2.6	1.6	2.6	1.1	2.0	2.6	1.6	2.6	2.4	1.2	1.0	1.9	2.2	2.6	2.0	2.3	3.0	1.6	1.4	3.7	3.7	3.3	0.8	2.4	2.3	1.7	0.8	0.9	1.6	1.3	2.0	2.1	2.9	2.7	2.9	2.4	3.2	2.4	1.7	2.1	96.3
OMG	2.2	1.5	1.8	2.5	1.9	1.6	2.5	1.5	2.3	2.4	2.8	1.2	1.9	2.5	2.0	2.7	3.1	0.8	1.3	1.4	2.3	3.2	2.3	1.8	3.3	1.6	1.2	2.8	4.2	2.7	1.2	1.9	1.2	1.0	0.9	2.1	1.6	1.8	1.6	1.3	2.3	2.3	2.2	3.0	3.1	2.6	2.3	2.6	95.8
QTUM	1.5	1.5	1.3	2.6	1.8	1.5	2.6	1.7	3.0	1.6	2.2	1.3	2.0	2.5	2.3	3.3	2.4	1.0	1.5	1.7	1.7	2.9	2.8	1.8	3.2	1.2	1.9	2.8	3.2	4.5	1.0	2.1	1.7	1.8	0.9	1.3	1.7	0.9	1.3	1.6	2.7	2.6	2.1	2.5	2.7	3.2	2.2	2.3	95.5
REQ	2.4	2.6	3.2	2.3	2.0	1.2	1.9	1.4	2.2	1.7	1.7	1.1	1.4	2.9	3.0	1.1	1.7	2.7	1.3	1.8	1.5	3.3	1.0	2.8	3.4	1.4	2.4	2.2	1.3	2.1	3.5	3.3	1.5	2.2	1.9	0.5	2.3	2.0	1.2	2.2	3.6	2.1	1.1	3.6	1.7	1.4	2.3	2.8	96.5
RLC	2.2	1.5	2.2	2.1	1.9	1.5	2.1	1.9	2.5	1.5	2.1	1.0	2.1	2.3	3.0	3.0	2.3	1.2	2.2	1.8	1.7	2.8	2.1	2.0	2.7	1.3	2.1	2.4	2.9	3.5	0.9	3.5	2.4	2.2	1.7	1.3	1.6	0.6	1.4	2.0	2.8	2.2	1.9	2.1	2.3	2.6	2.3	2.7	96.5
SC	1.7	1.5	1.9	2.7	2.0	2.0	2.8	1.8	2.7	2.2	2.4	2.2	2.2	2.6	1.6	2.8	2.2	1.2	1.4	2.0	2.1	2.4	2.0	2.2	2.8	1.9	1.8	2.9	2.7	2.9	0.9	1.7	2.3	1.8	0.5	0.8	1.5	1.7	1.8	2.0	2.5	2.7	2.3	2.4	2.4	2.4	2.0	2.5	97.7
SNT	1.3	1.1	1.4	2.8	1.8	1.3	2.1	1.5	2.4	1.1	2.4	0.8	2.6	2.6	2.4	3.4	2.2	1.4	2.3	2.1	2.2	2.2	2.1	2.3	2.7	1.1	2.1	2.4	2.4	3.0	0.8	1.5	1.7	3.8	1.7	1.6	1.7	0.9	1.9	1.9	3.0	2.7	1.9	3.2	2.4	3.1	2.5	2.5	96.2
STORJ	0.6	2.1	1.7	2.5	1.3	1.1	2.5	1.6	3.2	2.0	1.8	1.6	1.6	1.9	2.5	3.7	2.1	1.6	2.2	2.1	2.0	1.9	1.5	1.5	2.7	1.4	2.1	2.5	3.8	3.4	0.5	1.4	1.7	3.0	4.0	1.3	0.8	1.0	2.0	1.3	2.4	2.6	2.1	3.1	3.5	3.1	1.9	2.3	96.0
SYS	1.5	2.1	1.0	2.7	2.1	1.0	1.4	2.0	2.7	2.1	2.1	2.0	2.0	2.2	2.3	3.4	2.4	1.2	2.0	1.8	2.2	2.3	2.2	1.6	2.5	1.2	1.8	2.4	4.4	3.2	1.5	1.7	1.2	2.3	1.9	3.2	1.5	1.8	0.8	1.6	2.5	2.1	2.8	2.3	2.4	3.0	1.7	1.9	96.8
TRX	1.6	1.1	1.3	3.2	2.1	1.7	2.7	2.6	2.9	1.8	2.5	2.3	2.0	2.9	1.1	3.2	2.6	1.4	1.3	2.0	2.3	2.6	2.3	2.0	3.0	1.9	1.3	2.5	2.6	3.1	1.1	1.8	1.9	2.1	0.9	1.3	2.4	1.3	1.2	1.8	2.5	2.6	1.8	2.6	1.7	3.0	1.8	2.4	97.6
VGX	0.8	1.4	1.3	2.3	1.7	1.9	2.6	1.8	2.9	1.5	1.8	2.5	1.5	2.2	2.4	4.0	2.5	1.3	2.1	1.2	1.6	1.8	2.6	1.4	1.9	2.4	2.1	2.3	5.4	2.8	0.8	0.9	1.9	1.4	1.2	1.6	1.6	7.2	1.6	1.9	1.2	2.3	2.2	1.5	3.2	2.8	1.5	1.7	92.8
WAVES	1.5	1.7	1.4	2.0	1.6	1.4	2.7	2.4	2.0	1.2	2.2	2.6	1.9	1.5	2.0	2.1	2.1	2.2	1.4	1.7	1.8	1.4	1.1	3.1	2.1	2.7	2.5	2.9	3.4	1.8	2.0	1.5	2.0	2.0	1.6	1.5	1.5	2.0	5.6	1.5	1.8	2.8	1.7	2.4	4.4	2.0	1.5	2.0	94.4
XEM	1.2	1.2	3.1	1.9	2.7	2.0	2.4	1.8	2.2	1.7	2.1	1.3	2.0	2.6	2.2	2.8	2.3	1.6	1.8	2.3	2.4	2.3	1.8	2.4	2.1	2.4	1.6	2.8	2.6	2.5	0.9	1.7	2.7	1.9	0.6	0.8	1.8	1.6	1.6	4.0	2.3	2.1	2.1	2.7	2.1	1.7	2.7	2.6	96.0
XLM	1.4	0.9	1.5	3.3	1.9	1.5	1.9	1.3	1.8	1.3	2.2	1.7	2.3	3.0	1.7	2.6	2.4	1.3	1.5	2.0	2.2	3.1	2.4	2.3	3.3	1.2	1.3	3.4	3.2	2.7	0.9	1.6	1.6	2.7	1.0	1.4	1.6	1.2	1.8	1.7	4.4	2.2	3.2	3.2	2.7	2.5	1.8	2.3	95.6
XMR	1.7	1.2	1.0	2.8	2.5	2.0	3.1	1.8	2.9	1.5	3.0	1.0	2.3	2.7	1.8	2.7	2.3	1.6	1.1	1.8	2.0	2.2	1.5	3.0	3.0	1.6	2.2	2.8	2.5	2.6	1.2	2.2	2.2	2.2	0.9	0.8	1.9	0.9	1.8	1.9	2.0	3.8	2.4	2.7	2.3	2.5	2.1	2.1	96.2
XNO	1.6	1.0	1.4	3.3	2.1	1.9	2.6	1.0	1.9	1.9	2.7	1.7	2.6	3.0	1.6	1.9	2.1	0.6	1.4	1.5	2.6	2.8	2.8	1.9	3.7	0.9	1.9	3.2	3.0	2.8	1.0	1.4	1.1	1.9	0.3	1.7	1.8	2.1	2.3	1.2	3.3	2.6	4.0	3.4	2.3	2.8	1.7	1.6	96.0
XRP	1.4	1.6	1.4	3.3	1.9	1.2	2.4	1.4	2.8	2.0	2.1	1.7	1.7	3.1	2.1	3.1	2.6	1.5	1.4	1.9	2.2	3.0	2.1	1.9	3.5	1.8	1.8	2.6	3.2	2.9	0.9	1.7	1.4	2.4	1.1	1.0	1.3	1.0	1.3	1.8	3.2	2.6	2.0	3.4	2.3	2.7	1.9	2.5	96.6
XTZ	1.4	0.8	1.6	2.4	2.1	1.9	3.1	1.0	1.8	1.4	2.3	0.9	2.3	2.5	1.4	2.4	1.9	0.9	0.7	2.5	2.6	3.0	2.1	2.1	3.0	1.4	0.7	3.8	4.3	2.9	0.6	2.2	1.8	1.8	1.0	1.5	2.5	1.9	2.1	1.8	3.6	2.0	3.1	3.1	5.3	1.6	1.3	2.1	94.8
ZEC	1.4	1.1	1.1	3.4	1.8	1.6	2.4	1.7	3.0	1.3	2.8	1.7	2.0	2.6	2.2	3.6	3.1	1.5	1.7	1.3	1.5	2.3	1.9	2.4	3.2	1.0	2.5	2.5	2.7	3.5	0.7	1.6	1.6	2.2	1.0	1.1	1.4	0.9	1.4	1.5	2.4	3.1	1.6	2.4	2.1	4.4	3.1	2.5	95.6
ZEN	1.4	1.1	1.9	2.9	1.8	1.7	2.2	1.7	2.9	2.1	2.7	1.7	1.9	2.4	2.7	3.7	3.3	1.5	2.5	1.3	1.7	2.5	1.7	1.9	2.8	1.3	2.5	2.4	2.8	3.1	0.5	2.1	2.4	1.8	1.3	1.0	0.7	0.6	1.0	2.0	1.9	2.9	1.8	2.3	1.8	3.7	3.8	2.9	96.2
ZRX	1.6	1.4	2.3	3.2	1.7	1.5	2.3	1.8	2.7	2.0	2.4	1.6	2.1	2.6	2.1	3.1	2.6	1.4	2.0	1.6	1.7	2.7	2.3	1.9	3.2	1.8	2.1	2.7	3.0	3.0	0.8	2.0	2.0	1.7	0.8	1.3	1.3	1.0	1.7	1.7	2.5	2.6	2.0	2.3	2.3	3.1	2.3	3.0	97.1
Contribution to self and others	78.9	70.9	84.1	130.9	96.7	82.6	117.6	86.4	124.8	88.4	115.1	75.5	100.7	123.6	102.2	136.3	116.4	68.8	80.4	84.2	100.2	122.2	95.7	99.9	142.6	78.3	95.6	126.8	143.0	135.4	49.5	88.5	89.6	93.0	48.3	68.4	79.2	67.9	76.3	88.2	121.9	124.4	105.8	130.6	117.1	127.2	104.6	115.2	**Total spillover index**
Contribution to others	75.2	65.0	80.4	127.4	93.5	79.1	114.1	83.5	121.6	84.9	111.4	71.9	96.9	120.0	97.0	132.9	112.8	64.9	75.4	81.3	96.5	119.1	91.1	96.9	138.8	75.1	92.3	123.1	138.8	130.9	46.0	85.0	87.3	89.3	44.3	65.2	76.8	60.8	70.8	84.3	117.5	120.6	101.8	127.2	111.9	122.8	100.8	112.3	**96.2 %**
Net spillovers	-21.1	-29.1	-15.9	30.9	-3.4	-17.4	17.6	-13.6	24.8	-11.6	15.1	-24.5	0.7	23.6	2.1	36.3	16.4	-31.2	-19.6	-15.8	0.2	22.2	-4.3	-0.2	42.6	-21.7	-4.5	26.8	43.0	35.4	-50.5	-11.5	-10.3	-7.0	-51.7	-31.6	-20.7	-32.0	-23.7	-11.8	21.9	24.4	5.8	30.6	17.1	27.2	4.6	15.2	

Volatility spillover table 2021

Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC
ADA	3.6	0.8	1.6	2.6	2.1	1.9	1.0	1.7	3.4	2.8	2.0	1.4	1.5	3.4	0.7	1.3	5.0	2.5	1.5	1.4	1.5	3.8	0.7	2.1	2.6
ANT	1.4	4.3	2.1	1.6	2.5	2.3	1.5	1.4	1.2	2.0	2.1	3.0	2.3	2.3	1.5	1.5	1.6	3.5	1.5	3.6	2.3	1.8	3.2	2.8	1.6
BAT	1.8	1.6	4.0	2.9	1.2	1.9	1.8	1.0	3.6	2.2	1.5	2.0	2.8	2.2	1.6	1.8	2.0	3.6	0.6	2.5	1.7	2.9	3.3	1.9	3.1
BCH	3.5	0.4	1.6	4.7	2.3	3.5	2.4	1.7	3.7	3.1	2.4	0.9	1.5	2.8	2.6	2.1	3.2	1.5	1.0	1.1	1.8	2.2	0.8	1.0	3.7
BNB	3.9	0.8	1.5	1.2	4.9	0.7	1.3	1.1	3.5	1.6	5.7	0.4	1.7	3.6	1.2	0.9	3.5	0.6	2.4	3.9	4.8	2.2	0.7	1.3	1.9
BTC	3.4	1.1	0.9	3.2	3.2	4.4	3.0	2.4	2.9	2.1	4.0	1.7	1.1	2.6	1.8	2.2	3.2	0.5	2.2	2.5	2.4	3.0	1.5	0.6	2.8
BTG	2.7	1.1	1.6	2.0	2.9	2.0	3.8	0.7	4.0	3.1	6.0	1.4	1.0	3.5	2.6	1.4	3.9	0.5	1.8	2.7	2.3	2.6	1.0	1.1	2.2
CVC	1.6	3.9	3.1	0.7	1.7	1.7	0.8	8.1	1.6	0.5	4.5	1.9	1.2	1.2	1.4	1.3	1.2	1.6	2.4	4.3	1.6	3.0	2.8	0.7	1.4
DASH	3.1	1.3	2.2	2.8	2.3	1.9	1.6	1.8	4.2	2.5	3.5	0.5	1.8	3.5	2.1	1.9	3.6	1.4	1.3	2.0	2.2	2.8	1.1	1.3	3.1
DCR	3.5	1.1	1.8	3.0	2.6	1.8	2.1	2.0	2.8	5.0	1.8	1.0	3.0	4.4	0.6	1.1	4.0	1.2	1.8	2.7	2.7	3.4	0.7	1.6	2.4
DGB	4.4	0.9	0.8	1.0	3.4	0.8	0.9	1.7	4.2	1.1	10.1	0.5	0.5	4.2	3.4	1.0	5.9	0.6	2.6	1.2	1.7	2.6	0.4	1.0	2.3
DOGE	2.0	0.7	2.1	3.5	0.9	2.8	0.9	2.3	2.6	2.6	1.7	3.5	2.7	2.3	1.9	2.4	2.2	2.8	1.1	2.3	1.5	2.3	2.1	1.9	2.5
ENJ	2.6	1.8	2.1	1.4	2.2	2.2	0.8	0.9	1.6	2.0	3.4	4.6	3.4	2.5	1.1	1.1	2.5	2.3	1.6	3.2	2.3	2.2	2.0	1.8	1.8
EOS	2.4	1.1	1.7	2.8	1.7	2.2	1.3	1.3	4.3	3.0	3.3	0.5	1.5	4.3	2.5	2.7	3.9	1.3	1.2	1.6	1.6	2.7	1.0	1.5	2.0
ERG	2.7	1.3	0.3	3.0	2.0	1.4	0.8	2.8	2.3	2.6	2.9	2.8	0.8	2.8	5.5	0.9	2.5	4.0	3.3	1.1	1.3	1.0	1.5	3.3	3.0
ETC	1.6	2.0	1.4	4.1	1.4	3.2	2.4	2.2	2.8	1.7	5.1	0.8	1.2	1.6	3.1	4.6	2.4	1.8	1.0	2.6	2.2	2.1	1.9	0.5	2.2
ETH	3.3	0.7	1.2	2.3	2.5	1.7	1.3	0.9	3.5	2.4	4.1	0.5	1.2	3.4	1.6	1.4	4.9	1.2	1.7	2.6	2.3	4.0	0.7	1.1	2.5
GLM	2.3	0.7	3.7	1.8	1.1	0.6	1.1	1.7	2.0	1.7	2.4	0.8	2.5	2.6	0.5	1.0	3.2	6.4	1.4	4.0	1.6	3.5	0.6	3.8	2.3
GNO	3.3	2.0	0.1	0.5	4.6	0.2	1.3	1.9	0.8	1.2	7.5	1.7	0.3	3.0	0.9	0.1	2.5	1.3	8.4	6.8	4.1	3.1	2.5	3.1	0.3
ICX	2.7	1.3	2.6	1.3	2.9	2.1	2.4	1.3	1.4	2.7	1.9	3.6	2.8	2.1	0.6	1.1	1.8	2.2	3.1	6.9	4.1	3.4	1.5	1.5	1.6
KCS	2.6	1.3	1.7	2.1	3.5	1.4	0.9	1.5	2.5	1.5	5.2	1.1	1.7	2.3	1.0	1.8	2.2	1.2	2.2	4.6	5.2	2.0	1.3	1.2	1.4
LINK	2.3	2.1	2.0	2.3	0.6	2.1	1.0	1.5	3.5	1.8	1.7	0.5	1.4	2.3	1.6	1.6	5.5	1.5	1.0	1.0	0.8	6.5	1.7	1.3	2.6
LRC	2.1	3.8	1.8	1.3	1.6	2.1	1.6	1.2	1.9	2.5	1.0	2.1	2.6	2.6	2.8	2.4	1.7	1.4	2.2	3.5	2.7	2.1	6.8	1.8	1.2
LSK	2.2	1.6	2.2	2.0	1.2	1.1	1.8	3.2	1.8	2.2	1.5	2.8	1.6	3.8	2.1	1.3	2.9	3.3	1.8	2.1	1.3	2.7	0.7	5.1	2.0
LTC	3.1	1.4	1.3	2.8	2.3	2.2	1.8	1.8	3.9	1.9	4.0	0.9	1.2	2.9	3.3	1.3	4.3	1.2	1.5	1.7	1.5	3.6	1.3	1.2	3.7
MANA	2.3	3.0	2.8	1.7	2.2	2.4	1.1	0.7	3.5	1.6	2.1	2.3	2.9	2.1	1.5	1.6	1.9	1.6	1.3	3.3	2.7	1.8	4.5	0.8	2.1
MIOTA	2.6	1.9	1.7	0.7	1.8	0.6	0.5	2.2	2.5	0.9	7.5	0.8	1.4	3.5	1.6	0.9	3.7	1.5	0.9	2.2	2.1	2.5	1.3	1.2	1.1
NEO	3.4	0.3	2.2	2.3	3.5	1.0	1.7	1.4	3.7	3.8	2.4	1.5	2.4	4.7	1.9	1.3	4.2	1.5	0.9	1.7	2.9	1.7	0.4	2.1	2.9
OMG	2.5	0.8	2.1	2.2	2.9	0.5	1.6	0.9	2.1	2.6	1.0	3.5	3.1	3.0	3.0	1.5	2.3	1.7	4.1	5.0	4.7	3.0	0.5	2.0	2.7
QTUM	2.2	1.0	2.4	2.3	0.7	1.3	1.5	1.7	2.6	2.9	1.7	1.9	2.3	2.8	5.1	1.4	3.1	3.0	1.6	2.5	1.7	2.9	0.5	1.9	2.0
REQ	1.9	0.7	3.4	2.0	1.1	0.6	1.7	1.6	1.4	1.7	2.6	1.2	2.5	1.9	1.6	1.1	2.4	6.0	1.6	4.2	1.3	3.2	1.3	2.8	2.9
RLC	3.0	0.7	2.4	2.3	2.9	1.4	1.3	2.2	2.6	1.5	2.0	0.8	2.2	2.4	1.1	1.5	2.7	2.7	1.8	2.9	3.4	2.2	0.9	2.3	2.8
SC	2.5	0.7	1.7	3.8	1.3	2.5	0.8	0.7	3.4	2.9	2.5	0.7	2.5	2.7	0.5	3.1	3.4	1.6	2.0	1.5	1.2	3.9	2.0	1.3	2.5
SNT	2.6	1.2	1.2	1.9	3.5	1.7	2.4	1.6	1.4	1.8	3.7	1.9	1.1	2.1	1.4	1.8	2.0	2.4	3.3	3.3	3.0	1.8	1.8	2.5	1.1
STORJ	1.2	1.7	2.1	1.8	0.9	2.3	0.9	1.6	1.7	2.1	1.3	1.5	3.1	1.9	1.4	1.2	1.8	5.5	1.1	2.0	1.3	1.8	3.1	3.0	2.3
SYS	1.4	1.9	1.1	1.7	2.7	2.1	2.2	4.9	1.3	1.9	2.9	3.8	0.9	2.2	3.7	2.2	1.8	0.6	1.7	4.3	2.2	2.5	1.3	1.0	1.6
TRX	2.4	1.6	1.6	2.0	2.1	1.9	1.6	2.2	2.6	2.1	3.5	1.3	2.0	2.4	1.7	2.0	2.5	1.1	2.2	2.4	2.3	2.1	1.6	0.9	1.5
VGX	2.7	2.1	2.1	2.8	1.5	3.7	0.8	1.0	2.0	1.4	3.2	2.7	2.0	1.6	2.7	2.4	1.7	1.8	2.1	3.7	1.7	1.9	3.1	1.0	1.7
WAVES	2.3	2.9	0.8	0.8	1.1	1.1	0.4	0.9	2.6	1.2	6.7	2.2	0.7	2.3	0.8	0.6	4.6	1.1	3.1	3.3	2.2	4.6	2.1	2.3	0.8
XEM	2.9	1.3	1.7	2.5	3.4	2.3	2.2	2.1	2.0	2.7	2.4	1.9	2.7	3.6	2.2	2.5	2.4	1.0	1.6	3.6	3.4	1.4	1.1	1.3	2.2
XLM	2.9	0.9	1.8	3.0	1.8	3.8	1.6	2.2	3.1	1.8	3.1	0.9	1.1	1.9	2.7	2.5	2.6	0.8	1.5	1.7	1.2	2.7	2.2	0.7	1.8
XMR	3.8	1.7	0.5	1.2	3.3	1.8	1.1	1.2	3.2	1.3	7.6	1.5	0.5	2.5	1.7	0.7	4.8	0.8	3.4	3.6	2.7	3.8	1.8	0.5	1.8
XNO	2.9	1.6	0.7	2.5	1.5	2.1	1.1	1.2	1.9	2.3	3.9	2.4	1.4	2.1	1.8	2.6	3.5	1.4	2.2	4.0	1.4	2.7	1.2	1.6	2.2
XRP	3.2	2.0	1.6	2.1	1.1	2.6	0.7	0.9	3.8	1.4	4.3	1.7	1.3	1.7	2.5	1.1	3.8	1.3	1.8	2.1	1.3	3.5	2.4	1.3	2.0
XTZ	2.3	1.5	2.1	2.4	2.2	1.4	1.8	1.0	3.1	3.0	2.7	1.2	2.6	3.0	2.7	2.2	3.0	0.9	1.8	2.7	2.5	4.1	1.4	0.8	1.6
ZEC	3.7	1.6	0.7	1.4	3.4	2.2	0.9	1.8	3.1	1.5	5.9	1.4	0.7	1.9	1.1	1.1	3.2	0.5	3.3	2.8	2.6	3.6	2.3	0.4	1.4
ZEN	1.2	1.2	2.7	1.4	1.0	2.2	0.5	2.2	1.8	3.1	2.2	1.0	3.3	2.6	2.5	3.2	2.0	2.0	3.2	3.0	2.3	1.2	1.6	0.9	1.0
ZRX	2.9	0.6	3.2	2.2	2.6	1.3	1.4	1.2	3.1	1.3	3.5	0.9	2.6	2.4	1.8	1.5	2.7	2.8	0.9	2.4	2.5	2.9	0.4	2.3	2.3
Contribution to self and others	126.7	71.9	88.0	103.4	106.0	90.9	69.0	85.1	128.4	102.5	167.7	79.7	88.4	129.6	95.2	79.9	145.4	92.5	97.9	139.8	109.9	132.9	80.5	79.4	100.5
Contribution to others	123.0	67.7	84.0	98.7	101.1	86.5	65.2	77.0	124.2	97.5	157.6	76.2	85.0	125.3	89.7	75.2	140.5	86.2	89.5	132.9	104.7	126.4	73.7	74.3	96.8
Net spillover	26.6	-28.1	-12.1	3.4	6.0	-9.1	-31.0	-14.9	28.4	2.5	67.6	-20.3	-11.6	29.5	-4.8	-20.1	45.4	-7.5	-2.1	39.7	9.9	32.9	-19.5	-20.6	0.5

Tickers	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	1.4	0.6	2.3	2.3	3.3	1.4	2.4	2.6	1.8	1.4	1.2	1.7	2.8	3.9	1.5	2.7	2.2	1.5	2.2	3.4	1.8	0.7	2.4	96.4
ANT	1.6	2.8	1.8	2.3	2.0	2.7	1.9	1.4	2.6	1.8	2.0	1.0	1.4	3.7	2.7	1.4	0.6	2.2	1.4	2.5	1.5	1.5	2.7	95.7
BAT	2.5	1.4	2.3	2.5	2.4	3.6	3.1	1.5	2.0	1.8	1.3	2.1	1.6	1.5	2.6	1.8	1.1	0.9	1.5	3.3	0.8	1.5	1.9	96.1
BCH	1.7	0.9	2.3	1.8	2.7	1.4	1.6	3.4	1.9	0.8	1.3	2.2	2.6	1.0	1.8	4.1	1.6	1.9	2.6	2.4	1.8	1.0	1.9	95.3
BNB	1.9	2.4	2.0	1.6	2.6	0.6	1.3	1.5	1.3	0.6	0.5	2.7	1.0	0.8	3.4	2.4	2.0	0.7	3.8	1.6	4.2	1.2	4.6	95.1
BTC	1.0	1.3	0.9	1.2	2.6	0.4	0.8	3.0	1.0	0.2	2.4	1.8	2.5	0.4	2.3	5.0	2.0	3.2	3.0	1.5	2.6	0.8	2.0	95.6
BTG	1.0	1.0	2.7	2.0	3.5	1.2	0.5	1.5	0.4	0.5	1.3	2.1	1.8	1.1	1.7	3.0	2.7	2.7	2.1	1.7	4.4	0.8	2.7	96.2
CVC	2.9	4.8	1.2	0.6	0.9	2.3	2.8	2.0	2.1	2.1	1.1	1.7	2.0	1.2	0.3	1.5	2.7	2.8	1.2	2.0	3.8	1.6	2.2	91.9
DASH	2.4	2.2	2.4	2.3	3.0	0.8	1.6	1.9	1.1	0.6	0.9	2.2	2.1	1.1	2.7	2.3	2.3	1.2	2.6	2.1	2.5	0.9	3.2	95.8
DCR	1.6	1.4	2.8	2.6	4.3	1.2	1.3	2.3	1.2	0.5	1.3	1.7	1.7	1.1	3.0	3.3	1.1	0.9	2.7	2.0	1.6	0.8	1.6	95.0
DGB	0.9	2.5	1.6	1.1	3.9	1.3	1.0	1.6	0.8	0.7	0.5	1.5	1.9	1.1	1.4	2.6	3.6	0.8	3.7	0.9	4.4	0.9	4.1	90.0
DOGE	1.9	1.5	1.6	2.2	2.2	2.1	1.4	3.0	2.3	1.8	1.8	1.8	2.4	2.2	1.6	3.1	2.6	1.6	1.7	2.9	1.6	2.7	0.8	96.5
ENJ	2.1	1.0	2.1	2.5	1.2	1.0	1.0	3.4	0.7	0.4	4.0	1.7	2.0	1.2	2.2	3.0	2.2	4.1	1.6	1.7	4.0	1.9	1.4	96.6
EOS	1.4	1.6	2.6	2.7	3.5	1.0	1.4	2.3	1.5	0.5	1.4	2.0	2.8	2.0	2.1	3.3	1.5	1.9	2.5	3.7	2.0	1.0	1.9	95.8
ERG	1.3	1.7	1.8	2.4	3.3	2.9	1.8	2.4	1.8	1.1	0.7	1.7	4.3	2.1	1.0	2.5	1.4	1.3	1.9	1.1	2.5	1.9	1.7	94.5
ETC	1.8	1.1	0.7	1.4	2.3	2.0	0.7	2.3	2.2	1.0	2.5	1.2	3.0	1.4	0.8	3.4	1.4	3.0	2.4	2.5	3.4	1.4	2.3	95.4
ETH	1.2	1.6	2.1	1.8	2.7	1.1	1.5	2.2	1.1	1.2	1.1	1.8	3.1	1.5	1.8	4.0	2.7	2.7	2.4	2.9	3.0	1.2	2.4	95.1
GLM	2.6	2.2	2.6	2.5	2.7	5.6	2.6	1.4	2.5	4.0	0.4	1.5	0.7	1.8	1.4	1.1	1.5	0.4	1.9	2.2	1.9	1.3	2.2	93.7
GNO	0.2	2.7	1.4	1.6	2.6	0.9	0.4	1.2	0.6	0.6	0.2	0.9	1.1	0.2	2.1	2.2	4.1	2.5	2.1	1.0	7.3	0.7	2.2	91.6
ICX	1.6	1.3	2.0	1.8	1.4	2.6	1.1	1.9	0.8	1.3	2.8	1.5	1.1	1.6	2.9	2.8	0.7	2.1	1.5	1.4	2.4	1.9	2.5	93.2
KCS	1.9	1.7	1.3	1.4	1.3	1.2	1.5	2.1	1.9	0.7	1.4	2.8	1.3	1.7	2.4	2.9	1.8	1.2	2.5	3.0	4.5	2.0	4.2	94.8
LINK	1.1	1.1	1.4	2.1	2.4	1.1	2.6	1.7	1.2	1.6	1.9	1.4	3.9	3.2	0.9	3.7	4.4	4.0	1.7	4.6	2.1	0.6	1.0	93.5
LRC	1.3	3.6	1.6	1.9	2.1	1.3	1.2	1.9	2.2	0.6	2.7	1.0	1.8	2.9	2.7	1.7	1.4	1.8	2.4	2.2	2.0	1.6	1.5	93.3
LSK	1.0	2.5	2.0	2.7	4.1	2.8	3.0	1.4	2.2	1.9	1.1	1.0	1.3	3.0	1.3	1.7	2.0	1.9	2.5	1.9	1.4	1.1	2.2	94.9
LTC	1.8	1.2	1.9	2.1	2.8	1.3	1.5	1.9	0.8	0.6	0.9	1.4	3.1	1.1	2.2	3.4	3.5	3.1	2.1	2.3	3.0	0.4	2.0	96.3
MANA	4.7	1.4	2.1	2.7	1.0	1.4	2.2	2.6	0.7	0.6	2.5	2.6	2.3	1.0	3.7	1.7	1.5	0.9	1.8	1.6	2.0	2.0	3.5	95.3
MIOTA	1.4	5.7	1.0	1.0	2.0	2.1	2.6	2.1	1.9	1.2	0.8	2.9	1.6	3.2	0.8	1.7	2.5	0.9	4.2	2.4	4.9	2.2	3.5	94.3
NEO	2.5	1.8	4.5	3.1	3.6	0.8	1.4	1.5	1.2	0.6	1.1	2.9	0.7	1.7	3.4	1.7	1.3	0.4	2.6	1.8	1.9	1.2	2.7	95.5
OMG	2.2	1.1	2.7	4.3	1.9	1.3	1.4	1.3	1.1	0.6	2.0	1.3	1.1	0.7	3.1	2.0	1.6	1.3	1.3	2.2	2.5	2.1	2.1	95.7
QTUM	1.2	1.3	1.9	1.9	3.7	4.5	2.4	1.8	3.3	2.6	1.2	1.8	2.3	1.9	1.1	2.2	0.6	0.8	2.3	3.3	1.0	3.1	1.1	96.4
REQ	1.5	2.1	2.0	1.8	2.6	8.7	3.1	1.5	2.3	4.3	0.6	1.2	1.1	2.3	0.8	0.5	1.0	1.1	1.3	2.1	2.2	1.4	1.8	91.3
RLC	2.4	1.9	2.7	1.9	1.8	2.4	3.7	1.3	1.8	1.9	0.7	3.1	1.1	2.0	2.9	1.3	1.7	1.3	3.2	2.1	2.0	1.7	3.5	96.3
SC	1.8	2.6	1.4	1.5	2.9	2.0	1.7	3.4	2.5	0.9	1.4	1.5	2.4	2.3	1.7	4.3	2.0	1.6	2.5	4.7	1.6	0.6	1.1	96.6
SNT	1.7	1.7	2.2	2.2	1.7	2.1	1.1	2.4	3.6	2.1	2.2	2.1	0.8	1.1	2.2	2.6	2.0	2.2	2.0	2.1	4.1	1.3	2.3	96.4
STORJ	1.3	2.1	1.6	1.9	2.5	4.5	1.9	2.5	3.4	6.0	1.5	1.2	2.2	1.9	2.7	2.2	1.3	3.2	2.5	1.7	1.0	1.0	1.5	94.0
SYS	1.0	1.3	1.3	1.9	1.4	1.6	1.6	1.9	1.2	1.5	5.4	1.2	1.3	3.1	1.8	1.8	3.1	2.4	0.7	2.5	4.2	2.9	1.3	94.6
TRX	1.8	1.6	2.2	1.6	1.8	3.0	2.2	2.0	1.7	2.7	1.2	4.7	2.1	2.2	2.5	2.2	1.8	0.8	2.5	2.9	3.3	1.9	2.0	95.2
VGX	0.8	1.8	1.1	1.9	0.9	2.3	1.2	4.0	1.2	0.7	2.4	1.8	7.1	1.5	1.2	3.9	1.4	2.2	1.3	1.8	2.4	3.0	1.0	92.9
WAVES	0.6	1.6	1.6	1.2	2.2	1.2	1.5	1.4	0.7	0.8	1.0	1.6	1.4	7.6	0.3	2.4	4.0	2.1	2.5	2.8	5.8	1.8	2.7	92.4
XEM	2.1	1.5	2.1	2.6	2.4	1.1	0.5	2.5	1.0	0.5	3.0	2.2	1.8	1.2	4.6	2.4	1.4	1.7	2.2	1.2	2.1	1.5	2.3	95.4
XLM	2.0	1.4	1.2	0.9	2.2	2.0	2.0	3.8	1.9	0.8	0.9	1.4	5.6	1.2	1.4	6.2	2.2	3.7	1.7	3.2	1.7	1.2	1.2	93.8
XMR	0.8	0.9	1.2	1.1	1.5	0.9	0.9	1.7	0.3	0.2	1.6	1.1	2.2	0.5	1.7	3.7	5.5	3.9	2.4	1.2	6.7	0.7	2.7	94.5
XNO	1.1	1.6	1.7	1.8	1.7	3.2	1.2	2.7	1.2	1.0	3.6	1.1	2.6	0.9	1.1	2.8	2.6	4.9	2.4	2.6	2.2	1.8	2.5	95.1
XRP	1.7	2.1	1.0	0.9	2.1	1.4	1.3	3.1	1.1	1.5	0.3	1.4	5.5	2.8	1.5	4.3	3.0	3.3	2.7	2.2	2.5	0.9	2.1	97.3
XTZ	1.3	2.1	1.4	1.8	2.5	2.0	2.7	1.5	1.7	1.0	1.9	2.5	1.7	1.5	2.3	2.9	1.2	1.6	2.5	5.2	2.1	1.2	1.6	94.8
ZEC	1.5	1.4	1.7	0.6	1.1	0.8	0.6	2.4	0.2	0.4	2.8	2.0	2.5	0.7	1.3	3.9	4.6	4.8	2.0	2.2	6.8	1.1	2.4	93.2
ZEN	3.4	3.3	1.9	2.0	2.0	2.2	1.0	2.4	2.3	1.0	2.0	3.0	1.8	1.4	1.4	1.3	1.1	2.5	2.8	1.9	3.0	5.4	1.7	94.7
ZRX	3.2	2.2	2.1	2.1	1.6	3.6	3.2	1.4	1.7	1.7	1.5	2.0	1.3	2.4	1.9	1.7	2.1	0.8	1.9	2.4	1.8	1.3	4.5	95.5
Contribution to self and others	81.8	90.3	89.4	92.1	112.5	98.5	80.8	102.7	75.7	62.9	78.3	88.4	105.5	87.7	93.9	128.5	102.1	98.6	106.9	113.0	138.2	72.7	108.8	**Total spillover index**
Contribution to others	77.0	84.6	84.9	87.8	108.8	89.8	77.1	99.3	72.1	56.8	73.0	83.7	98.4	80.1	89.3	122.3	96.6	93.6	104.2	107.8	131.4	67.4	104.3	**94.8 %**
Net spillover	-18.3	-9.7	-10.6	-7.9	12.4	-1.5	-19.2	2.7	-24.3	-37.1	-21.7	-11.5	5.5	-12.3	-6.1	28.5	2.1	-1.5	6.9	13.0	38.2	-27.3	8.8	

Return spillover table 2022

Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	3.5	1.7	2.5	2.4	1.9	2.1	1.4	2.3	2.0	2.0	2.2	2.5	2.4	1.8	2.0	1.9	2.0	2.9	1.8	2.3	2.3	1.9	2.1	1.9	2.5	2.5	2.9	2.0	2.2	2.0	1.0	1.3	2.5	2.2	2.1	2.4	1.7	2.2	1.8	2.2	1.9	1.9	1.5	1.9	1.6	2.2	1.8	2.1	96.5
ANT	2.5	3.9	2.2	2.6	1.3	1.5	0.9	2.1	2.1	2.6	2.6	1.5	2.2	2.3	1.6	1.6	1.8	2.4	1.7	1.5	1.9	2.0	1.8	1.1	2.1	3.0	2.8	2.3	2.0	2.6	1.7	1.8	2.0	1.5	2.3	2.1	2.0	2.8	2.1	2.9	2.0	1.8	1.1	2.5	2.0	2.5	2.7	1.9	96.1
BAT	2.7	2.0	3.0	2.4	2.4	2.2	1.3	2.4	2.0	1.6	2.5	1.9	2.4	1.9	1.6	1.6	2.2	2.4	1.9	2.4	2.3	2.3	2.1	1.5	2.5	2.5	2.8	2.3	2.5	2.5	1.0	1.4	2.3	2.0	2.2	2.4	1.8	1.1	1.8	2.4	2.2	1.7	1.8	2.2	2.0	2.0	1.9	1.9	97.0
BCH	1.9	1.9	2.0	2.8	2.0	2.5	1.6	2.2	2.5	1.7	2.4	2.0	2.1	2.3	1.0	1.9	2.7	1.7	2.4	1.9	1.9	2.6	2.1	1.5	2.3	2.3	2.0	2.4	2.4	2.4	1.9	1.7	1.6	1.8	2.3	2.0	1.9	1.6	2.1	2.3	2.1	2.5	1.8	2.3	2.1	2.6	2.3	2.1	97.3
BNB	2.2	1.6	2.5	2.2	2.7	2.2	2.0	2.5	2.1	1.6	1.7	2.3	2.2	2.0	2.0	1.8	2.3	2.7	1.9	2.4	2.6	2.5	1.7	1.5	1.9	2.4	2.5	2.5	2.5	2.5	0.8	0.9	2.1	2.1	1.8	1.8	1.3	2.1	1.8	2.0	2.1	2.8	2.4	2.1	2.5	2.0	1.9	2.5	97.3
BTC	1.8	1.4	2.1	2.2	2.1	3.8	1.7	2.0	2.1	2.1	2.1	1.1	2.2	2.1	1.3	1.5	3.1	2.2	2.9	2.1	2.2	3.2	1.8	1.8	1.7	2.5	2.4	2.5	2.3	2.2	1.3	1.5	2.0	2.1	1.8	1.7	1.6	2.1	1.6	2.2	2.2	3.0	1.6	2.1	2.2	2.8	1.5	2.3	96.2
BTG	2.2	1.9	2.1	2.3	2.3	1.9	3.6	2.1	2.3	2.4	2.0	2.3	1.8	1.9	1.5	2.8	2.4	2.2	2.1	1.9	2.0	2.1	2.0	2.1	1.7	1.9	2.2	2.4	2.5	2.6	1.5	0.9	1.8	1.9	1.6	1.3	1.5	2.1	2.0	2.4	1.9	3.0	2.1	1.7	2.2	2.2	2.4	2.1	96.4
CVC	2.1	2.0	2.6	2.5	2.3	2.1	1.1	2.9	2.2	1.7	2.3	1.8	2.4	1.7	1.6	1.7	2.0	2.6	1.7	2.3	2.5	2.5	2.0	1.7	2.1	2.8	2.6	2.5	2.3	2.5	1.1	1.3	2.2	2.3	2.4	2.2	1.6	1.1	1.7	2.6	2.0	1.8	1.9	2.2	2.3	2.2	2.0	2.3	97.1
DASH	2.0	2.0	2.3	2.6	2.0	2.0	1.6	2.5	2.8	1.7	2.5	2.2	2.1	2.1	1.3	1.8	2.3	2.0	1.9	2.2	1.9	2.1	2.0	1.7	2.2	2.2	2.3	2.5	2.5	2.6	1.3	1.2	2.0	2.0	2.5	1.9	1.7	1.2	1.6	2.6	2.2	2.2	2.0	2.3	2.1	2.3	2.7	2.2	97.1
DCR	2.1	1.8	2.5	3.5	2.0	2.1	1.0	3.0	2.6	3.5	3.0	1.4	2.2	1.7	0.8	2.6	2.7	1.9	2.1	2.1	2.0	2.2	2.1	1.4	2.9	2.6	2.5	2.5	2.6	2.4	1.6	1.4	2.3	1.2	2.5	2.0	1.7	0.8	1.5	2.4	1.9	1.2	2.4	1.9	1.6	2.2	2.1	1.9	96.5
DGB	2.4	2.0	2.4	2.8	1.7	2.3	1.4	2.2	2.3	2.1	3.1	1.4	2.2	2.1	1.3	1.8	2.2	2.1	1.9	2.1	1.5	2.0	2.4	1.8	2.3	2.1	2.5	2.5	2.4	2.7	2.3	1.4	2.3	1.5	2.5	1.8	2.7	1.0	2.2	2.8	2.2	2.1	1.0	2.1	1.9	2.1	2.6	2.1	97.0
DOGE	3.7	1.5	2.1	2.3	1.9	1.5	2.1	2.0	2.1	2.1	1.6	4.8	2.1	1.6	1.6	2.7	1.4	3.4	1.0	2.6	2.1	1.7	2.0	1.8	2.4	2.3	2.8	1.8	2.3	1.8	1.5	1.0	2.9	2.3	2.0	2.2	1.7	2.1	2.0	2.2	1.5	1.6	2.6	1.7	1.5	2.1	2.1	2.3	95.2
ENJ	2.6	2.2	2.3	2.3	2.1	2.2	1.3	2.3	2.1	1.8	2.2	2.3	2.7	2.0	1.6	1.9	2.3	2.3	2.1	2.0	2.5	2.3	2.1	1.6	2.1	2.7	2.3	2.0	2.4	2.3	1.3	1.4	2.0	2.1	2.3	2.3	1.7	1.7	1.7	2.5	1.9	2.2	1.7	2.3	2.0	2.3	2.2	1.9	97.3
EOS	2.1	2.3	2.2	2.2	1.9	2.4	1.8	1.9	2.3	1.6	2.2	1.6	2.2	3.2	1.6	1.7	2.4	2.4	2.0	2.2	1.9	2.3	1.9	1.7	2.2	2.3	2.4	2.2	2.4	2.5	1.6	1.9	1.9	2.0	2.0	1.8	1.3	1.6	1.1	2.2	2.7	2.6	1.3	2.7	2.4	2.6	2.2	2.4	96.8
ERG	2.3	1.7	2.6	1.7	2.2	2.7	1.4	2.6	2.0	1.8	2.2	1.2	2.5	2.1	3.4	1.6	2.6	2.0	2.7	2.4	2.4	2.5	1.7	2.0	1.7	2.3	2.3	2.1	2.2	2.2	1.2	1.8	2.2	2.0	2.2	2.4	1.3	2.4	1.1	2.1	2.3	2.1	1.7	2.1	2.3	2.1	1.3	2.1	96.6
ETC	2.3	2.4	2.1	2.7	1.8	1.9	2.1	2.6	2.1	2.8	2.1	2.4	2.0	1.7	1.1	3.0	2.1	2.9	1.7	2.1	2.8	2.0	1.7	1.2	2.3	2.7	2.6	2.2	2.1	2.0	0.8	1.0	2.2	1.6	2.0	1.8	2.0	2.9	2.0	2.3	1.5	2.1	2.8	1.7	1.4	2.4	1.9	2.3	97.1
ETH	1.8	1.8	2.3	2.5	2.0	2.9	1.9	2.2	2.5	2.2	2.4	1.6	2.2	2.3	1.0	2.1	3.3	2.0	3.0	2.0	2.0	2.7	1.9	1.4	1.9	2.3	2.2	2.4	2.6	2.5	1.2	1.2	2.0	1.6	2.0	1.7	1.4	1.6	1.2	2.3	2.0	3.0	1.9	2.1	2.0	3.1	2.1	2.2	96.8
GLM	1.9	1.8	2.6	2.2	3.0	2.1	1.9	2.6	2.1	1.3	1.9	1.8	2.5	1.9	1.5	1.8	2.4	2.9	2.0	2.5	2.8	3.0	2.1	1.5	1.8	2.6	2.4	2.3	2.6	2.6	1.2	1.2	2.1	2.5	1.9	1.9	1.0	1.2	1.2	2.0	1.9	2.4	2.2	2.0	2.6	2.2	1.9	2.4	97.1
GNO	1.6	1.9	2.2	2.2	1.8	3.0	1.6	2.1	2.5	2.2	2.3	1.7	2.2	2.3	1.2	2.1	3.5	1.9	3.7	2.0	1.8	3.0	1.8	1.4	1.7	2.2	1.8	2.3	2.5	2.4	1.5	1.6	2.1	1.7	2.1	1.6	1.5	1.8	1.1	2.2	1.9	3.2	2.0	1.8	1.9	3.5	2.1	2.1	96.3
ICX	2.3	1.6	2.5	2.4	2.4	2.4	1.4	2.4	2.3	1.5	2.2	1.5	2.2	2.2	1.2	1.8	2.4	2.6	2.1	2.8	2.1	2.6	2.1	1.7	2.0	2.2	2.4	2.4	2.6	2.4	1.0	1.5	2.3	2.3	2.2	2.0	1.6	1.7	1.7	2.3	2.3	2.2	1.7	2.1	2.3	1.9	2.0	2.3	97.2
KCS	2.6	1.6	2.2	2.2	2.2	2.0	1.2	2.4	2.0	2.3	1.6	2.2	2.3	1.6	2.0	1.8	2.3	3.3	1.9	1.9	3.0	2.4	1.3	1.5	2.2	2.9	2.8	2.1	2.1	1.9	1.2	1.3	2.5	2.5	1.9	2.1	1.2	2.8	2.0	2.2	1.6	2.2	2.2	2.1	1.9	2.8	1.6	2.5	97.0
LINK	1.9	1.5	2.3	2.6	2.2	2.7	1.6	2.4	2.2	2.0	2.2	1.5	2.3	2.1	0.8	1.9	2.6	2.5	2.5	2.2	2.1	3.2	2.1	1.4	1.7	2.6	2.3	2.7	2.5	2.5	1.2	1.6	2.1	2.0	1.9	1.8	1.4	1.7	1.9	2.4	1.9	2.5	1.6	1.9	2.2	2.4	2.0	2.3	96.8
LRC	2.7	1.7	2.3	2.6	2.2	2.1	1.8	2.1	2.1	1.7	2.5	2.2	2.6	2.0	1.1	2.1	2.4	2.0	2.3	2.1	1.9	2.4	3.0	1.6	2.3	2.3	2.3	1.9	2.5	2.4	1.9	1.9	1.8	1.8	2.3	2.4	1.8	1.6	1.4	2.4	1.8	2.0	1.1	1.9	2.1	2.4	2.3	1.9	97.0
LSK	2.2	1.3	1.9	2.4	2.1	2.7	1.7	2.3	2.3	2.1	1.9	1.4	2.0	2.1	1.7	1.5	2.2	2.8	1.8	2.1	2.6	2.3	1.5	2.7	2.2	2.3	2.8	2.5	2.2	2.0	1.0	1.2	2.1	2.7	1.9	1.7	1.8	1.8	2.9	2.4	2.3	2.7	1.3	2.1	2.3	2.4	2.0	2.0	97.3
LTC	2.4	1.8	2.4	2.8	2.1	2.2	1.4	2.4	2.6	1.9	2.3	1.6	2.1	2.0	1.5	1.7	2.3	2.5	1.8	2.0	2.2	2.1	1.8	1.6	3.0	2.5	2.9	2.5	2.2	2.1	1.1	1.1	2.2	2.0	2.1	2.0	1.7	1.8	1.8	2.2	2.1	2.0	2.3	2.1	1.7	2.7	2.1	2.4	97.0
MANA	2.3	2.5	2.4	2.7	2.0	2.2	0.9	2.4	2.0	1.8	2.3	1.5	2.8	1.8	1.5	1.7	2.1	2.7	1.6	1.8	2.8	2.4	2.1	1.4	2.4	3.5	2.9	2.3	2.2	2.4	1.1	1.2	1.9	2.3	2.2	2.5	1.4	1.8	1.3	2.8	1.8	1.8	1.3	2.4	2.1	2.6	2.4	2.0	96.5
MIOTA	2.5	2.0	2.5	2.4	2.3	2.7	1.1	2.3	1.9	1.8	2.0	1.8	2.3	1.8	1.6	1.3	2.3	3.0	1.9	2.1	2.9	2.5	1.6	1.3	2.5	3.1	3.3	2.3	2.0	1.9	0.7	1.3	2.2	2.4	1.9	2.3	1.5	2.3	1.9	2.1	2.0	2.1	1.9	2.2	1.8	2.7	1.5	2.4	96.7
NEO	2.0	1.6	2.5	2.8	2.3	2.6	1.6	2.5	2.5	1.6	2.6	1.5	2.1	2.1	1.0	1.6	2.4	2.0	2.1	2.2	2.3	2.4	1.8	1.7	2.1	2.4	2.4	3.3	2.5	2.7	1.0	0.8	2.0	2.1	2.3	1.4	2.1	1.3	2.0	2.7	2.3	2.3	1.6	2.2	2.2	2.2	2.2	2.3	96.8
OMG	2.3	1.7	2.5	2.5	2.3	2.2	1.5	2.3	2.3	1.5	2.4	2.4	2.4	2.2	1.1	1.9	2.5	2.2	2.4	2.5	2.1	2.3	2.3	1.7	2.2	2.1	2.2	2.2	2.8	2.5	1.3	1.3	2.2	1.9	2.4	2.1	1.8	1.1	1.7	2.3	2.3	2.1	1.7	2.3	2.1	2.1	2.3	1.9	97.2
QTUM	2.1	2.0	2.5	2.4	2.2	2.4	1.8	2.3	2.3	1.7	2.4	2.2	2.3	2.3	1.0	1.9	2.5	2.0	2.1	2.3	2.0	2.7	2.1	1.4	1.9	2.3	2.2	2.5	2.6	2.9	1.2	1.4	1.8	1.8	2.2	1.9	1.5	1.5	1.5	2.5	2.3	2.5	1.7	2.4	2.3	2.1	2.3	2.1	97.2
REQ	1.6	1.9	1.4	2.2	1.2	2.6	1.5	2.0	2.1	1.8	2.6	1.6	2.3	2.1	1.6	1.8	3.1	2.4	3.9	1.9	2.0	2.3	2.5	2.1	1.5	1.9	1.2	1.6	2.2	2.1	5.7	2.3	1.7	1.8	2.6	1.8	2.1	1.5	1.4	2.7	1.9	1.9	1.3	2.6	2.2	2.2	2.5	1.1	94.3
RLC	2.5	2.5	2.5	1.5	1.7	2.0	1.7	1.6	1.8	1.3	2.4	1.2	2.4	2.6	1.9	1.6	2.1	1.6	2.5	2.1	1.7	3.4	3.1	1.6	1.8	2.1	1.7	1.5	1.9	2.5	2.5	5.1	1.7	1.6	2.3	3.5	2.7	1.5	2.0	2.0	1.8	1.9	1.3	1.8	2.0	1.9	2.1	1.4	94.9
SC	2.4	1.9	2.5	2.4	2.3	2.2	1.0	2.6	2.1	1.9	2.1	1.5	2.5	2.0	1.6	2.0	2.2	3.0	1.9	2.6	2.6	2.4	1.7	1.7	2.2	2.7	2.5	2.1	2.5	2.0	0.6	1.3	3.0	2.5	2.3	2.2	2.0	1.3	2.0	2.0	1.9	1.9	2.1	1.8	1.9	2.1	1.8	2.5	97.0
SNT	2.2	1.6	2.6	2.1	2.7	2.2	1.4	2.5	2.3	1.1	1.8	1.7	2.7	2.2	1.7	1.5	2.0	2.6	1.7	2.7	3.0	2.8	1.8	1.9	1.9	3.0	2.7	2.2	2.4	2.3	0.7	1.5	1.9	3.2	2.3	2.5	1.0	1.5	1.2	2.3	2.2	2.2	1.7	2.4	2.5	2.0	1.8	2.4	96.8
STORJ	2.4	2.0	2.4	2.5	1.9	2.0	1.1	2.6	2.4	1.6	2.5	2.1	2.3	1.9	1.5	1.7	2.0	2.7	1.9	2.6	2.2	1.9	1.9	1.8	2.3	2.2	2.3	2.2	2.4	2.2	1.4	1.6	2.6	2.2	2.9	2.2	2.2	1.3	2.2	2.5	2.1	1.9	1.8	2.2	1.7	1.9	2.2	2.0	97.2
SYS	2.8	2.3	2.7	2.2	1.9	1.9	0.9	2.4	2.1	1.6	2.3	2.2	2.7	1.8	2.1	1.4	2.0	2.4	2.0	2.3	2.5	2.7	2.2	1.3	2.3	2.9	2.4	1.7	2.2	2.1	1.4	2.3	2.3	2.0	2.7	3.6	1.4	1.9	1.2	2.4	1.8	1.4	1.7	2.2	2.0	2.0	2.1	1.6	96.4
TRX	3.6	2.0	2.4	2.4	1.1	2.0	0.8	2.3	2.0	1.6	3.4	1.3	2.1	1.6	1.8	1.4	1.7	1.4	2.0	2.1	1.1	1.4	2.2	2.4	1.9	1.8	2.1	2.2	2.1	2.2	2.0	1.1	2.9	1.3	3.2	2.2	5.9	2.6	4.3	2.8	2.3	1.7	1.0	2.3	1.3	1.2	2.0	1.8	94.1
VGX	3.2	2.2	1.3	1.4	1.2	1.2	2.2	1.8	1.4	1.5	1.3	4.0	1.6	0.9	2.9	1.2	1.1	3.0	2.4	1.3	2.6	1.0	1.1	1.9	1.6	2.5	3.3	1.6	1.2	1.2	3.0	1.8	1.8	2.5	2.1	1.7	3.3	10.6	2.4	2.6	0.9	1.8	2.3	2.3	1.6	1.4	1.4	1.5	89.4
WAVES	2.4	1.3	1.8	2.4	2.0	2.2	2.3	2.3	2.0	1.8	2.0	1.4	1.8	1.5	1.4	1.5	2.3	2.7	2.4	1.8	1.6	2.5	1.8	2.0	2.2	2.0	2.5	2.5	1.8	2.1	1.4	1.6	2.3	2.1	2.1	1.8	2.3	3.5	4.3	2.3	2.0	2.7	1.0	2.1	1.8	2.7	1.9	1.9	95.7
XEM	2.6	2.7	2.5	2.2	1.8	2.0	1.3	2.3	2.1	1.5	2.6	1.8	2.5	1.7	1.9	1.3	1.9	1.9	1.7	2.0	2.4	2.3	2.1	1.8	1.8	2.7	2.5	2.4	2.1	2.6	1.7	1.4	1.9	1.8	2.5	2.5	2.3	1.8	2.2	3.2	1.8	2.0	1.6	2.2	2.1	2.0	2.5	1.6	96.8
XLM	2.3	1.9	2.4	2.5	2.1	2.5	1.6	2.1	2.3	1.7	2.4	1.5	2.1	2.3	1.5	1.3	2.3	2.1	2.0	2.0	1.9	2.3	1.8	1.9	2.1	2.3	2.6	2.6	2.4	2.6	1.4	1.0	2.1	2.0	2.1	1.8	1.9	1.6	2.4	2.4	2.7	2.6	1.1	2.6	2.4	2.1	2.4	2.2	97.3
XMR	1.6	1.4	2.1	2.1	2.3	2.8	2.3	1.9	2.6	1.7	2.3	1.4	2.3	2.6	1.0	2.1	3.1	1.8	3.0	2.1	1.5	2.2	1.9	1.9	1.6	1.8	1.7	2.4	2.8	2.6	1.5	1.1	2.0	2.1	2.1	1.3	1.9	0.8	1.6	2.3	2.6	3.9	1.5	2.6	2.5	2.7	2.4	2.6	96.1
XNO	1.5	1.7	2.4	2.3	2.4	2.2	1.7	2.6	2.5	1.7	2.0	2.2	2.2	1.9	1.6	1.9	2.6	2.7	2.6	2.9	2.6	2.6	1.7	1.5	1.5	2.1	1.9	2.3	2.7	2.6	1.3	1.2	2.1	2.5	2.2	1.7	1.1	1.4	0.8	2.5	1.9	1.9	3.8	1.7	2.4	2.1	2.3	2.0	96.2
XRP	2.4	2.3	2.4	2.2	2.1	2.3	1.5	2.1	2.2	1.5	2.3	1.8	2.4	2.2	1.5	1.2	2.1	1.9	1.9	1.9	2.2	2.4	1.8	1.6	2.0	2.9	2.6	2.3	2.3	2.6	1.7	1.1	1.8	2.0	2.3	1.9	1.7	1.9	2.1	2.6	2.7	2.4	1.2	3.2	2.4	2.2	2.4	2.1	96.9
XTZ	1.9	2.0	2.3	2.3	2.4	2.6	1.5	2.2	2.1	1.7	2.0	2.2	2.3	2.5	1.4	1.5	2.3	2.5	1.9	2.2	2.4	2.4	1.7	1.6	1.7	2.6	2.5	2.4	2.4	2.4	1.0	1.2	2.0	2.3	1.8	1.9	1.5	1.9	1.8	2.3	2.5	2.6	1.6	2.5	2.9	2.1	2.1	2.5	97.1
ZEC	1.8	1.9	2.3	2.5	2.0	2.4	1.8	2.2	2.6	1.9	2.2	1.7	2.3	2.2	1.5	2.1	2.8	2.1	2.4	1.9	2.0	2.3	2.0	1.6	2.4	2.4	2.4	2.2	2.3	2.3	1.1	1.3	2.0	2.1	2.2	1.9	1.3	0.7	1.6	2.5	2.0	2.5	1.5	2.2	2.2	3.9	2.5	2.3	96.1
ZEN	2.3	1.9	2.2	2.6	2.0	2.0	1.6	2.0	2.4	1.7	2.3	2.0	2.1	2.4	0.8	1.9	2.3	2.6	2.0	2.1	1.8	2.1	2.2	1.5	2.4	2.2	2.3	2.1	2.6	2.5	1.5	1.4	2.3	2.0	2.4	2.1	1.7	1.5	1.9	2.4	2.2	2.6	1.3	2.3	2.1	2.7	3.1	1.8	97.0
ZRX	2.1	1.9	2.3	2.7	2.1	2.0	1.4	2.6	2.3	1.7	2.4	1.8	2.2	2.2	1.4	2.2	2.0	2.7	1.6	2.5	2.2	2.3	2.0	1.7	2.3	2.5	2.4	2.4	2.4	2.4	0.8	1.7	2.2	2.3	2.2	1.9	2.0	1.0	2.0	2.1	2.1	1.8	2.1	2.0	2.1	2.0	1.9	3.1	96.9
Contribution to self and others	110.3	92.2	110.4	114.6	98.5	108.3	74.9	110.3	106.2	87.8	108.4	91.0	108.4	97.5	72.4	86.7	111.4	114.3	102.4	103.7	105.2	113.5	94.2	80.0	100.2	116.8	116.1	108.8	111.8	112.0	69.0	70.2	102.3	98.4	106.0	97.8	87.7	91.1	89.1	114.7	98.2	107.1	83.8	104.0	99.5	110.6	101.3	101.2	**Total spillover index**
Contribution to others	106.8	88.3	107.4	111.9	95.8	104.5	71.3	107.4	103.4	84.3	105.3	86.1	105.7	94.3	69.1	83.8	108.1	111.4	98.7	100.9	102.1	110.3	91.2	77.3	97.2	113.3	112.8	105.5	109.1	109.2	63.2	65.1	99.3	95.1	103.1	94.2	81.8	80.6	84.7	111.5	95.5	103.2	80.0	100.8	96.6	106.7	98.3	98.1	**96.5 %**
Net spillovers	10.3	-7.8	10.4	14.6	-1.5	8.3	-25.1	10.3	6.2	-12.2	8.3	-9.1	8.4	-2.5	-27.6	-13.3	11.4	14.3	2.4	3.7	5.2	13.5	-5.8	-20.1	0.2	16.8	16.1	8.7	11.8	12.0	-31.1	-29.8	2.3	-1.6	6.0	-2.2	-12.3	-8.9	-11.0	14.6	-1.8	7.1	-16.2	4.0	-0.5	10.6	1.3	1.2	

Volatility spillover table 2022

Tickers	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX	Contribution from others
ADA	5.7	0.5	3.6	1.4	3.6	4.7	1.8	3.2	1.5	0.3	2.4	0.4	3.5	0.5	1.7	0.7	0.8	0.2	0.5	2.0	1.7	3.4	4.2	3.8	1.8	3.6	2.8	2.5	1.9	3.8	1.0	2.8	0.3	0.7	2.1	1.1	3.1	0.5	0.9	3.0	4.7	1.6	0.7	1.8	2.9	1.6	2.3	0.8	94.3
ANT	4.2	5.8	2.0	1.7	2.5	0.4	1.7	2.3	1.6	1.4	1.9	1.0	2.7	1.6	2.4	1.0	1.0	1.6	2.2	0.6	1.3	2.7	1.7	2.7	2.9	3.6	2.8	2.2	0.9	1.5	2.4	2.4	1.4	1.7	2.9	3.7	2.7	1.7	2.0	1.6	1.1	2.1	2.9	0.8	3.2	1.5	1.9	2.5	94.3
BAT	1.9	0.8	4.3	2.7	3.1	3.7	2.9	1.5	2.4	0.8	1.5	1.2	3.2	1.2	1.2	2.5	1.3	0.5	0.9	1.7	1.7	3.4	2.3	1.9	2.3	2.2	1.7	2.0	2.8	3.4	1.5	2.3	1.3	1.7	1.6	0.9	4.4	2.6	1.4	2.1	2.8	2.6	1.2	2.3	2.7	2.1	2.6	1.4	95.7
BCH	1.8	0.7	3.3	4.2	2.8	2.8	3.4	1.6	3.0	1.4	1.5	0.9	3.0	2.1	0.8	2.8	1.9	0.5	1.3	1.7	2.6	3.2	1.3	2.2	4.0	2.0	2.3	2.3	3.4	2.8	1.1	2.0	0.6	1.4	1.8	1.1	3.4	0.9	1.6	2.3	2.0	2.8	1.1	1.5	2.4	2.3	3.1	1.3	95.8
BNB	1.8	0.7	3.1	2.3	5.0	3.4	2.0	2.4	2.9	0.6	1.9	0.9	3.2	0.6	0.8	2.1	1.9	1.2	1.0	1.4	2.5	4.2	1.9	1.8	1.9	3.5	2.7	2.3	2.9	3.5	1.4	1.6	0.7	1.4	1.6	1.4	3.3	1.0	1.2	2.3	2.7	2.3	0.3	2.5	3.5	1.8	3.5	1.3	95.0
BTC	2.5	0.4	4.0	2.3	3.5	5.8	3.2	1.8	2.2	0.9	1.3	0.5	3.1	0.8	1.5	2.3	1.2	0.3	0.9	2.3	2.8	3.6	1.9	1.8	2.2	1.7	1.7	3.1	3.7	4.3	0.3	2.3	0.7	0.6	1.5	0.9	3.5	0.7	0.7	2.9	4.0	2.7	0.8	2.9	1.9	2.7	3.1	0.6	94.2
BTG	1.7	0.6	3.9	3.6	2.6	4.1	6.4	1.8	1.7	1.1	0.7	0.3	2.8	1.9	0.6	3.7	2.2	0.8	1.1	1.6	3.1	3.3	0.5	2.3	3.5	1.1	1.0	3.0	3.5	2.7	1.3	1.3	0.4	1.8	2.6	0.9	3.4	1.2	0.6	4.2	3.3	2.1	0.3	2.5	1.4	1.8	2.8	1.0	93.6
CVC	3.1	1.1	2.4	2.0	3.6	2.7	1.3	3.4	2.5	0.7	2.4	1.2	2.9	0.7	1.0	1.2	2.4	0.7	1.8	1.3	2.2	3.0	2.4	2.4	2.0	3.3	3.0	2.9	2.3	3.4	1.3	1.9	0.7	1.2	1.9	1.1	4.3	1.3	1.5	2.0	2.7	2.5	0.4	1.7	2.8	2.8	3.1	1.8	96.6
DASH	1.5	0.8	2.8	3.3	3.1	2.8	1.8	1.7	4.4	0.7	2.1	0.8	3.0	0.8	0.5	2.4	1.6	1.0	1.6	1.7	1.9	3.1	2.3	1.3	2.4	2.2	2.6	3.0	3.3	4.3	1.0	2.4	0.6	1.5	1.2	1.4	3.3	1.4	2.3	1.7	2.1	3.3	0.7	2.0	2.4	2.5	3.9	1.5	95.6
DCR	1.7	0.8	3.1	3.0	2.9	3.3	4.8	1.6	1.9	4.5	1.6	0.9	2.6	2.9	1.5	2.5	1.7	0.6	1.3	2.5	4.0	2.7	0.9	2.1	3.3	1.2	1.7	1.8	2.9	1.8	1.4	1.4	1.2	1.9	1.6	1.4	2.4	2.1	1.0	2.8	1.7	2.5	0.7	2.3	1.1	1.3	2.5	2.7	95.5
DGB	4.4	0.8	1.8	1.0	3.6	2.1	1.0	4.5	1.7	0.8	4.2	0.7	2.5	1.4	1.5	2.4	2.3	0.5	1.8	1.6	1.2	2.5	3.6	3.2	0.8	4.4	4.3	2.3	1.2	2.4	1.9	1.2	2.5	1.8	2.0	2.3	1.3	1.1	3.1	1.7	2.8	1.5	0.5	1.9	2.5	1.5	2.4	1.8	95.8
DOGE	1.6	1.2	2.3	2.1	1.2	2.6	2.0	1.0	1.9	2.6	1.4	4.6	1.6	4.3	5.7	1.0	1.2	2.6	0.8	2.1	1.1	1.0	2.0	2.2	3.0	1.0	1.5	2.1	1.4	1.6	4.1	2.0	0.8	2.8	2.7	2.0	2.5	2.1	3.3	1.5	1.7	1.4	3.5	2.1	0.9	2.1	1.8	2.2	95.4
ENJ	2.7	0.8	3.5	2.1	4.8	4.0	2.0	2.3	2.4	0.6	2.0	0.8	3.6	0.8	1.0	1.4	1.2	0.6	0.8	1.4	2.2	4.4	2.6	1.8	2.1	3.7	2.7	2.2	2.7	3.6	0.9	1.9	0.3	1.3	1.6	1.2	4.4	0.8	1.1	2.4	3.1	2.3	0.8	2.3	3.4	1.8	2.9	0.9	96.4
EOS	2.1	1.4	3.3	2.9	2.1	1.5	3.2	0.7	2.6	1.3	1.3	0.6	2.4	6.2	3.7	2.6	1.3	0.9	1.7	2.2	2.3	2.2	1.7	1.7	4.2	1.9	1.3	1.6	2.2	2.8	2.6	2.3	1.3	1.3	1.7	0.9	3.7	1.5	2.3	1.8	2.3	1.9	1.0	1.6	2.8	1.3	2.6	1.2	93.8
ERG	3.5	1.5	3.8	1.8	4.2	2.6	2.2	2.0	2.2	1.9	2.9	1.3	3.8	1.4	1.9	1.4	1.3	1.3	1.5	1.5	2.8	3.5	3.1	2.7	2.8	3.9	2.8	1.4	1.8	2.6	0.9	1.9	0.8	0.7	1.9	1.8	2.1	2.6	1.2	1.4	1.7	0.7	1.7	1.9	2.6	1.2	2.2	1.8	98.1
ETC	2.0	0.9	3.2	3.1	3.3	3.5	3.5	2.6	2.6	0.9	1.9	0.4	2.8	1.4	0.7	3.4	1.9	1.7	1.2	1.0	2.6	2.9	2.0	1.8	2.9	1.9	2.0	3.6	2.9	3.8	1.3	1.2	0.8	1.8	2.6	1.3	2.7	1.5	1.4	2.1	2.7	1.8	1.0	1.8	1.8	2.2	3.2	0.6	96.6
ETH	2.2	0.5	3.9	2.3	3.0	5.1	4.1	0.9	1.7	0.7	0.6	0.8	2.6	1.6	3.0	2.5	3.3	1.1	1.8	2.0	2.7	3.8	1.1	1.5	2.4	1.5	0.9	1.4	3.4	2.4	2.3	1.7	0.9	0.7	1.5	1.4	4.7	2.0	0.8	3.0	3.3	2.7	1.3	2.7	2.1	1.7	1.8	0.7	96.7
GLM	4.8	1.0	2.9	1.4	2.9	4.0	2.2	2.2	2.0	0.7	2.7	1.9	3.2	1.5	1.5	1.7	1.0	4.5	0.8	1.3	1.5	2.4	4.2	2.1	2.0	2.3	2.2	2.4	1.4	3.7	0.8	2.9	0.9	2.0	2.4	2.9	1.1	1.3	1.1	2.5	3.5	0.5	1.2	3.2	1.5	0.3	2.3	1.4	95.5
GNO	4.4	0.4	2.3	1.7	2.2	3.1	1.6	1.5	2.3	0.5	1.6	1.4	2.5	0.7	1.9	1.8	2.7	2.1	3.1	2.2	1.2	3.2	2.7	2.5	1.1	2.5	1.8	2.1	2.0	2.8	2.0	3.3	0.9	1.8	1.8	2.5	1.5	1.1	2.2	2.7	3.3	3.0	0.8	2.1	3.4	1.4	2.6	1.5	96.9
ICX	1.4	1.1	2.3	1.7	2.7	2.9	1.9	2.0	1.8	1.0	2.2	0.6	2.8	0.5	2.2	0.6	0.9	0.9	2.0	4.5	1.8	4.0	1.8	2.5	1.1	3.3	3.1	1.9	2.6	2.5	0.7	1.9	0.8	2.3	1.1	1.1	3.1	1.6	2.1	2.9	3.4	4.8	1.0	2.0	3.5	2.3	3.2	2.0	95.5
KCS	3.2	1.1	3.4	1.8	3.9	3.7	2.5	1.6	2.3	0.9	1.3	0.7	3.0	1.5	1.7	2.1	1.9	0.3	1.3	1.3	2.9	3.4	2.5	1.7	1.9	2.3	1.5	3.1	2.8	4.1	1.4	2.3	1.4	0.6	1.8	1.2	4.1	2.1	0.9	2.1	3.4	2.0	0.9	1.6	3.0	2.9	2.9	0.4	97.2
LINK	3.7	0.6	4.3	1.8	4.2	4.9	2.2	1.7	1.7	0.3	1.3	0.3	3.6	0.1	1.7	1.0	1.3	0.3	0.8	2.3	2.2	5.1	2.6	2.4	1.7	3.4	2.2	1.5	3.5	3.2	1.0	2.4	0.8	0.4	1.1	0.8	4.8	1.0	0.6	3.4	4.2	2.8	0.6	2.1	3.7	1.6	2.4	0.7	94.9
LRC	4.7	1.1	2.9	1.1	4.4	5.2	1.5	2.8	1.5	0.8	2.0	1.5	2.5	0.9	1.7	1.1	0.5	1.7	1.1	1.9	2.0	3.0	6.2	2.0	1.0	3.4	2.1	1.7	1.9	3.8	0.9	1.6	0.6	2.0	1.2	1.2	2.4	2.0	1.1	2.7	3.9	0.9	2.6	2.8	2.5	1.3	1.8	0.8	93.7
LSK	3.8	1.0	2.4	1.9	2.2	1.8	2.2	3.1	1.6	1.1	2.6	0.6	2.5	2.5	1.1	1.3	4.5	1.0	1.4	2.6	2.1	2.2	2.8	4.3	1.9	3.0	2.9	1.6	2.5	2.3	2.0	1.8	2.9	2.0	2.3	0.8	2.2	1.0	1.3	2.7	2.3	1.3	1.0	2.1	2.5	1.2	2.2	1.8	95.7
LTC	3.0	0.8	4.4	2.9	3.6	4.7	2.9	1.4	2.5	0.6	1.1	0.6	3.2	1.5	1.6	2.2	1.9	1.3	1.1	1.0	2.8	3.4	2.2	1.9	3.4	2.0	1.7	2.0	3.7	3.5	0.6	2.3	1.1	1.4	1.9	1.3	4.2	0.8	1.2	2.0	2.3	2.0	1.4	2.1	2.1	1.7	2.3	0.9	96.6
MANA	1.7	1.7	2.5	2.0	3.7	2.6	1.5	2.6	2.1	1.0	2.3	1.0	3.2	1.0	1.0	0.8	1.2	1.0	1.3	2.4	1.9	3.9	2.0	2.5	2.0	4.3	3.3	1.6	2.3	2.2	1.2	1.7	0.7	1.8	1.8	1.1	3.6	1.6	1.5	2.4	2.9	2.9	1.2	2.7	3.9	1.9	2.4	2.1	95.7
MIOTA	2.9	1.0	2.6	2.2	4.4	2.3	1.4	3.4	2.6	0.6	3.7	0.3	3.3	0.9	1.7	1.6	0.9	0.2	1.3	1.3	1.9	3.5	2.3	2.8	2.0	4.3	5.2	2.4	1.6	2.7	1.8	1.5	1.0	1.0	1.7	1.6	3.3	0.8	2.0	1.3	2.4	3.4	0.5	1.3	3.2	2.1	3.0	1.1	94.8
NEO	1.7	0.5	2.5	2.7	2.8	3.1	3.1	2.3	2.9	0.7	2.1	0.8	3.0	1.0	0.4	2.5	1.1	0.4	1.5	1.9	2.7	2.8	1.8	1.8	2.3	2.2	2.5	4.8	2.8	4.9	1.4	2.0	1.5	1.7	2.3	1.3	3.1	0.8	1.7	2.1	2.5	2.4	0.7	1.8	2.0	2.9	3.9	0.7	95.2
OMG	2.2	0.6	4.3	2.4	3.9	5.5	2.8	1.8	2.3	1.0	1.5	0.5	3.1	0.7	1.0	2.3	1.7	0.3	1.0	2.1	2.8	3.7	2.3	1.8	2.1	2.1	2.1	2.6	3.9	4.3	0.6	1.8	0.4	0.6	1.2	0.7	4.6	0.8	0.7	2.5	3.6	2.7	0.8	2.7	2.3	2.7	2.8	0.5	96.1
QTUM	2.1	0.6	3.1	2.6	3.1	3.3	2.2	2.0	3.2	0.7	2.1	1.3	3.2	1.0	0.4	2.0	1.9	0.4	1.7	1.4	1.9	3.0	2.9	1.6	2.2	2.2	2.1	3.5	2.9	4.9	1.6	2.3	0.9	1.6	1.9	1.2	2.2	0.8	1.9	2.3	2.7	2.3	1.0	3.2	2.4	2.1	3.4	1.1	95.2
REQ	0.9	0.8	2.8	3.2	2.3	2.2	3.0	0.8	3.1	1.9	1.5	0.7	2.2	4.7	2.8	4.5	3.5	1.1	0.6	0.8	3.2	2.0	1.2	0.8	2.7	1.2	1.2	2.6	3.3	2.7	9.7	1.1	1.5	1.6	1.9	1.6	1.4	0.6	0.4	1.9	1.6	1.5	0.9	2.6	1.5	2.1	2.4	1.4	90.3
RLC	2.9	2.0	2.7	2.1	2.0	1.5	2.1	1.1	2.7	1.5	2.0	0.4	3.0	2.1	2.3	1.4	1.9	0.8	2.9	3.0	1.8	3.0	3.1	2.1	2.2	2.3	1.9	1.8	2.8	3.4	1.2	3.3	1.6	2.2	1.8	2.5	1.8	0.8	1.7	2.4	2.1	2.0	0.7	2.2	2.6	1.3	3.3	2.1	96.8
SC	1.3	0.6	2.2	2.0	1.7	3.0	1.8	2.5	2.0	0.7	2.4	1.8	1.9	2.1	2.3	3.1	3.3	0.5	2.5	1.7	1.1	2.0	1.5	1.5	1.7	2.3	3.5	1.6	2.9	2.1	2.8	1.3	6.2	0.8	1.0	1.6	2.8	2.3	2.0	1.3	2.5	2.5	1.2	4.5	2.2	2.6	1.4	1.5	93.8
SNT	3.7	1.8	1.9	1.4	1.7	2.9	1.7	3.0	1.1	0.6	1.5	0.7	2.3	1.1	2.1	1.0	0.7	2.4	1.3	2.9	1.2	2.6	2.2	3.5	1.4	2.6	1.9	2.6	1.3	2.0	1.4	2.8	1.4	4.4	2.5	1.0	2.4	1.5	2.7	3.9	5.1	2.3	1.4	1.3	3.0	1.7	2.5	1.8	95.6
STORJ	2.3	0.9	3.0	2.0	2.3	2.2	2.5	2.0	1.8	0.7	1.6	1.6	2.4	2.0	2.0	1.9	1.5	1.8	1.3	1.8	1.9	2.1	1.4	1.9	2.5	1.9	1.4	2.8	1.9	2.6	1.1	1.9	1.1	3.0	3.2	1.4	7.3	2.2	2.5	1.5	2.1	1.8	1.0	1.9	2.1	3.0	2.2	3.0	96.9
SYS	3.1	2.1	2.5	2.3	3.4	3.2	1.9	1.4	2.7	1.0	1.7	1.0	2.4	2.0	2.5	1.4	1.6	0.9	2.2	1.7	1.6	3.3	3.9	0.7	2.2	2.7	1.8	1.6	2.9	3.2	0.9	1.8	1.1	1.4	1.3	3.6	2.7	2.9	1.5	1.2	2.0	2.4	1.5	2.5	3.1	1.9	2.3	1.3	96.4
TRX	3.0	0.6	4.3	2.8	3.6	2.5	1.8	1.9	2.3	1.4	1.6	0.9	2.9	1.8	0.9	1.6	1.3	1.6	1.4	0.9	2.7	2.1	1.2	2.3	3.6	1.4	2.4	3.3	3.0	3.3	1.0	1.7	0.6	1.4	1.5	0.7	10.6	1.5	0.6	1.3	1.4	2.6	1.2	0.4	1.2	5.0	1.8	1.6	89.4
VGX	1.6	1.7	2.3	2.4	2.1	2.4	3.3	1.7	1.6	1.6	0.8	1.0	1.4	0.7	1.4	1.4	2.4	3.5	2.5	3.1	1.5	2.4	3.1	1.7	1.5	1.5	1.4	1.2	2.6	2.1	0.4	1.2	1.5	3.1	1.2	0.8	2.2	9.4	2.3	2.7	3.0	3.1	1.3	1.9	1.7	2.2	2.0	2.2	90.6
WAVES	3.0	2.0	1.2	2.4	2.0	0.9	1.3	3.1	2.8	0.9	2.9	1.5	2.2	0.6	1.4	1.0	1.6	1.2	1.4	1.4	1.2	1.9	1.7	2.6	2.1	2.8	3.6	4.1	0.9	2.3	1.3	2.3	1.6	2.8	2.8	2.8	2.0	1.6	6.0	0.8	1.5	3.2	1.9	0.9	3.3	1.8	3.3	2.3	94.0
XEM	2.7	0.7	3.0	1.8	3.3	3.6	2.3	2.1	1.7	0.4	1.6	1.5	3.1	0.5	1.2	1.4	1.5	0.6	0.5	2.1	1.9	3.7	1.9	2.7	1.7	2.9	2.4	2.1	2.4	2.8	1.5	2.1	0.5	1.5	1.8	0.9	5.2	1.2	0.9	4.1	4.1	3.5	0.2	2.7	3.4	2.3	2.4	2.1	95.9
XLM	2.3	0.7	2.7	2.0	3.0	4.2	2.2	2.5	2.1	0.4	1.5	0.7	2.8	0.8	1.9	1.5	0.9	0.6	1.3	2.8	1.4	4.0	1.9	2.1	1.4	2.8	1.9	2.6	2.5	3.0	1.5	2.0	0.4	2.0	2.0	0.9	1.5	0.8	1.7	3.8	5.6	3.1	0.7	3.3	3.3	2.1	3.3	1.4	94.4
XMR	1.3	0.4	3.2	2.9	3.2	4.3	3.0	1.5	2.0	1.1	1.3	0.6	2.8	0.1	2.4	1.3	0.6	0.2	1.1	2.5	2.1	3.9	0.5	2.2	2.0	1.8	2.7	3.1	3.2	3.0	0.3	1.8	0.2	1.0	1.0	0.4	6.7	2.0	0.9	2.7	4.1	7.2	0.2	1.6	2.5	3.5	3.4	0.4	92.8
XNO	2.3	2.4	2.1	4.3	1.6	2.4	2.2	1.4	3.6	0.9	1.8	1.7	2.0	1.2	2.2	2.6	1.9	1.5	0.9	1.7	1.6	2.5	2.6	0.8	3.5	1.2	1.8	2.0	2.9	2.2	1.5	1.8	1.9	1.2	1.4	3.2	1.7	2.9	2.2	1.6	1.6	2.4	5.1	2.3	1.2	1.8	2.4	2.1	94.9
XRP	2.0	0.9	2.4	1.2	2.9	5.6	2.1	2.0	1.2	1.3	1.1	2.0	2.5	2.2	2.4	1.2	1.2	0.6	1.6	3.0	2.4	3.7	2.7	1.5	1.2	2.7	1.3	1.3	2.6	2.6	1.6	2.2	0.7	1.6	1.5	0.7	2.0	1.5	0.9	3.7	4.9	2.5	2.6	5.8	3.0	1.2	1.5	1.0	94.2
XTZ	2.9	1.4	2.8	2.4	2.8	1.9	1.5	1.5	3.1	1.4	1.9	2.8	2.8	1.4	0.9	1.3	1.1	0.8	0.8	1.3	0.9	3.3	3.1	1.8	2.0	3.2	1.8	1.5	2.0	2.9	1.3	2.5	1.3	1.7	1.9	1.5	2.3	2.1	2.7	2.6	3.1	2.2	1.2	3.0	5.0	1.1	2.7	2.3	95.0
ZEC	1.1	0.4	2.9	3.0	2.8	3.2	2.5	1.8	3.0	2.6	1.3	0.9	2.4	0.9	1.8	2.4	1.7	0.6	1.3	1.8	2.8	2.6	1.2	1.7	2.5	1.6	2.6	3.7	3.6	3.2	1.3	2.2	0.6	1.1	1.7	0.6	4.0	1.1	1.6	1.4	2.2	4.5	0.7	1.2	1.9	5.9	3.3	0.7	94.1
ZEN	1.6	0.7	3.3	2.7	4.0	3.7	2.2	2.0	3.0	1.4	1.9	0.5	2.8	0.8	0.5	2.4	1.5	1.0	1.1	1.5	3.1	3.0	1.8	2.1	2.4	2.1	2.7	3.0	3.4	4.0	1.0	2.0	0.7	1.6	1.5	1.1	4.3	0.7	1.8	1.9	2.2	2.6	0.7	1.7	2.1	2.7	4.0	1.6	96.1
ZRX	3.3	1.5	2.6	2.4	2.4	1.8	1.4	1.7	2.6	0.4	2.0	0.7	2.7	1.2	1.4	1.3	1.8	1.7	1.1	1.8	0.9	3.1	1.6	1.8	2.4	3.1	1.5	1.4	2.0	2.4	0.9	2.1	0.9	2.5	2.1	2.1	3.6	1.3	2.7	3.3	3.5	1.7	1.0	2.3	4.5	1.5	2.7	5.4	94.6
Contribution to self and others	125.2	51.9	141.8	111.0	146.1	153.4	114.4	97.6	110.4	51.2	88.0	49.5	132.6	70.3	79.9	89.4	79.8	51.8	65.8	90.4	99.7	147.5	108.2	100.7	107.9	119.9	108.1	113.1	123.0	145.3	72.9	96.3	52.6	78.6	87.1	69.4	159.5	76.6	79.3	112.0	137.3	118.5	56.2	106.2	123.7	100.1	127.3	72.9	**Total spillover index**
Contribution to others	119.5	46.1	137.6	106.8	141.1	147.6	107.9	94.2	105.9	46.7	83.8	44.9	129.0	64.1	78.0	86.0	76.5	47.3	62.7	85.9	96.8	142.5	102.0	96.4	104.5	115.6	102.9	108.3	119.1	140.4	63.2	93.1	46.4	74.2	84.0	65.8	148.9	67.2	73.3	107.9	131.7	111.3	51.1	100.4	118.7	94.2	123.3	67.5	**95.0 %**
Net spillover	25.2	-48.1	41.9	11.0	46.1	53.4	14.4	-2.4	10.4	-48.9	-12.0	-50.5	32.6	-29.7	-20.1	-10.6	-20.2	-48.2	-34.2	-9.6	-0.3	47.5	8.3	0.7	7.9	19.9	8.1	13.1	23.0	45.2	-27.1	-3.7	-47.4	-21.5	-12.9	-30.6	59.5	-23.4	-20.7	12.0	37.3	18.6	-43.9	6.2	23.7	0.1	27.3	-27.1	

A.5 Directional spillover tables

The tables below illustrate the directional spillovers, along with their respective net spillovers, for all periods. Specifically, these results could also be found in any bottom row, or far right column of the above spillover tables. They are the off-diagonal column and row sums. Each list is arranged in a descending order based on its contribution to other assets.

A.5.1 Directional spillovers for Static period

Static period

Return					Volatility				
Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers	Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers
1	ETH	133.57	95.29	38.28	1	OMG	145.99	90.95	55.04
2	NEO	125.58	95.03	30.55	2	DASH	142.96	91.06	51.90
3	LTC	122.81	94.93	27.88	3	EOS	137.14	89.89	47.25
4	QTUM	118.02	94.77	23.25	4	ETH	136.96	91.83	45.13
5	OMG	115.95	94.63	21.32	5	QTUM	131.09	90.48	40.61
6	BTC	115.07	94.60	20.47	6	BAT	130.53	89.57	40.96
7	EOS	114.51	94.56	19.95	7	BCH	125.07	89.02	36.05
8	MIOTA	113.13	94.52	18.61	8	LSK	124.90	90.68	34.22
9	XMR	112.02	94.42	17.60	9	ICX	124.71	90.33	34.38
10	ZEC	111.39	94.44	16.95	10	XRP	122.54	88.17	34.37
11	BCH	110.32	94.44	15.88	11	ADA	120.92	89.01	31.91
12	DASH	110.29	94.44	15.85	12	LTC	119.11	91.23	27.88
13	ETC	109.13	94.33	14.80	13	BNB	116.72	90.66	26.06
14	SC	108.58	94.27	14.31	14	MIOTA	111.17	90.74	20.43
15	LSK	107.75	94.23	13.52	15	XLM	110.7	88.50	22.20
16	XLM	106.98	94.23	12.75	16	SC	108.49	89.60	18.89
17	BAT	106.88	94.16	12.72	17	XTZ	104.89	88.01	16.88
18	ZRX	102.07	93.97	8.10	18	ZRX	97.96	85.06	12.90
19	ADA	101.48	93.93	7.55	19	LINK	96.51	90.07	6.44
20	ICX	100.10	93.81	6.29	20	KCS	94.93	82.55	12.38
21	DGB	97.15	93.65	3.50	21	ETC	91.27	86.67	4.60
22	SNT	95.87	93.61	2.26	22	NEO	90.22	91.18	-0.96
23	BNB	95.83	93.64	2.19	23	GNO	88.74	85.18	3.56
24	XRP	93.64	93.47	0.17	24	DGB	85.24	88.00	-2.76
25	XEM	91.72	93.19	-1.47	25	BTC	84.42	90.01	-5.59
26	LINK	89.90	93.22	-3.32	26	RLC	82.18	85.18	-3.00
27	DCR	89.15	93.14	-3.99	27	TRX	81.16	85.86	-4.70
28	GLM	88.94	93.07	-4.13	28	SYS	73.61	84.63	-11.02
29	ZEN	88.80	93.12	-4.32	29	XMR	72.70	88.58	-15.88
30	CVC	86.84	92.91	-6.07	30	XEM	70.60	84.87	-14.27
31	XNO	84.70	92.84	-8.14	31	ZEC	69.41	90.02	-20.61
32	LRC	84.50	92.86	-8.36	32	GLM	69.03	85.60	-16.57
33	WAVES	82.85	92.63	-9.78	33	WAVES	68.92	81.56	-12.64
34	RLC	82.08	92.57	-10.49	34	LRC	63.54	83.25	-19.71
35	TRX	81.42	92.63	-11.21	35	SNT	55.98	84.12	-28.14
36	BTG	81.18	92.59	-11.41	36	MANA	55.91	84.51	-28.60
37	STORJ	80.62	92.43	-11.81	37	ZEN	54.01	87.59	-33.58
38	XTZ	79.94	92.49	-12.55	38	ENJ	54.00	88.53	-34.53
39	ENJ	79.18	92.39	-13.21	39	BTG	50.65	83.29	-32.64
40	ANT	77.79	92.23	-14.44	40	STORJ	44.02	79.68	-35.66
41	GNO	77.07	92.11	-15.04	41	CVC	43.58	79.33	-35.75
42	KCS	76.82	92.23	-15.41	42	XNO	41.53	81.14	-39.61
43	MANA	72.80	91.69	-18.89	43	VGX	33.29	77.48	-44.19
44	SYS	71.97	91.49	-19.52	44	ANT	33.27	89.94	-56.67
45	REQ	58.47	89.91	-31.44	45	DCR	32.37	80.22	-47.85
46	DOGE	49.97	88.77	-38.80	46	REQ	25.13	70.08	-44.95
47	VGX	49.23	88.45	-39.22	47	DOGE	9.75	36.03	-26.28
48	ERG	14.61	66.34	-51.73	48	ERG	0.60	8.48	-7.88

A.5.2 Directional spillovers for Temporal periods

Directional spillovers 2018

Return					Volatility				
Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers	Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers
1	ANT	159.02	95.66	63.36	1	ADA	130.99	95.20	35.79
2	NEO	142.10	96.07	46.03	2	LTC	124.81	95.47	29.34
3	SC	133.24	96.49	36.75	3	QTUM	123.46	94.95	28.51
4	DOGE	133.03	95.02	38.01	4	ICX	118.63	96.79	21.84
5	BAT	124.84	96.01	28.83	5	STORJ	118.16	94.70	23.46
6	MIOTA	124.17	96.20	27.97	6	SNT	117.31	95.24	22.07
7	XMR	123.58	94.88	28.70	7	ETH	115.39	96.04	19.35
8	XEM	121.58	95.20	26.38	8	OMG	110.98	96.18	14.80
9	ETH	120.13	96.68	23.45	9	XLM	110.40	94.92	15.48
10	ADA	120.04	96.56	23.48	10	TRX	109.09	95.24	13.85
11	ZRX	116.23	94.61	21.62	11	LRC	109.01	95.03	13.98
12	DASH	113.00	95.54	17.46	12	CVC	107.45	95.51	11.94
13	QTUM	110.63	96.47	14.16	13	BTC	107.16	95.97	11.19
14	SNT	109.62	95.92	13.70	14	NEO	106.14	96.07	10.07
15	DCR	108.19	95.98	12.21	15	BCH	106.14	95.27	10.87
16	KCS	107.29	95.78	11.51	16	RLC	104.80	95.46	9.34
17	REQ	106.08	96.27	9.81	17	DGB	104.36	98.43	5.93
18	ICX	105.63	96.73	8.90	18	REQ	101.57	95.31	6.26
19	DGB	104.21	96.11	8.10	19	BTG	101.32	94.46	6.86
20	BTC	102.03	97.11	4.92	20	MIOTA	99.27	95.92	3.35
21	CVC	98.00	95.83	2.17	21	ERG	98.41	96.10	2.31
22	OMG	96.32	96.89	-0.57	22	MANA	97.83	94.26	3.57
23	LSK	95.14	96.37	-1.23	23	XMR	96.75	96.79	-0.04
24	ZEC	94.78	96.63	-1.85	24	DCR	96.01	93.82	2.19
25	STORJ	91.78	96.54	-4.76	25	XRP	94.16	94.98	-0.82
26	XLM	91.77	96.46	-4.69	26	ENJ	93.71	96.69	-2.98
27	LTC	90.13	95.83	-5.70	27	SC	92.79	95.96	-3.17
28	LINK	88.52	93.52	-5.00	28	EOS	92.43	97.40	-4.97
29	WAVES	86.99	96.40	-9.41	29	DASH	90.99	95.85	-4.86
30	EOS	85.73	94.87	-9.14	30	LSK	90.77	95.00	-4.23
31	BCH	83.87	95.81	-11.94	31	GNO	90.25	95.79	-5.54
32	XNO	82.30	94.22	-11.92	32	SYS	90.19	93.44	-3.25
33	BTG	82.12	95.69	-13.57	33	BAT	87.70	96.35	-8.65
34	XRP	79.36	95.61	-16.25	34	ETC	85.95	93.34	-7.39
35	RLC	79.27	96.70	-17.43	35	VGX	85.79	95.78	-9.99
36	LRC	79.26	96.30	-17.04	36	XNO	84.11	93.58	-9.47
37	SYS	79.22	96.11	-16.89	37	BNB	83.62	96.25	-12.63
38	ETC	76.23	96.63	-20.40	38	XEM	82.31	93.29	-10.98
39	BNB	74.49	97.17	-22.68	39	KCS	81.51	95.29	-13.78
40	GNO	72.87	96.91	-24.04	40	ZEN	80.67	93.49	-12.82
41	MANA	72.66	93.71	-21.05	41	WAVES	77.87	96.39	-18.52
42	ENJ	71.99	95.87	-23.88	42	XTZ	76.81	96.29	-19.48
43	TRX	71.77	96.69	-24.92	43	ZEC	75.19	95.54	-20.35
44	ERG	67.88	92.12	-24.24	44	ZRX	74.85	95.57	-20.72
45	VGX	64.14	97.54	-33.40	45	GLM	74.67	96.99	-22.32
46	GLM	57.50	97.08	-39.58	46	ANT	72.31	96.28	-23.97
47	ZEN	54.49	95.53	-41.04	47	LINK	57.56	97.47	-39.91
48	XTZ	52.42	97.32	-44.90	48	DOGE	53.49	95.00	-41.51

Directional spillovers 2019

Return				
Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers
1	WAVES	129.02	95.00	34.02
2	XMR	126.90	95.63	31.27
3	ICX	126.71	95.31	31.40
4	KCS	121.87	94.81	27.06
5	DASH	118.70	96.26	22.44
6	ZEC	118.23	95.98	22.25
7	DCR	115.36	94.26	21.10
8	EOS	113.69	95.97	17.72
9	OMG	111.82	96.04	15.78
10	XNO	111.80	95.96	15.84
11	ERG	111.27	93.86	17.41
12	MIOTA	109.66	96.39	13.27
13	XEM	109.07	95.52	13.55
14	ETC	108.67	96.60	12.07
15	STORJ	105.08	91.21	13.87
16	BCH	102.99	96.73	6.26
17	BTC	99.76	96.20	3.56
18	NEO	99.70	95.61	4.09
19	LTC	99.60	95.30	4.30
20	ETH	99.44	96.50	2.94
21	BTG	98.79	96.19	2.60
22	SNT	98.74	94.80	3.94
23	REQ	98.69	95.72	2.97
24	LRC	98.42	94.49	3.93
25	VGX	97.53	95.39	2.14
26	LSK	96.60	95.79	0.81
27	XRP	93.69	96.33	-2.64
28	XTZ	93.14	96.40	-3.26
29	BAT	92.36	94.56	-2.20
30	GNO	92.18	91.79	0.39
31	CVC	91.44	94.79	-3.35
32	QTUM	90.86	96.73	-5.87
33	ZRX	87.96	95.98	-8.02
34	LINK	86.85	94.98	-8.13
35	TRX	85.98	96.66	-10.68
36	XLM	85.71	96.38	-10.67
37	GLM	83.96	95.89	-11.93
38	DOGE	82.30	95.72	-13.42
39	ADA	80.67	97.12	-16.45
40	ZEN	78.30	92.61	-14.31
41	MANA	77.81	91.68	-13.87
42	SC	76.71	96.81	-20.10
43	SYS	72.07	95.04	-22.97
44	DGB	69.35	94.54	-25.19
45	BNB	64.06	93.48	-29.42
46	RLC	59.63	93.94	-34.31
47	ANT	49.61	94.38	-44.77
48	ENJ	47.94	93.36	-45.42

Volatility				
Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers
1	DGB	131.08	94.51	36.57
2	ZEN	128.32	88.26	40.06
3	BTC	125.06	96.77	28.29
4	SYS	122.63	92.63	30.00
5	RLC	119.36	93.75	25.61
6	ICX	115.33	94.44	20.89
7	ZRX	114.64	96.96	17.68
8	XLM	113.65	94.10	19.55
9	DASH	112.89	94.51	18.38
10	ETC	112.04	94.56	17.48
11	ETH	108.67	96.08	12.59
12	BTG	108.50	95.55	12.95
13	BNB	107.24	96.02	11.22
14	LTC	105.05	95.26	9.79
15	CVC	103.18	97.21	5.97
16	EOS	102.55	97.10	5.45
17	ADA	102.12	96.87	5.25
18	REQ	101.78	94.27	7.51
19	BCH	99.67	96.21	3.46
20	GLM	99.18	95.67	3.51
21	XMR	98.99	94.15	4.84
22	OMG	97.13	95.92	1.21
23	STORJ	95.59	93.93	1.66
24	XNO	94.51	95.20	-0.69
25	ZEC	93.83	95.14	-1.31
26	ANT	93.12	94.71	-1.59
27	NEO	91.51	96.85	-5.34
28	KCS	91.35	95.05	-3.70
29	LINK	87.44	93.83	-6.39
30	MIOTA	87.34	96.04	-8.70
31	SNT	86.13	93.27	-7.14
32	DCR	85.72	96.08	-10.36
33	MANA	85.01	92.56	-7.55
34	DOGE	83.92	92.22	-8.30
35	XRP	82.69	95.89	-13.20
36	XTZ	79.65	94.69	-15.04
37	QTUM	79.00	94.23	-15.23
38	ENJ	77.78	94.51	-16.73
39	LRC	75.67	97.09	-21.42
40	GNO	74.92	91.96	-17.04
41	SC	73.82	95.87	-22.05
42	BAT	73.78	95.04	-21.26
43	VGX	73.70	96.31	-22.61
44	XEM	73.66	95.72	-22.06
45	TRX	72.89	93.95	-21.06
46	ERG	70.84	92.35	-21.51
47	WAVES	70.58	93.74	-23.16
48	LSK	70.05	96.53	-26.48

Directional spillovers 2020

Return

Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers
1	TRX	131.30	95.90	35.30
2	BTC	127.40	96.10	31.30
3	XEM	115.70	93.60	22.10
4	KCS	112.90	95.60	17.30
5	QTUM	112.80	96.50	16.40
6	ADA	112.70	96.50	16.20
7	ZRX	111.40	95.20	16.20
8	XTZ	110.50	96.30	14.20
9	BAT	109.70	96.70	13.00
10	ETH	108.50	96.40	12.10
11	ENJ	106.50	94.80	11.70
12	VGX	103.90	95.20	8.70
13	ZEN	103.60	95.10	8.60
14	XRP	103.30	95.10	8.20
15	LINK	102.80	95.70	7.00
16	BCH	101.30	96.30	4.90
17	XLM	100.80	95.90	4.90
18	STORJ	100.60	94.70	6.00
19	MIOTA	100.40	96.50	3.90
20	GLM	99.10	96.20	3.00
21	LTC	95.90	97.30	-1.40
22	SC	95.80	95.10	0.70
23	BTG	95.50	94.30	1.10
24	XMR	94.00	96.20	-2.20
25	ZEC	93.70	96.10	-2.30
26	BNB	93.70	96.60	-2.90
27	REQ	93.50	93.00	0.60
28	ETC	93.30	96.40	-3.10
29	MANA	92.50	96.60	-4.10
30	DASH	92.20	95.40	-3.20
31	ICX	92.10	95.10	-2.90
32	NEO	91.60	96.10	-4.50
33	DCR	91.20	96.90	-5.70
34	EOS	90.90	96.30	-5.40
35	DGB	90.90	93.60	-2.60
36	SNT	90.20	94.30	-4.10
37	SYS	87.90	95.00	-7.10
38	CVC	87.20	94.80	-7.50
39	ANT	85.00	96.80	-11.90
40	OMG	83.80	96.50	-12.70
41	XNO	81.80	96.90	-15.10
42	DOGE	80.70	96.90	-16.20
43	LRC	80.40	94.80	-14.30
44	RLC	80.20	96.00	-15.80
45	LSK	74.90	96.00	-21.10
46	GNO	68.10	94.40	-26.30
47	ERG	67.10	93.10	-26.00
48	WAVES	50.20	94.90	-44.70

Volatility

Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers
1	LRC	123.30	97.10	26.20
2	XTZ	120.80	97.30	23.50
3	BNB	119.80	97.20	22.50
4	ICX	119.40	97.30	22.20
5	QTUM	116.50	97.40	19.20
6	ETH	116.10	97.30	18.80
7	DCR	115.00	97.00	18.00
8	ETC	113.50	97.00	16.50
9	EOS	111.80	97.30	14.50
10	ADA	111.00	96.60	14.30
11	BAT	110.90	97.30	13.60
12	ENJ	110.40	97.00	13.40
13	DOGE	110.10	97.30	12.90
14	TRX	109.70	97.30	12.40
15	VGX	109.50	96.50	13.00
16	OMG	109.30	96.80	12.50
17	BCH	106.80	97.20	9.70
18	LSK	106.50	97.40	9.10
19	MANA	105.50	96.90	8.60
20	DASH	105.40	97.00	8.40
21	SYS	105.30	95.70	9.60
22	BTC	104.70	96.50	8.20
23	XMR	102.70	96.30	6.40
24	LINK	101.90	97.60	4.30
25	LTC	101.30	97.50	3.80
26	XNO	100.40	97.30	3.20
27	REQ	97.50	96.60	0.90
28	STORJ	96.90	97.30	-0.40
29	MIOTA	96.20	97.10	-0.90
30	RLC	95.50	97.20	-1.80
31	GLM	94.60	96.80	-2.20
32	SC	93.60	96.80	-3.20
33	XRP	93.30	97.10	-3.90
34	GNO	92.90	95.80	-3.00
35	KCS	91.20	96.90	-5.70
36	ANT	89.70	97.30	-7.70
37	BTG	86.70	94.40	-7.70
38	SNT	84.00	97.60	-13.60
39	WAVES	83.60	96.60	-13.00
40	XLM	83.20	97.10	-13.90
41	CVC	79.30	94.30	-15.00
42	ZRX	79.10	96.60	-17.60
43	ZEN	71.50	95.90	-24.50
44	DGB	70.20	94.90	-24.70
45	NEO	69.80	97.20	-27.40
46	ERG	60.90	95.70	-34.80
47	ZEC	37.80	98.30	-60.50
48	XEM	31.00	95.30	-64.30

Directional spillovers 2021

Return						Volatility					
Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers		Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers	
1	OMG	138.80	95.82	42.98		1	DGB	157.58	89.95	67.63	
2	LTC	138.76	96.21	42.55		2	ETH	140.49	95.13	45.36	
3	ETC	132.91	96.58	36.33		3	ICX	132.88	93.17	39.71	
4	QTUM	130.90	95.48	35.42		4	ZEC	131.36	93.21	38.15	
5	BCH	127.44	96.59	30.85		5	LINK	126.37	93.51	32.86	
6	XRP	127.23	96.61	30.62		6	EOS	125.30	95.77	29.53	
7	NEO	123.10	96.30	26.80		7	DASH	124.16	95.76	28.40	
8	ZEC	122.82	95.62	27.20		8	ADA	123.01	96.37	26.64	
9	DASH	121.59	96.77	24.82		9	XLM	122.29	93.81	28.48	
10	XMR	120.61	96.21	24.40		10	QTUM	108.79	96.35	12.44	
11	EOS	120.00	96.40	23.60		11	XTZ	107.77	94.75	13.02	
12	LINK	119.05	96.82	22.23		12	KCS	104.74	94.82	9.92	
13	XLM	117.46	95.58	21.88		13	ZRX	104.31	95.47	8.84	
14	BTG	114.12	96.49	17.63		14	XRP	104.24	97.30	6.94	
15	ETH	112.82	96.47	16.35		15	BNB	101.11	95.12	5.99	
16	ZRX	112.27	97.08	15.19		16	SC	99.32	96.58	2.74	
17	XTZ	111.85	94.76	17.09		17	BCH	98.72	95.31	3.41	
18	DGB	111.36	96.26	15.10		18	VGX	98.41	92.88	5.53	
19	XNO	101.81	96.01	5.80		19	DCR	97.45	94.96	2.49	
20	ZEN	100.77	96.21	4.56		20	LTC	96.82	96.33	0.49	
21	ERG	97.01	94.89	2.12		21	XMR	96.60	94.45	2.15	
22	LSK	96.93	97.11	-0.18		22	XNO	93.64	95.11	-1.47	
23	ENJ	96.88	96.17	0.71		23	REQ	89.83	91.33	-1.50	
24	KCS	96.54	96.32	0.22		24	ERG	89.69	94.51	-4.82	
25	BNB	93.53	96.90	-3.37		25	GNO	89.52	91.62	-2.10	
26	MIOTA	92.33	96.79	-4.46		26	XEM	89.31	95.43	-6.12	
27	LRC	91.05	95.34	-4.29		27	OMG	87.78	95.69	-7.91	
28	SNT	89.25	96.21	-6.96		28	BTC	86.54	95.61	-9.07	
29	SC	87.32	97.66	-10.34		29	GLM	86.18	93.66	-7.48	
30	RLC	85.00	96.54	-11.54		30	ENJ	85.03	96.59	-11.56	
31	DCR	84.90	96.52	-11.62		31	NEO	84.91	95.49	-10.58	
32	XEM	84.27	96.04	-11.77		32	MIOTA	84.64	94.31	-9.67	
33	CVC	83.51	97.07	-13.56		33	BAT	83.97	96.05	-12.08	
34	ICX	81.33	97.08	-15.75		34	TRX	83.70	95.24	-11.54	
35	BAT	80.42	96.28	-15.86		35	WAVES	80.10	92.40	-12.30	
36	BTC	79.09	96.45	-17.36		36	RLC	77.11	96.34	-19.23	
37	TRX	76.84	97.57	-20.73		37	CVC	77.04	91.91	-14.87	
38	GNO	75.39	94.99	-19.60		38	MANA	77.04	95.32	-18.28	
39	ADA	75.24	96.35	-21.11		39	DOGE	76.18	96.49	-20.31	
40	MANA	75.14	96.83	-21.69		40	ETC	75.24	95.38	-20.14	
41	DOGE	71.85	96.35	-24.50		41	LSK	74.31	94.93	-20.62	
42	WAVES	70.75	94.43	-23.68		42	LRC	73.71	93.25	-19.54	
43	SYS	65.20	96.80	-31.60		43	SYS	72.97	94.64	-21.67	
44	ANT	64.99	94.08	-29.09		44	SNT	72.07	96.40	-24.33	
45	GLM	64.89	96.06	-31.17		45	ANT	67.66	95.74	-28.08	
46	VGX	60.79	92.81	-32.02		46	ZEN	67.37	94.68	-27.31	
47	REQ	45.99	96.47	-50.48		47	BTG	65.20	96.21	-31.01	
48	STORJ	44.27	95.99	-51.72		48	STORJ	56.84	93.97	-37.13	

Directional spillovers 2022

Return						Volatility				
Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers		Nr.	Ticker	Contribution to others	Contribution from others	Net spillovers
1	MANA	113.29	96.48	16.81		1	TRX	148.89	89.42	59.47
2	MIOTA	112.84	96.70	16.14		2	BTC	147.60	94.24	53.36
3	BCH	111.85	97.25	14.60		3	LINK	142.45	94.94	47.51
4	XEM	111.45	96.83	14.62		4	BNB	141.10	95.02	46.08
5	GLM	111.40	97.12	14.28		5	QTUM	140.39	95.16	45.23
6	LINK	110.25	96.78	13.47		6	BAT	137.59	95.72	41.87
7	QTUM	109.17	97.15	12.02		7	XLM	131.71	94.41	37.30
8	OMG	109.05	97.21	11.84		8	ENJ	128.96	96.36	32.60
9	ETH	108.14	96.76	11.38		9	ZEN	123.30	96.05	27.25
10	BAT	107.42	97.02	10.40		10	ADA	119.49	94.30	25.19
11	CVC	107.37	97.08	10.29		11	OMG	119.08	96.12	22.96
12	ADA	106.84	96.54	10.30		12	XTZ	118.69	94.99	23.70
13	ZEC	106.66	96.09	10.57		13	MANA	115.57	95.71	19.86
14	ENJ	105.72	97.28	8.44		14	XMR	111.32	92.76	18.56
15	NEO	105.49	96.76	8.73		15	NEO	108.34	95.24	13.10
16	DGB	105.30	96.96	8.34		16	BTG	107.94	93.58	14.36
17	BTC	104.52	96.20	8.32		17	XEM	107.91	95.90	12.01
18	DASH	103.35	97.11	6.24		18	BCH	106.78	95.77	11.01
19	XMR	103.15	96.10	7.05		19	DASH	105.94	95.59	10.35
20	STORJ	103.11	97.15	5.96		20	LTC	104.48	96.62	7.86
21	KCS	102.13	96.95	5.18		21	MIOTA	102.91	94.83	8.08
22	ICX	100.86	97.18	3.68		22	LRC	101.99	93.74	8.25
23	XRP	100.82	96.86	3.96		23	XRP	100.38	94.19	6.19
24	SC	99.27	96.99	2.28		24	KCS	96.84	97.16	-0.32
25	GNO	98.74	96.33	2.41		25	LSK	96.40	95.72	0.68
26	ZEN	98.26	96.97	1.29		26	ZEC	94.22	94.08	0.14
27	ZRX	98.05	96.85	1.20		27	CVC	94.20	96.56	-2.36
28	LTC	97.19	97.02	0.17		28	RLC	93.05	96.75	-3.70
29	XTZ	96.64	97.14	-0.50		29	ETC	85.96	96.59	-10.63
30	BNB	95.82	97.29	-1.47		30	ICX	85.93	95.49	-9.56
31	XLM	95.49	97.26	-1.77		31	STORJ	83.95	96.86	-12.91
32	SNT	95.13	96.76	-1.63		32	DGB	83.84	95.82	-11.98
33	EOS	94.33	96.79	-2.46		33	ERG	77.99	98.13	-20.14
34	SYS	94.21	96.39	-2.18		34	ETH	76.51	96.71	-20.20
35	LRC	91.20	96.96	-5.76		35	SNT	74.16	95.62	-21.46
36	ANT	88.31	96.13	-7.82		36	WAVES	73.34	94.01	-20.67
37	DOGE	86.12	95.17	-9.05		37	ZRX	67.48	94.62	-27.14
38	WAVES	84.73	95.68	-10.95		38	VGX	67.20	90.57	-23.37
39	DCR	84.32	96.53	-12.21		39	SYS	65.81	96.44	-30.63
40	ETC	83.77	97.05	-13.28		40	EOS	64.08	93.77	-29.69
41	TRX	81.76	94.07	-12.31		41	REQ	63.21	90.27	-27.06
42	VGX	80.56	89.42	-8.86		42	GNO	62.71	96.86	-34.15
43	XNO	80.04	96.21	-16.17		43	XNO	51.08	94.94	-43.86
44	LSK	77.29	97.34	-20.05		44	GLM	47.25	95.46	-48.21
45	BTG	71.30	96.38	-25.08		45	DCR	46.67	95.52	-48.85
46	ERG	69.06	96.63	-27.57		46	SC	46.37	93.80	-47.43
47	RLC	65.08	94.88	-29.80		47	ANT	46.14	94.26	-48.12
48	REQ	63.23	94.28	-31.05		48	DOGE	44.90	95.43	-50.53

A.6 Marginal model estimates (eGARCH model)

The tables exhibit the outcomes of the Marginal model, specifically the eGARCH model. The estimates are located in the top rows, while the corresponding p-values are presented below. Statistical significance levels are indicated by asterisks, where:

*** denotes significance at a 1% threshold level,

** denotes significance at a 5% threshold level, and

* denotes significance at a 10% threshold level.

The term "ar" denotes the parameter for gamma, while gamma1, gamma2, and so on are represented by alpha in our equation.

eGARCH estimates part 1

coef_names	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS
alpha1	-0.001	0.078	-0.020	0.040	0.011	0.033	0.029	0.055	0.012	0.000	0.018	-0.001	0.006	-0.067
	(0.953)	(0.007)***	(0.703)	(0.259)	(0.708)	(0.000)***	(0.341)	(0.129)	(0.774)	(0.988)	(0.316)	(0.855)	(0.815)	(0.197)
alpha2		-0.015	0.008			0.022		-0.061	-0.005			0.095		0.032
		(0.844)	(0.972)			(0.000)***		(0.083)*	(0.911)			(0.027)**		(0.409)
alpha3			0.032			0.015		0.013	0.006			-0.078		0.149
			(0.856)			(0.000)***		(0.000)***	(0.871)			(0.075)*		(0.006)***
ar1	1.538	0.059	-1.277	0.832	-0.075		-0.469	0.500	0.019	0.484	-0.545	-0.942	0.391	0.893
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.002)***		(0.000)***	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
ar2	-0.161	-0.574	-1.123	-0.953			-0.867		0.942	-1.034	-1.066		-0.989	0.109
	(0.000)***	(0.000)***	(0.000)***	(0.000)***			(0.000)***		(0.000)***	(0.000)***	(0.000)***		(0.000)***	(0.000)***
ar3	-0.414	0.607	-0.108							0.393	-0.327			-0.009
	(0.000)***	(0.000)***	(0.000)***							(0.000)***	(0.000)***			(0.000)***
beta1	0.929	-0.212	1.000	0.241	0.822	-0.614	0.671	1.000	0.540	0.323	0.720	1.000	0.631	0.213
	(0.000)***	(0.610)	(0.000)***	(0.014)**	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
beta2		0.559	0.494	0.195	-0.243	0.617	0.257	0.542	0.587	0.158	0.262	0.543	0.321	0.751
		(0.020)**	(0.000)***	(0.035)**	(0.019)**	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.126)	(0.000)***	(0.000)***	(0.000)***	(0.000)***
beta3		0.582	-0.498	0.533	0.381	0.981		-0.544	-0.161	0.473		-0.544		
		(0.001)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***		(0.000)***	(0.000)***	(0.000)***		(0.000)***		
gamma1	0.325	0.274	0.277	0.382	0.344	0.262	0.381	0.388	0.358	0.296	0.222	0.678	0.290	0.294
	(0.000)***	(0.000)***	(0.484)	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
gamma2		0.321	-0.055			0.307		-0.161	0.092			-0.298		0.214
		(0.001)***	(0.919)			(0.000)***		(0.000)***	(0.082)*			(0.000)***		(0.000)***
gamma3			-0.183			0.122		-0.203	-0.194			-0.328		-0.133
			(0.310)			(0.000)***		(0.000)***	(0.002)***			(0.000)***		(0.065)*
ma1	-1.599	-0.117	1.174	-0.939		-0.041	0.426	-0.594	-0.087	-0.572	0.434	0.818	-0.496	-1.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)***		(0.012)**	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
ma2	0.274	0.542	1.005	1.052			0.859		-0.935	1.048	1.052	-0.130	1.027	
	(0.000)***	(0.000)***	(0.000)***	(0.000)***			(0.000)***		(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	
ma3	0.362	-0.639		-0.100					0.061	-0.487	0.224		-0.096	
	(0.000)***	(0.000)***		(0.000)***					(0.000)***	(0.000)***	(0.000)***		(0.000)***	
mu	-0.001	0.001	0.001	-0.001	0.001	0.001	-0.001	0.000	0.000	0.000	-0.002	-0.001	-0.001	-0.001
	(0.032)**	(0.532)	(0.001)***	(0.296)	(0.136)	(0.149)	(0.050)*	(0.932)	(0.728)	(0.586)	(0.000)***	(0.005)***	(0.192)	(0.000)***
omega	-0.400	-0.383	-0.021	-0.170	-0.241	-0.105	-0.393	-0.012	-0.191	-0.264	-0.099	-0.008	-0.253	-0.189
	(0.002)***	(0.005)***	(0.000)***	(0.016)**	(0.003)***	(0.000)***	(0.010)**	(0.000)***	(0.009)***	(0.002)***	(0.363)	(0.000)***	(0.026)**	(0.000)***
shape	3.532	4.158	4.270	2.701	3.631	2.951	2.747	3.525	3.223	3.270	3.586	2.642	3.391	2.780
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***

eGARCH estimates part 2

coef_names	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO
alpha1	0.052	0.050	-0.112	0.035	-0.022	0.038	-0.048	-0.001	0.031	0.027	0.003	0.070	0.053	0.025
	(0.348)	*(0.262)*	*(0.019)***	*(0.058)**	*(0.828)*	*(0.224)*	*(0.257)*	*(0.957)*	*(0.306)*	*(0.337)*	*(0.868)*	*(0.092)**	*(0.056)**	*(0.462)*
alpha2	0.009	0.099	0.027	0.009			-0.005				0.001	-0.025	0.012	0.080
	(0.864)	*(0.001)****	*(0.332)*	*(0.000)****			*(0.929)*				*(0.928)*	*(0.645)*	*(0.690)*	*(0.007)****
alpha3	-0.002	-0.106	0.107	-0.039			0.080				0.021	-0.016	0.018	0.014
	(0.963)	*(0.018)***	*(0.056)**	*(0.050)**			*(0.033)***				*(0.085)**	*(0.703)*	*(0.502)*	*(0.677)*
ar1	0.352	-1.141	0.913	-0.632	0.875		1.430	0.324	-0.263	0.218	-0.079	0.576	-0.122	1.679
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****		*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.003)****	*(0.000)****	*(0.000)****
ar2	-0.992	-1.090	0.100		-1.151		-0.977	-0.965	-0.832	-0.986	-0.006			-1.072
	*(0.000)****	*(0.000)****	*(0.046)***		*(0.000)****		*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.784)*			*(0.000)****
ar3	-0.018	-0.097	-0.025		0.237				0.135	-0.049				0.052
	*(0.000)****	*(0.000)****	*(0.861)*		*(0.000)****				*(0.000)****	*(0.000)****				*(0.000)****
beta1	1.000	0.557	0.671	1.000	0.902	0.640	1.000	0.973	0.633	0.614	-0.460	0.979	-0.611	-0.108
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.032)***	*(0.000)****	*(0.000)****	*(0.000)****	*(0.034)***	*(0.000)****	*(0.000)****	*(0.000)****	*(0.445)*
beta2	-0.006	0.919	0.927	0.791		-0.043	0.343		-0.058	0.007	0.406		0.599	0.284
	(0.488)	*(0.000)****	*(0.000)****	*(0.000)****		*(0.941)*	*(0.000)****		*(0.813)*	*(0.990)*	*(0.000)****		*(0.000)****	*(0.060)**
beta3		-0.491	-0.624	-0.792		0.359	-0.350		0.370	0.332	0.928		0.918	0.755
		*(0.000)****	*(0.000)****	*(0.000)****		*(0.229)*	*(0.000)****		*(0.002)****	*(0.329)*	*(0.000)****		*(0.000)****	*(0.003)****
gamma1	0.459	0.456	0.194	0.329	0.446	0.365	0.475	0.198	0.376	0.413	0.249	0.465	0.268	0.247
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.100)**	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
gamma2	-0.171	0.147	0.096	-0.126			-0.016				0.287	-0.116	0.354	0.277
	*(0.014)***	*(0.001)****	*(0.027)***	*(0.000)****			*(0.833)*				*(0.000)****	*(0.171)*	*(0.000)****	*(0.000)****
gamma3	-0.183	-0.437	-0.153	-0.199			-0.317				0.144	-0.173	0.167	0.042
	*(0.001)****	*(0.000)****	*(0.012)***	*(0.000)****			*(0.000)****				*(0.006)****	*(0.008)****	*(0.000)****	*(0.713)*
ma1	-0.546	1.053	-0.982	0.549	-0.960	-0.079	-1.488	-0.374	0.160	-0.271		-0.651		-1.764
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****		*(0.000)****		*(0.000)****
ma2	1.064	0.990		-0.094	1.210	0.054	1.070	0.996	0.795	1.006				1.210
	*(0.000)****	*(0.000)****		*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****				*(0.000)****
ma3	-0.174				-0.325		-0.064	-0.041	-0.214					-0.132
	*(0.000)****				*(0.000)****		*(0.000)****	*(0.000)****	*(0.000)****					*(0.000)****
mu	-0.004	0.000	0.002	0.001	0.000	0.000	-0.001	0.002	-0.001	-0.001	0.000	0.000	0.000	0.000
	(0.112)	*(0.952)*	*(0.521)*	*(0.096)**	*(0.494)*	*(0.200)*	*(0.287)*	*(0.238)*	*(0.390)*	*(0.000)****	*(0.822)*	*(0.054)**	*(0.830)*	*(0.642)*
omega	-0.028	-0.079	-0.156	-0.003	-0.543	-0.244	-0.046	-0.149	-0.288	-0.270	-0.734	-0.111	-0.530	-0.387
	(0.378)	*(0.000)****	*(0.000)****	*(0.000)****	*(0.239)*	*(0.053)**	*(0.000)****	*(0.000)****	*(0.008)****	*(0.313)*	*(0.011)***	*(0.000)****	*(0.000)****	*(0.026)***
shape	3.153	2.747	3.406	3.474	3.058	4.455	3.562	5.216	3.741	3.678	3.417	3.653	3.683	3.542
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.001)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****

eGARCH estimates part 3

coef_names	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX
alpha1	-0.065	0.015	0.035	0.021	0.057	0.066	-0.023	-0.002	0.096	0.045	0.025	0.004	0.069	0.031	0.026	-0.009	0.005	0.019	0.042	0.003
	(0.956)	*(0.001)****	*(0.500)*	*(0.462)*	*(0.135)*	*(0.848)*	*(0.873)*	*(0.617)*	*(0.407)*	*(0.359)*	*(0.560)*	*(0.962)*	*(0.118)*	*(0.000)****	*(0.625)*	*(0.889)*	*(0.884)*	*(0.561)*	*(0.000)****	*(0.897)*
alpha2	0.094	0.048	-0.050		-0.044	-0.049	0.023	-0.030	-0.118	-0.076	-0.055	0.015	-0.057	0.024	-0.019	0.023	0.052	0.065	0.015	-0.003
	(0.947)	*(0.000)****	*(0.302)*		*(0.494)*	*(0.978)*	*(0.902)*	*(0.013)***	*(0.489)*	*(0.108)*	*(0.337)*	*(0.692)*	*(0.006)****	*(0.000)****	*(0.774)*	*(0.775)*	*(0.000)****	*(0.033)***	*(0.000)****	*(0.899)*
alpha3		-0.048	0.020		0.003	-0.002		0.042	0.102		0.056	0.006	0.010	0.019		0.025	-0.026		-0.004	0.025
		*(0.000)****	*(0.890)*		*(0.948)*	*(0.998)*		*(0.011)***	*(0.574)*		*(0.238)*	*(0.912)*	*(0.662)*	*(0.000)****		*(0.655)*	*(0.396)*		*(0.000)****	*(0.000)****
ar1	-1.753	-0.522	0.995	1.282		2.228	1.365		1.377	1.925	-0.463	-0.125		-0.599		-0.993	0.437	-0.755	-0.160	-1.980
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****		*(0.000)****	*(0.000)****		*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****		*(0.000)****		*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
ar2	-1.092	-1.006		-0.813		-1.779	-0.989		-0.323	-1.284	-0.997	-0.041				-0.012		-1.006		-0.989
	*(0.000)****	*(0.000)****		*(0.000)****		*(0.000)****	*(0.000)****		*(0.000)****	*(0.000)****	*(0.000)****	*(0.057)**				*(0.666)*		*(0.000)****		*(0.000)****
ar3	-0.055	-0.062		-0.070		0.435			-0.056	0.204	-0.050					0.047		-0.061		
	*(0.000)****	*(0.000)****		*(0.422)*		*(0.000)****			*(0.000)****	*(0.000)****	*(0.100)*					*(0.003)****		*(0.000)****		
beta1	0.963	0.793	1.000	0.424	1.000	0.976	0.977	1.000	0.980	0.432	0.960	0.731	0.868	-0.533	1.000	0.986	0.710	-0.436	-0.231	0.768
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.645)*	*(0.000)****	*(0.000)****	*(0.000)****	*(0.193)*	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
beta2		0.983	0.367	-0.111	0.562			0.722		0.272		0.903	0.673	0.492	-0.061		0.918	0.743	0.194	0.828
		*(0.000)****	*(0.000)****	*(0.351)*	*(0.000)****			*(0.000)****		*(0.147)*		*(0.000)****	*(0.000)****	*(0.000)****	*(0.959)*		*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
beta3		-0.777	-0.368	0.637	-0.564			-0.723		0.166		-0.636	-0.545	0.964	0.042		-0.637	0.593	0.933	-0.599
		*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****			*(0.000)****		*(0.330)*		*(0.000)****	*(0.000)****	*(0.000)****	*(0.971)*		*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
gamma1	0.285	0.331	0.427	0.304	0.347	0.468	0.307	0.306	0.513	0.581	0.437	0.354	0.408	0.209	0.352	0.497	0.432	0.274	0.237	0.306
	(0.884)	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.970)*	*(0.525)*	*(0.000)****	*(0.368)*	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
gamma2	-0.054	-0.038	-0.213		-0.072	-0.328	-0.163	-0.110	-0.238	0.061	-0.156	0.064	-0.103	0.260	-0.179	-0.037	-0.040	0.358	0.277	0.056
	(0.986)	*(0.000)****	*(0.664)*		*(0.000)****	*(0.972)*	*(0.060)**	*(0.000)****	*(0.469)*	*(0.746)*	*(0.086)**	*(0.000)****	*(0.000)****	*(0.000)****	*(0.539)*	*(0.745)*	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
gamma3		-0.287	-0.172		-0.242	0.055		-0.184	0.003		-0.005	-0.360	-0.255	0.107		-0.213	-0.295		0.056	-0.322
		*(0.000)****	*(0.691)*		*(0.000)****	*(0.976)*		*(0.000)****	*(0.986)*		*(0.935)*	*(0.000)****	*(0.000)****	*(0.000)****		*(0.008)****	*(0.000)****		*(0.000)****	*(0.000)****
ma1	1.700	0.447	-1.148	-1.376	-0.078	-2.312	-1.427	-0.113	-1.504	-2.051	0.410		-0.080	0.434	-0.137	0.868	-0.506	0.678	0.047	1.945
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.001)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****		*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****
ma2	1.005	0.977	0.145	0.941	-0.021	1.934	1.077		0.503	1.509	0.982			-0.064		-0.123		0.951		0.921
	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.360)*	*(0.000)****	*(0.000)****		*(0.000)****	*(0.000)****	*(0.000)****			*(0.000)****		*(0.003)****		*(0.000)****		*(0.000)****
ma3					0.042	-0.521	-0.051			-0.326				-0.004		-0.061				-0.034
					*(0.065)**	*(0.000)****	*(0.000)****			*(0.000)****				*(0.000)****		*(0.005)****				*(0.000)****
mu	0.000	0.001	0.001	0.000	0.000	-0.001	0.001	0.001	0.002	-0.006	-0.001	0.000	-0.001	0.002	-0.002	-0.001	0.000	0.000	0.000	-0.001
	(0.894)	*(0.234)*	*(0.000)****	*(0.776)*	*(0.847)*	*(0.885)*	*(0.000)****	*(0.201)*	*(0.000)****	*(0.000)****	*(0.271)*	*(0.948)*	*(0.293)*	*(0.000)****	*(0.064)**	*(0.260)*	*(0.901)*	*(0.023)***	*(0.888)*	*(0.705)*
omega	-0.207	-0.004	-0.006	-0.265	-0.011	-0.134	-0.125	-0.005	-0.116	-0.627	-0.218	-0.018	-0.020	-0.472	-0.101	-0.078	-0.049	-0.574	-0.568	-0.019
	(0.861)	*(0.000)****	*(0.250)*	*(0.024)***	*(0.000)****	*(0.990)*	*(0.671)*	*(0.000)****	*(0.000)****	*(0.008)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.561)*	*(0.004)****	*(0.000)****	*(0.027)***	*(0.000)****	*(0.000)****
shape	3.900	3.516	3.264	4.362	3.813	3.231	3.452	3.923	2.976	2.911	3.217	3.251	3.710	4.230	3.229	2.557	3.810	4.091	4.107	5.178
	(0.812)	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.946)*	*(0.022)***	*(0.000)****	*(0.453)*	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****	*(0.000)****

A.7 Vector Autoregressive P-values

The tables below display p-values generated from the Vector Autoregressive (VAR) model containing eighter returns of the cryptocurrency data, or latent volatility components from the marginal model. The p-values provide a measure of the statistical significance of each variable in the model, indicating the probability of observing such extreme values by chance. These p-values provides insights into the relationship between variables in the model and determine which variables are most important for predicting future changes in the cryptocurrency market. Although non-significant p-values suggest that the observed relationship between variables may not be statistically significant, it does not necessarily imply the absence of a relationship between them. Numbers in bold denotes significance at a 5% threshold level.

Count < 0.05 – Counts the numbers of regressors significant at a 5% threshold level.

Count% < 0.05 – Numbers of regressors significant at a 5% threshold level in percent.

Count < 0.1 – Numbers of regressors significant at a 10% threshold level in percent.

Count% < 0.1 – Numbers of regressors significant at a 10% threshold level in percent.

The results presented are conducted using the HC2 robust standard error technique.

P-values for Vector Autoregression model of returns

Regressor	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX
ADA.l1	0.71	0.94	0.97	0.77	0.25	0.74	0.81	0.45	0.36	0.35	0.67	0.98	0.82	0.90	0.39	0.88	0.73	0.78	0.85	0.69	0.85	0.99	0.77	0.76	0.96	0.15	0.40	0.53	0.81	0.39	0.69	0.95	0.81	0.37	0.89	0.90	0.62	0.42	0.98	0.36	0.56	0.95	0.97	0.34	0.44	0.91	0.88	0.97
ANT.l1	0.12	0.42	0.43	0.65	0.20	0.76	0.74	0.41	0.80	0.58	0.20	0.78	1.00	0.21	0.07	0.91	0.67	0.45	0.47	0.13	0.58	0.49	0.91	0.91	0.58	0.72	0.34	0.63	0.91	0.48	0.66	0.34	0.14	0.41	0.69	0.94	0.36	0.81	0.54	0.31	0.97	0.43	0.55	0.76	0.95	0.52	0.45	0.47
BAT.l1	0.83	0.24	0.36	0.30	0.96	0.56	0.37	0.11	0.11	0.87	0.29	0.96	0.82	**0.04**	0.22	0.28	0.40	**0.04**	0.81	0.12	0.99	0.16	0.73	0.33	0.64	0.30	0.39	0.14	0.41	0.59	0.97	0.60	0.62	0.28	0.34	0.17	0.45	0.80	0.34	0.88	0.06	**0.03**	0.37	0.24	0.07	0.11	0.48	0.20
BCH.l1	0.17	0.60	0.32	0.55	0.84	0.20	0.10	0.56	0.72	0.37	0.68	0.51	0.54	0.99	0.34	0.19	0.92	0.87	0.95	0.63	0.25	0.60	0.73	0.76	0.48	0.87	0.99	0.37	0.72	0.72	0.74	0.84	0.77	0.73	0.90	0.30	0.28	0.61	0.15	0.74	0.62	0.62	0.76	0.54	0.35	0.90	0.90	0.31
BNB.l1	0.10	0.51	0.37	0.91	0.17	0.67	0.90	0.77	0.12	0.28	0.83	**0.02**	0.16	0.08	0.31	0.25	0.95	**0.05**	0.59	0.90	**0.05**	0.85	0.63	0.06	0.24	0.58	0.30	0.98	0.53	0.26	0.84	0.42	0.21	0.44	0.53	0.41	0.70	0.95	0.93	0.29	0.56	**0.03**	0.87	0.80	0.60	0.15	0.95	0.94
BTC.l1	0.88	0.18	0.53	0.44	0.90	0.32	0.76	0.49	0.26	0.53	0.76	0.62	0.95	0.86	0.73	0.63	0.28	0.31	0.11	0.41	0.55	0.94	0.70	0.12	0.45	**0.04**	0.53	0.90	0.90	0.73	0.18	0.35	0.59	0.94	0.52	0.66	0.43	0.50	0.19	0.50	0.82	0.73	0.05	0.29	0.36	0.51	0.17	0.45
BTG.l1	0.98	0.76	0.92	0.76	0.72	0.68	0.64	0.23	**0.01**	0.08	0.76	0.27	0.82	0.25	0.99	0.89	0.91	0.87	0.66	**0.02**	0.58	0.69	0.37	0.50	0.63	0.54	0.97	0.85	0.88	0.42	0.40	0.56	0.72	0.32	0.41	0.39	0.68	0.25	0.86	0.79	0.83	0.12	0.82	0.64	0.32	0.11	0.83	0.30
CVC.l1	0.93	0.23	0.61	0.39	0.88	0.46	**0.04**	0.12	0.81	**0.05**	0.95	**0.04**	0.71	0.31	0.60	0.09	0.74	0.81	0.37	0.30	0.99	0.16	0.67	0.48	0.49	0.60	0.96	0.79	0.48	0.50	0.29	0.31	0.87	0.43	0.77	0.32	0.61	0.83	0.82	0.17	0.84	0.43	0.38	0.94	0.84	0.37	0.20	0.61
DASH.l1	**0.04**	0.11	0.06	0.07	0.07	0.05	0.07	0.09	0.41	**0.00**	0.13	0.34	0.08	0.58	0.78	0.15	0.18	**0.02**	**0.01**	0.50	0.43	0.14	**0.03**	0.09	**0.05**	0.84	0.43	0.07	0.26	0.79	0.07	0.07	0.15	**0.04**	0.13	**0.01**	0.14	**0.00**	0.27	**0.01**	**0.03**	0.16	0.45	**0.02**	**0.02**	0.44	0.15	0.30
DCR.l1	0.45	0.22	0.09	0.36	0.70	0.93	0.35	0.09	0.81	**0.00**	0.77	0.66	0.60	0.20	0.41	0.69	0.18	0.43	0.19	0.08	0.59	0.11	0.16	0.76	0.42	0.17	0.95	0.46	0.52	0.72	0.20	**0.01**	0.25	0.47	0.12	0.15	0.91	0.09	0.63	0.48	0.42	0.92	0.32	0.47	0.16	0.16	0.16	0.56
DGB.l1	0.10	0.41	0.22	0.35	0.87	0.78	0.23	0.60	0.62	0.74	**0.01**	0.38	0.66	0.19	0.14	0.99	0.74	0.99	0.37	0.72	0.97	0.39	0.69	0.93	0.25	0.48	0.33	0.70	1.00	0.59	0.99	0.52	0.27	0.09	0.65	0.84	0.15	0.91	0.48	0.10	0.06	0.41	0.34	0.07	0.96	0.30	0.19	0.81
DOGE.l1	0.15	0.66	0.08	**0.02**	**0.01**	**0.02**	0.18	0.12	**0.01**	**0.00**	**0.00**	0.26	0.27	0.07	0.52	**0.05**	**0.01**	0.16	**0.04**	0.14	0.35	**0.03**	0.06	0.16	**0.01**	0.11	0.27	**0.03**	**0.01**	0.30	0.20	**0.05**	**0.01**	**0.04**	0.11	0.14	**0.01**	0.14	**0.02**	0.06	0.06	**0.00**	0.13	0.14	0.12	0.06	**0.04**	0.05
ENJ.l1	0.26	0.17	0.24	0.58	0.37	0.93	0.31	0.56	0.75	0.09	**0.03**	0.99	0.44	0.65	0.17	0.35	0.46	0.47	0.08	0.10	0.52	0.43	0.91	0.83	0.24	0.59	0.51	0.60	0.26	0.06	0.73	0.33	0.09	**0.04**	0.19	**0.01**	0.72	0.79	0.91	0.05	1.00	0.85	0.14	0.38	0.54	0.90	0.50	0.39
EOS.l1	0.65	0.14	0.16	0.36	0.70	0.75	0.06	0.76	0.80	0.61	0.64	1.00	**0.03**	0.19	0.44	0.42	0.21	0.35	1.00	0.81	0.23	0.18	0.62	0.71	0.24	0.59	0.46	0.33	0.35	0.61	0.09	0.35	0.69	0.58	0.74	0.61	0.55	0.47	0.85	0.17	0.64	0.54	0.38	0.66	0.69	0.97	0.28	0.47
ERG.l1	0.66	0.39	0.96	0.57	0.68	0.78	0.88	0.87	0.64	0.59	0.45	0.98	0.12	0.84	**0.00**	0.94	0.58	0.93	0.50	0.13	0.11	0.71	0.44	0.46	0.48	0.42	0.46	0.99	0.91	0.73	0.56	0.19	0.88	0.15	0.85	0.75	0.87	0.67	1.00	**0.04**	0.25	0.17	0.65	0.25	0.39	0.71	0.45	0.63
ETC.l1	0.47	0.08	0.25	0.98	**0.04**	0.25	0.59	**0.01**	0.42	0.09	0.13	0.68	0.09	0.95	0.27	0.65	0.15	0.28	**0.01**	0.47	0.83	0.18	0.63	0.66	0.71	0.05	0.87	0.68	0.52	0.69	**0.02**	**0.01**	0.40	0.14	0.32	0.57	0.07	0.33	0.14	0.38	0.19	0.36	0.32	**0.02**	0.86	0.13	0.39	0.12
ETH.l1	0.86	0.30	0.90	0.76	0.67	0.19	0.46	0.59	0.55	0.10	0.94	0.42	0.73	0.84	0.28	0.88	0.13	0.22	**0.00**	0.95	0.78	0.55	0.38	0.57	0.24	0.80	0.96	0.51	0.40	0.21	0.70	0.15	0.79	0.92	0.98	0.69	0.91	0.27	0.56	0.67	0.90	0.69	0.44	0.21	0.97	0.22	**0.00**	0.21
GLM.l1	0.82	0.68	0.29	0.32	0.12	0.62	**0.02**	0.67	0.19	0.61	0.52	0.37	0.08	0.23	0.85	0.17	0.18	**0.00**	0.47	0.86	0.37	0.19	0.53	**0.05**	0.10	0.82	0.95	0.54	0.19	0.26	0.34	0.40	0.68	0.88	0.55	0.37	0.30	0.88	0.90	0.50	0.10	0.96	0.24	**0.01**	0.88	**0.04**	0.19	0.57
GNO.l1	0.42	0.93	0.71	0.74	0.26	0.09	0.45	0.88	0.82	0.24	0.41	0.32	0.85	0.56	0.83	0.84	0.49	0.92	**0.01**	0.95	0.90	0.98	0.86	0.53	0.60	0.53	0.53	0.77	0.40	0.63	0.21	0.62	0.66	0.56	0.95	0.26	0.55	0.81	0.56	0.53	0.41	0.58	0.17	0.96	0.53	0.71	0.72	0.36
ICX.l1	0.81	0.63	0.51	0.71	0.72	0.54	0.12	0.29	0.97	0.54	0.98	0.87	0.87	0.08	0.58	0.15	0.05	0.51	**0.02**	0.10	0.12	0.15	0.96	0.13	0.22	0.60	0.45	0.46	0.22	**0.01**	0.28	**0.04**	0.51	0.41	0.43	0.11	0.83	0.20	0.75	0.76	0.37	0.21	0.86	0.33	0.96	0.54	0.06	0.58
KCS.l1	0.96	0.19	0.38	0.19	0.30	0.14	0.72	0.44	0.15	0.06	0.20	**0.03**	0.38	**0.04**	0.15	0.15	0.81	0.40	**0.04**	0.59	0.15	0.61	0.59	0.28	**0.02**	0.09	0.30	0.74	0.43	0.06	0.70	0.31	**0.04**	0.62	0.10	0.65	0.70	0.79	0.38	0.91	0.69	0.27	0.17	0.61	0.23	0.11	0.71	0.43
LINK.l1	0.25	0.85	0.39	0.78	1.00	0.30	0.88	0.47	0.62	0.22	0.21	0.16	0.17	0.14	0.85	0.88	0.99	0.98	0.18	0.96	0.96	0.63	0.25	0.41	0.42	0.37	0.83	0.95	0.22	0.99	0.67	0.35	0.30	0.75	0.94	0.71	0.45	0.75	0.46	0.61	0.81	0.40	0.95	0.07	0.31	0.52	0.09	0.90
LRC.l1	0.34	0.38	0.62	0.42	0.67	0.38	0.51	0.88	0.25	0.21	0.57	0.51	0.22	0.26	0.27	0.16	0.12	0.52	0.15	0.21	**0.04**	**0.03**	0.62	0.48	**0.03**	0.86	0.23	0.55	0.16	**0.03**	0.42	0.95	0.06	0.52	0.25	0.31	0.98	0.33	0.39	0.37	0.10	0.44	0.76	0.96	0.14	0.16	**0.02**	0.54
LSK.l1	0.08	0.91	0.99	0.55	0.89	0.87	0.95	0.57	0.95	0.23	0.88	**0.04**	0.32	0.83	0.46	0.39	0.58	0.07	0.69	0.43	0.61	0.49	0.37	0.77	0.64	0.68	0.33	0.65	0.80	0.66	0.43	0.91	0.42	0.43	0.36	0.60	0.60	0.80	0.28	0.75	0.62	0.57	0.28	0.66	0.55	0.52	0.21	0.84
LTC.l1	0.93	0.66	0.53	0.31	0.20	0.93	0.91	0.66	0.47	0.32	0.79	0.39	0.72	0.34	0.89	0.49	0.32	0.24	0.44	0.51	0.24	0.20	0.76	0.95	0.12	0.07	0.22	0.45	0.80	0.84	0.13	0.94	0.76	0.64	0.50	0.75	0.26	0.08	0.61	0.13	0.78	0.91	0.91	0.97	0.21	0.76	0.05	0.85
MANA.l1	0.60	0.07	0.71	0.39	0.45	0.26	0.76	0.63	0.29	0.26	0.63	0.86	0.20	0.27	**0.03**	0.60	0.94	0.51	0.69	0.47	0.28	0.97	0.66	0.84	0.43	0.66	0.48	0.66	0.20	0.50	**0.02**	0.94	0.91	0.27	**0.03**	0.66	0.19	0.84	0.09	0.46	0.56	0.59	**0.03**	0.64	0.52	0.57	0.45	0.21
MIOTA.l1	0.75	0.77	0.78	0.45	0.86	0.67	0.76	0.19	0.40	0.18	0.77	0.74	0.46	0.68	0.23	0.91	0.67	0.63	0.56	0.67	0.71	0.27	0.24	0.93	0.61	0.36	0.80	0.70	0.48	0.39	0.23	0.45	0.92	0.63	0.48	0.65	0.67	0.87	0.41	0.80	0.94	0.18	0.35	0.41	0.80	0.76	0.25	0.95
NEO.l1	0.70	0.17	0.29	0.07	0.17	0.15	0.15	0.45	**0.04**	0.19	0.15	0.10	0.45	0.21	0.82	0.15	0.10	0.39	0.37	**0.01**	0.25	0.39	0.96	0.47	0.15	0.57	0.34	0.83	0.94	0.59	0.12	0.22	**0.04**	0.29	0.51	0.37	0.15	0.05	0.62	0.70	0.18	0.21	0.52	0.29	0.14	**0.03**	0.90	0.07
OMG.l1	0.81	0.22	0.90	0.14	0.57	0.20	0.38	0.82	**0.04**	0.87	0.08	0.17	0.67	0.21	0.28	0.30	0.49	0.33	0.88	0.79	0.63	0.79	0.71	0.87	0.16	0.31	0.51	0.43	0.58	0.34	0.34	0.64	0.15	0.36	0.52	0.80	**0.03**	0.15	0.40	0.45	0.87	0.11	0.73	0.27	0.97	0.08	0.62	0.28
QTUM.l1	0.69	0.15	0.49	0.20	0.86	0.86	0.17	0.93	0.50	0.14	0.24	0.24	0.88	0.28	0.47	0.20	0.24	0.67	0.91	0.93	0.17	0.95	0.26	0.60	0.53	0.06	1.00	0.65	0.07	0.74	0.95	0.68	0.26	0.53	0.54	0.80	0.31	0.88	0.44	0.06	0.99	0.43	0.92	0.28	0.56	**0.01**	0.77	0.68
REQ.l1	0.42	0.28	0.22	0.86	0.82	0.82	0.61	0.94	0.67	0.81	0.77	0.47	0.08	0.74	0.87	0.39	0.96	0.38	0.82	0.41	0.72	0.78	0.32	0.40	0.79	0.54	0.88	0.88	0.29	0.83	0.53	0.05	0.61	0.72	0.42	0.99	0.99	1.00	0.55	0.91	0.72	0.76	0.14	0.76	0.48	0.90	0.46	0.44
RLC.l1	0.47	0.85	0.57	0.33	0.72	0.71	0.43	0.62	0.99	0.53	0.12	0.19	0.27	0.50	0.46	0.95	0.61	0.86	0.44	0.73	0.92	0.30	0.92	0.33	0.97	0.41	0.70	0.82	0.86	0.90	0.37	0.28	0.80	0.54	0.75	0.55	0.66	0.08	0.87	0.79	0.49	0.49	0.21	0.50	0.93	0.82	0.85	0.64
SC.l1	0.49	0.43	0.49	0.18	0.93	**0.01**	0.26	0.58	0.16	0.35	0.83	0.45	0.19	0.82	0.48	0.39	0.81	0.57	0.20	0.62	0.30	0.97	0.75	0.41	0.46	0.39	0.97	0.57	0.92	0.34	0.10	0.52	0.35	0.31	0.09	0.99	0.09	0.12	0.47	0.91	0.32	0.50	0.63	0.62	0.09	0.99	0.83	0.79
SNT.l1	0.38	0.32	0.10	0.61	0.15	0.92	0.18	0.07	0.38	0.92	0.32	0.37	0.13	0.85	0.35	0.19	0.77	0.23	0.91	0.86	0.51	0.35	0.67	0.17	0.51	0.65	0.90	0.12	0.33	0.52	0.79	0.28	0.28	0.42	0.77	0.27	0.33	**0.01**	0.75	0.98	0.75	0.69	0.97	0.81	0.62	0.19	0.78	0.39
STORJ.l1	0.38	0.56	0.63	0.35	0.22	0.39	0.31	0.19	0.99	0.22	0.11	0.61	0.87	0.88	0.25	0.63	0.58	0.54	0.40	0.49	0.13	0.62	0.85	0.51	0.73	0.59	0.98	0.91	0.67	0.64	0.64	0.65	0.74	0.63	**0.01**	0.18	0.83	0.47	0.76	0.58	0.43	0.14	0.90	0.36	0.33	0.79	0.30	0.54
SYS.l1	0.50	0.77	0.62	0.29	0.86	0.52	0.83	0.91	0.99	0.56	0.29	0.37	0.18	0.34	0.23	0.32	0.42	0.78	0.31	0.24	0.41	0.15	0.06	0.80	0.86	0.46	1.00	0.69	0.78	0.88	0.34	0.38	0.28	0.73	0.65	**0.01**	0.24	0.57	0.41	0.12	0.44	0.40	0.14	0.57	0.89	0.35	0.54	0.21
TRX.l1	0.33	0.97	0.49	0.33	**0.04**	0.39	0.91	0.98	0.28	0.42	**0.00**	0.35	0.12	0.45	0.84	0.82	0.94	0.70	0.28	0.24	0.58	0.86	**0.02**	0.38	0.77	0.74	0.37	0.50	0.48	0.91	0.82	0.83	**0.01**	0.07	0.79	0.13	0.10	0.21	0.66	0.12	0.27	0.87	0.67	0.10	0.08	0.41	0.56	0.30
VGX.l1	0.62	0.12	0.58	0.22	0.23	0.95	0.61	0.33	0.48	0.37	0.45	0.73	0.25	0.21	0.82	0.84	0.65	0.29	0.52	0.59	0.07	0.86	0.39	0.13	0.72	0.27	0.99	0.77	0.96	0.70	0.34	0.13	0.32	0.54	0.32	0.53	0.79	0.75	0.26	0.34	0.30	0.44	0.71	0.08	0.19	0.44	0.49	0.23
WAVES.l1	0.29	0.48	0.21	0.86	0.31	0.87	0.81	0.18	0.99	0.28	0.23	0.58	0.33	0.80	0.07	0.95	0.87	0.35	0.67	0.62	0.13	0.82	0.76	0.53	0.51	0.43	0.34	0.53	0.49	0.83	0.45	0.26	0.16	0.20	0.69	0.19	0.65	0.14	0.74	0.54	0.36	0.52	0.71	0.73	0.47	0.93	0.65	0.70
XEM.l1	0.32	0.08	0.07	**0.05**	**0.02**	**0.01**	**0.01**	0.35	**0.03**	0.30	0.36	**0.02**	0.25	**0.04**	0.78	**0.02**	0.43	0.08	0.93	0.31	0.08	0.07	**0.04**	**0.03**	0.76	0.47	0.05	**0.05**	0.15	**0.01**	0.14	**0.04**	0.20	**0.02**	0.15	0.66	0.74	0.41	0.07	**0.00**	**0.03**	**0.02**	0.90	**0.03**	**0.01**	**0.00**	0.13	**0.02**
XLM.l1	0.12	0.58	0.14	0.70	0.40	**0.02**	0.91	0.17	0.08	0.37	0.24	0.97	0.06	0.18	0.98	0.84	0.07	0.84	0.60	0.37	0.87	0.27	0.58	0.79	0.57	**0.01**	0.39	0.97	0.36	0.62	0.10	0.16	0.82	0.06	0.16	0.28	0.06	0.56	0.18	0.08	0.13	0.35	0.11	0.21	0.13	0.35	0.08	0.55
XMR.l1	**0.01**	0.22	**0.02**	0.90	0.15	0.99	0.12	0.08	0.62	0.25	0.20	0.11	0.11	0.38	0.27	**0.03**	0.50	0.52	0.11	0.74	0.52	0.56	**0.03**	0.27	0.11	0.92	0.47	0.17	0.30	0.11	0.11	**0.04**	0.14	**0.02**	**0.02**	0.32	0.98	0.74	0.72	0.46	0.11	**0.00**	0.60	0.29	0.09	0.15	0.44	0.06
XNO.l1	0.70	0.14	0.74	0.93	0.31	0.39	0.57	0.69	0.84	0.26	0.38	0.90	0.60	0.99	0.68	0.66	0.68	0.37	0.75	0.71	**0.02**	0.28	0.61	0.30	0.67	0.46	0.53	0.49	0.17	0.65	0.75	1.00	0.76	0.68	0.20	0.32	0.64	0.06	**0.03**	0.64	0.41	0.84	0.40	0.16	0.71	0.72	0.18	0.08
XRP.l1	0.27	0.21	0.08	0.46	0.71	0.09	0.98	**0.05**	**0.03**	0.15	0.57	0.98	0.23	0.29	0.92	0.28	0.07	0.09	0.47	0.36	0.13	0.16	0.68	0.13	0.38	**0.02**	0.10	0.11	0.81	0.59	0.67	0.22	0.19	0.08	0.56	0.33	0.57	0.35	0.27	0.50	0.14	0.06	**0.02**	0.69	0.12	0.16	0.28	0.63
XTZ.l1	0.84	0.73	0.60	0.41	0.18	0.16	0.80	0.58	0.45	0.88	0.19	0.28	0.50	0.36	0.28	0.93	0.37	0.28	0.65	0.06	0.21	0.34	0.11	0.21	0.23	0.71	0.35	0.36	0.44	0.93	0.84	0.54	0.33	0.91	0.52	0.32	0.60	0.15	0.26	0.79	0.73	0.81	0.43	0.24	0.89	0.50	**0.03**	0.12
ZEC.l1	0.46	0.92	0.91	0.31	0.78	0.57	0.54	0.54	0.65	0.20	0.77	0.79	0.86	0.96	0.60	0.59	0.64	0.76	0.89	0.66	0.98	0.44	0.89	0.78	0.65	0.93	0.60	0.38	0.40	0.51	0.90	0.67	0.86	0.52	0.88	0.64	0.60	0.66	0.13	0.36	0.57	0.51	0.28	0.81	0.24	0.32	0.31	0.96
ZEN.l1	0.13	0.60	0.53	0.23	0.62	0.70	0.33	0.78	0.46	0.72	0.99	0.61	0.54	0.07	0.38	0.33	0.21	0.18	0.26	0.88	0.53	0.97	0.86	0.63	0.10	0.67	0.45	0.24	**0.03**	0.23	0.23	0.60	0.72	0.98	0.13	0.80	0.61	0.79	0.83	0.28	0.99	0.45	0.19	0.73	0.39	0.74	0.13	0.19
ZRX.l1	0.72	0.16	0.17	**0.00**	0.35	0.78	**0.01**	0.29	0.46	**0.02**	0.34	0.07	0.67	0.28	0.75	**0.01**	0.18	0.10	0.89	0.47	0.69	0.49	0.71	0.31	0.35	0.70	0.70	0.11	0.54	**0.04**	0.18	1.00	0.27	0.50	0.17	0.60	0.53	0.73	0.51	0.41	0.59	0.69	0.33	0.68	0.31	0.24	0.65	1.00
const	0.65	0.78	0.99	0.36	0.16	0.75	0.44	0.67	0.39	0.74	0.77	0.40	0.60	0.76	0.67	0.97	0.65	0.92	0.89	0.57	0.78	0.31	0.85	0.41	0.91	0.36	0.59	0.42	0.43	0.48	0.96	0.98	0.52	0.61	0.79	0.81	0.47	0.64	0.70	0.31	1.00	0.95	0.63	1.00	0.50	0.41	0.74	0.76
Count < 0.05	2	0	1	3	4	4	4	2	6	5	4	5	1	3	2	4	1	4	7	2	3	2	4	2	4	3	0	2	2	4	2	6	4	5	3	3	2	2	2	3	2	5	2	4	2	4	4	1
Count % < 0.05	4%	0%	2%	6%	8%	8%	8%	4%	12%	10%	8%	10%	2%	6%	4%	8%	2%	8%	14%	4%	6%	4%	8%	4%	8%	6%	0%	4%	4%	8%	4%	12%	8%	10%	6%	6%	4%	4%	4%	6%	4%	10%	4%	8%	4%	8%	8%	2%
Count < 0.1	3	3	7	5	5	7	7	6	7	9	5	6	6	7	4	5	5	8	8	5	5	3	6	4	5	7	1	3	3	6	4	8	6	9	5	3	5	7	4	8	6	6	3	7	6	6	8	5
Count % < 0.1	6%	6%	14%	10%	10%	14%	14%	12%	14%	18%	10%	12%	12%	14%	8%	10%	10%	16%	16%	10%	10%	6%	12%	8%	10%	14%	2%	6%	6%	12%	8%	16%	12%	18%	10%	6%	10%	14%	8%	16%	12%	12%	6%	14%	12%	12%	16%	10%

P-values for Vector Autoregression model of volatility (Part 1/4)

Regressor	ADA	ANT	BAT	BCH	BNB	BTC	BTG	CVC	DASH	DCR	DGB	DOGE	ENJ	EOS	ERG	ETC	ETH	GLM	GNO	ICX	KCS	LINK	LRC	LSK	LTC	MANA	MIOTA	NEO	OMG	QTUM	REQ	RLC	SC	SNT	STORJ	SYS	TRX	VGX	WAVES	XEM	XLM	XMR	XNO	XRP	XTZ	ZEC	ZEN	ZRX
ADA.l1	**0.00**	0.40	0.34	0.70	0.68	0.66	0.99	0.14	0.48	0.96	0.68	0.40	0.21	0.55	0.98	0.11	**0.03**	0.09	**0.01**	0.23	0.32	0.28	0.52	0.63	0.88	0.44	0.56	**0.01**	0.30	0.18	0.08	0.17	1.00	0.78	0.96	0.25	0.58	0.98	0.65	0.85	0.36	0.11	0.86	0.93	0.24	0.34	0.64	0.21
ANT.l1	0.55	**0.00**	0.09	0.65	0.41	0.61	0.20	0.69	0.13	0.77	0.40	0.68	0.38	0.34	0.56	0.14	0.21	**0.04**	0.48	0.95	0.17	0.95	0.62	0.14	0.72	0.56	0.56	0.76	0.53	**0.03**	0.11	0.58	0.11	0.90	0.12	0.24	0.31	0.45	0.30	0.48	0.94	0.17	0.26	0.80	**0.01**	0.58	0.55	0.64
BAT.l1	0.14	0.45	**0.00**	0.94	0.09	0.11	0.22	0.12	0.58	0.38	0.68	0.23	0.93	0.52	0.28	0.13	0.19	0.26	0.21	0.62	0.55	0.24	0.53	0.25	0.37	0.71	0.38	0.95	**0.02**	0.79	0.22	0.83	0.58	0.72	0.80	0.98	0.86	0.35	0.48	0.23	0.83	0.41	0.40	0.74	0.99	0.51	0.81	0.71
BCH.l1	0.97	**0.01**	0.33	**0.00**	0.45	**0.01**	0.30	0.24	0.07	0.77	0.73	0.29	0.19	**0.01**	0.35	**0.05**	0.62	0.18	0.94	0.55	0.58	0.77	0.92	0.15	0.42	0.71	0.71	0.12	0.95	0.58	0.29	0.69	0.55	0.78	0.15	0.08	0.84	0.06	0.36	0.25	0.53	0.37	0.38	0.12	0.73	0.07	0.51	0.14
BNB.l1	0.89	0.70	**0.01**	**0.01**	**0.00**	0.10	**0.02**	**0.02**	0.08	0.09	0.49	0.34	0.32	**0.02**	0.48	0.77	**0.03**	0.54	**0.02**	0.51	0.47	0.66	**0.01**	0.65	0.27	0.13	0.51	0.12	**0.04**	0.62	0.73	**0.05**	0.10	0.44	0.21	0.13	0.91	**0.02**	**0.03**	**0.02**	**0.02**	0.99	0.11	0.09	**0.00**	0.58	**0.01**	**0.00**
BTC.l1	0.65	0.74	0.69	0.36	0.42	0.77	0.16	0.44	**0.01**	0.38	0.18	0.30	0.89	0.33	0.32	0.60	0.84	0.29	**0.03**	0.22	0.20	0.46	0.76	0.83	**0.05**	0.11	0.41	0.57	0.78	0.97	0.98	0.33	**0.01**	0.97	1.00	0.98	**0.01**	0.90	0.51	0.16	**0.05**	0.42	0.25	0.85	0.79	0.55	0.58	0.16
BTG.l1	0.27	0.94	0.48	**0.05**	0.86	0.71	**0.00**	0.75	0.11	0.97	0.49	0.24	0.77	0.65	0.41	0.06	0.87	0.41	0.42	0.59	0.22	0.18	0.17	0.78	0.72	0.96	0.57	0.50	0.80	0.75	0.40	0.80	0.95	0.68	0.34	0.84	0.58	0.46	0.42	0.26	0.96	0.55	0.35	0.88	0.84	0.33	**0.03**	0.41
CVC.l1	0.09	0.61	0.34	0.89	0.32	0.79	0.64	**0.00**	0.93	0.63	0.34	0.38	0.73	0.87	0.50	0.15	0.33	0.06	0.22	0.12	0.42	0.17	0.65	0.45	0.82	0.15	0.24	0.46	0.08	0.06	0.81	0.52	0.64	0.94	0.91	0.28	0.19	0.72	0.16	0.23	0.88	0.55	0.18	0.41	0.82	0.16	0.71	0.43
DASH.l1	0.83	**0.01**	0.34	0.84	0.43	0.13	0.12	0.30	**0.00**	0.08	0.89	0.80	0.33	0.62	0.45	0.35	0.23	0.51	0.58	0.44	0.64	0.81	0.66	0.13	**0.00**	0.25	0.34	0.20	0.35	0.13	0.31	0.85	0.46	0.30	0.08	0.51	0.88	0.11	0.07	0.86	0.27	0.27	0.60	0.18	0.43	**0.00**	**0.00**	0.35
DCR.l1	0.40	0.79	0.34	0.77	0.19	0.77	0.17	0.37	0.36	**0.03**	0.16	0.44	0.40	0.75	0.33	0.57	0.53	0.21	**0.05**	0.17	0.51	0.70	0.35	0.11	0.85	0.40	0.51	0.82	0.16	0.17	0.79	0.09	0.26	0.52	0.93	0.13	0.37	0.15	0.06	0.80	0.53	0.76	0.74	0.32	0.28	0.52	0.19	0.58
DGB.l1	0.25	0.92	0.09	0.11	0.48	0.58	**0.01**	**0.05**	0.37	0.78	**0.00**	0.81	0.76	0.64	0.55	0.23	0.08	0.10	0.92	0.45	0.07	0.07	0.67	0.69	0.57	0.21	0.66	0.52	0.75	0.07	0.41	0.10	0.40	**0.03**	0.55	0.07	0.82	0.56	0.29	0.67	0.42	0.65	0.22	0.26	0.99	0.56	0.43	0.28
DOGE.l1	0.72	0.98	0.99	0.88	0.92	0.86	0.72	0.42	0.74	0.43	0.61	**0.01**	0.78	0.73	0.39	0.77	0.95	0.65	0.83	0.20	0.81	0.11	0.95	0.73	0.91	0.80	0.94	0.91	0.75	0.19	0.94	0.07	0.29	0.49	0.77	0.95	**0.05**	**0.00**	0.81	0.83	0.87	0.91	0.92	0.50	0.38	0.43	0.92	0.96
ENJ.l1	0.68	0.21	0.22	0.99	0.91	0.66	0.46	0.84	0.50	0.44	0.87	0.41	**0.00**	**0.01**	0.35	0.30	0.11	0.54	0.48	0.15	0.14	0.67	0.82	0.98	0.89	0.21	**0.04**	0.28	0.39	0.54	0.58	0.08	0.35	0.26	0.47	1.00	0.09	0.62	0.55	0.17	**0.03**	0.15	0.55	0.49	0.35	0.49	0.34	0.86
EOS.l1	0.10	0.25	0.11	0.76	0.55	0.56	0.66	0.37	0.80	0.34	0.86	0.38	0.46	**0.00**	0.44	0.67	0.94	0.34	0.90	0.88	0.62	0.85	0.88	0.16	0.88	0.43	**0.04**	0.88	0.49	0.72	0.12	0.68	0.46	0.49	0.77	0.90	0.30	0.68	0.81	0.30	0.16	0.95	0.68	0.75	0.67	0.06	0.15	0.51
ERG.l1	0.57	0.62	1.00	0.67	0.13	0.85	0.49	0.63	0.27	0.69	0.62	0.84	0.71	0.44	0.20	0.99	0.94	0.88	0.55	**0.02**	0.96	0.45	0.31	0.21	**0.02**	0.75	0.86	0.87	0.97	0.33	**0.01**	0.95	0.77	0.32	0.98	0.55	0.71	0.18	0.28	0.92	0.92	0.75	0.45	0.49	0.77	0.91	0.85	0.48
ETC.l1	0.65	0.33	0.91	0.26	0.77	0.50	0.76	0.45	0.21	0.48	0.66	0.80	0.27	0.13	0.20	**0.00**	0.59	0.30	0.23	0.59	0.48	0.73	0.26	0.41	0.30	0.75	0.17	0.56	0.31	0.12	**0.03**	0.17	0.20	0.27	0.60	0.45	0.73	0.54	0.78	0.28	1.00	0.48	0.40	0.65	0.42	1.00	0.38	0.85
ETH.l1	0.28	**0.00**	0.57	0.50	0.99	**0.01**	0.53	0.22	0.57	0.47	0.36	0.38	0.26	**0.00**	0.56	**0.00**	**0.00**	**0.02**	0.64	**0.01**	0.19	0.89	0.95	**0.05**	0.80	0.68	0.06	**0.00**	**0.00**	**0.00**	0.17	0.61	**0.00**	0.34	0.21	0.40	**0.05**	0.41	0.39	**0.03**	0.12	0.62	0.28	0.96	0.29	0.07	0.65	0.50
GLM.l1	0.55	0.23	0.63	0.20	0.42	0.45	0.44	0.12	0.50	0.96	0.76	0.53	0.69	0.33	0.28	0.47	0.51	**0.00**	0.74	0.54	0.99	0.55	0.93	0.14	0.52	0.59	**0.05**	0.11	0.66	0.09	0.55	0.96	0.63	0.36	0.35	0.15	**0.02**	0.66	0.88	**0.01**	0.24	0.92	0.18	0.75	0.63	0.77	0.97	0.20
GNO.l1	0.94	0.43	0.12	0.39	0.39	**0.00**	0.72	0.93	0.20	0.72	0.60	0.39	0.55	0.76	0.65	0.08	0.08	0.79	**0.00**	0.26	0.75	0.09	0.44	0.54	**0.00**	0.19	0.43	0.44	0.51	0.45	0.53	**0.04**	0.96	0.25	0.69	0.09	0.44	0.93	0.96	0.21	0.07	0.97	0.73	0.53	0.73	0.51	0.13	0.19
ICX.l1	0.10	0.84	0.56	0.80	0.72	0.06	0.53	0.84	0.37	0.92	0.71	0.98	0.51	**0.02**	0.35	0.15	0.28	0.75	0.28	**0.00**	0.41	0.62	0.19	0.90	0.81	0.31	0.09	0.44	0.83	0.64	**0.03**	0.33	0.16	0.51	0.35	0.49	0.36	0.70	0.77	0.15	0.09	0.88	0.19	0.88	0.60	0.48	0.43	0.34
KCS.l1	0.53	0.21	**0.02**	0.58	0.40	0.56	0.96	0.20	0.30	0.26	0.56	0.85	0.29	0.44	0.87	0.64	0.90	0.33	0.60	0.22	**0.00**	0.86	0.11	0.68	0.71	0.07	0.39	**0.01**	0.45	0.22	0.67	0.26	0.26	0.38	0.45	0.43	0.98	0.20	0.24	0.07	0.16	0.13	0.42	0.10	**0.01**	0.22	0.24	0.07
LINK.l1	0.44	0.09	0.47	0.40	0.22	0.29	0.14	0.84	0.27	0.97	0.70	0.56	0.53	0.53	0.37	0.40	0.34	0.55	0.29	0.34	0.92	**0.00**	0.17	0.41	0.32	0.35	0.93	0.48	0.88	0.22	0.84	0.35	0.45	0.35	0.91	0.40	0.54	0.87	0.59	0.17	0.89	0.73	0.19	0.58	0.61	0.68	**0.03**	0.32
LRC.l1	0.11	0.77	0.26	0.08	0.76	0.07	0.06	0.15	**0.05**	1.00	0.07	0.37	0.82	0.10	0.52	0.55	0.67	0.67	0.74	0.22	0.98	0.69	**0.00**	**0.04**	0.35	0.78	0.14	0.61	0.58	0.96	0.96	0.44	0.73	0.22	0.30	0.27	0.06	0.98	0.34	0.44	0.55	0.25	0.07	**0.03**	0.79	0.44	0.31	0.15
LSK.l1	0.58	**0.04**	0.49	0.14	0.65	**0.04**	**0.03**	0.52	0.69	0.80	**0.02**	0.24	0.82	0.25	0.38	0.63	0.98	0.31	0.89	0.64	0.76	0.16	0.48	**0.00**	**0.02**	0.83	0.39	0.31	0.08	**0.01**	0.31	0.23	0.10	0.63	0.46	0.26	0.76	0.21	0.43	0.17	0.11	0.25	0.91	0.73	0.25	**0.01**	0.26	0.39
LTC.l1	0.32	0.51	0.75	0.92	0.49	0.21	0.59	0.50	0.56	0.86	0.74	0.33	0.86	0.78	0.35	0.87	0.34	0.19	0.99	0.99	0.96	0.39	0.54	0.57	**0.00**	0.41	0.89	0.64	0.84	0.81	0.92	0.07	0.89	0.64	0.18	0.82	0.45	0.49	0.69	**0.03**	0.86	0.34	0.44	0.22	**0.05**	0.92	0.31	0.12
MANA.l1	0.16	0.32	0.16	0.88	0.26	0.20	0.11	0.75	0.59	0.40	0.96	0.26	**0.01**	0.07	0.83	0.19	0.09	0.19	0.56	0.59	0.42	0.48	0.80	0.79	0.09	**0.00**	0.41	0.30	0.70	0.30	0.37	0.29	0.63	0.41	0.45	0.11	0.22	0.45	0.71	0.44	0.68	**0.05**	0.44	0.74	0.36	0.59	0.63	0.99
MIOTA.l1	0.72	0.07	0.17	0.54	0.70	0.59	0.37	0.43	0.54	0.68	0.35	0.21	0.69	0.34	0.32	0.68	0.26	0.20	0.13	0.70	0.98	0.43	0.13	0.34	0.68	0.10	**0.00**	**0.05**	0.82	0.71	0.43	0.73	0.82	0.81	0.19	0.83	0.14	0.78	0.55	0.44	**0.05**	0.09	0.16	0.82	0.41	0.48	0.93	0.56
NEO.l1	0.38	0.39	0.32	0.96	0.67	0.09	0.58	0.88	0.40	0.57	0.56	0.79	0.09	**0.05**	0.55	0.29	**0.01**	0.72	0.37	0.36	0.08	0.81	0.89	0.45	0.21	0.09	0.86	**0.00**	0.12	0.19	0.12	0.32	0.34	0.06	0.30	1.00	0.49	**0.05**	0.63	0.61	0.16	0.42	0.99	0.85	0.59	0.32	0.18	0.12
OMG.l1	0.54	**0.03**	0.57	0.24	0.92	0.33	0.51	0.95	0.91	0.65	0.89	0.53	0.67	0.52	0.15	0.36	0.42	0.35	0.65	**0.03**	0.84	0.13	0.64	0.14	0.77	0.28	0.08	0.66	**0.00**	0.74	0.91	0.33	0.40	0.25	0.67	0.50	0.11	0.68	0.32	0.34	0.13	0.14	0.39	0.33	0.62	0.18	0.60	0.07
QTUM.l1	0.61	0.34	0.61	0.49	0.91	**0.02**	0.58	0.68	0.82	0.29	0.20	0.11	0.24	**0.00**	0.31	0.21	0.75	0.41	0.95	0.97	**0.02**	0.79	0.14	0.62	0.43	0.72	0.42	0.50	0.39	**0.00**	0.28	0.64	**0.03**	0.51	0.80	0.54	0.76	0.84	0.58	0.15	0.51	0.47	0.98	0.57	0.26	0.18	0.54	0.06
REQ.l1	0.66	**0.00**	0.17	0.81	0.50	1.00	0.92	0.14	0.28	0.23	0.19	0.64	0.60	0.48	0.43	0.58	0.19	0.35	0.83	**0.05**	0.68	0.65	0.46	0.25	0.50	0.16	0.93	0.35	0.17	0.51	0.15	0.63	0.41	0.91	0.53	0.99	0.70	0.76	0.35	0.23	0.83	0.81	0.86	0.61	0.24	**0.00**	0.71	**0.05**
RLC.l1	0.82	0.07	0.24	0.96	0.28	0.36	0.22	0.21	0.72	0.44	0.74	0.44	0.80	0.93	0.42	0.75	0.61	0.28	0.58	0.96	0.78	0.25	0.68	0.26	0.91	0.88	**0.05**	0.57	0.23	0.25	0.84	**0.00**	0.59	0.65	0.67	0.86	0.93	0.84	0.58	0.71	0.58	0.37	0.11	0.40	0.27	0.58	0.78	0.07
SC.l1	0.93	0.40	0.83	0.58	0.66	0.49	0.12	0.91	0.33	0.31	0.16	0.72	0.54	0.53	0.26	0.67	0.72	0.62	0.31	0.30	0.11	0.92	0.45	0.14	0.44	0.26	0.19	0.82	0.98	**0.03**	**0.01**	0.78	**0.00**	0.33	0.25	0.83	0.34	**0.02**	0.53	0.29	0.35	0.12	0.51	0.55	0.29	0.12	0.18	0.29
SNT.l1	**0.05**	0.87	0.79	**0.05**	0.07	0.22	0.62	0.16	0.21	0.14	0.58	0.73	0.10	0.30	0.34	0.22	0.46	0.35	0.20	0.26	0.53	0.72	0.94	0.88	0.16	0.64	0.91	**0.03**	0.56	0.06	0.10	0.84	0.58	**0.00**	0.45	0.10	0.25	0.21	0.97	0.65	0.85	0.36	0.63	0.79	0.07	0.07	0.73	0.84
STORJ.l1	0.13	0.35	0.65	0.83	0.31	0.97	0.22	0.08	0.72	0.80	0.71	0.42	0.36	0.59	0.76	0.28	0.27	0.52	0.84	0.43	**0.00**	0.48	0.72	0.08	0.72	0.99	0.77	0.16	0.99	0.81	0.81	0.51	**0.02**	0.67	**0.00**	0.93	0.41	0.38	0.79	0.25	0.84	0.35	0.16	0.99	0.24	0.74	0.47	0.29
SYS.l1	0.06	0.20	0.09	0.94	0.77	0.42	0.31	0.34	0.76	0.70	0.22	0.54	0.71	0.63	0.31	0.50	0.56	0.84	0.59	0.71	0.24	0.59	0.52	0.15	0.30	0.97	0.43	0.22	0.08	0.23	0.24	0.94	0.43	**0.04**	0.27	**0.00**	0.20	0.16	0.94	0.42	0.41	0.78	0.09	0.86	0.18	0.82	0.67	0.09
TRX.l1	0.19	0.50	0.36	0.73	**0.05**	0.30	0.29	0.25	0.21	0.29	**0.02**	0.76	0.33	0.21	0.48	0.56	0.26	0.53	0.84	0.14	0.45	0.13	0.16	0.46	0.06	0.12	0.35	0.07	0.64	0.15	0.42	0.50	0.28	0.55	0.74	0.22	**0.00**	0.34	**0.00**	0.19	0.18	0.36	0.25	0.29	0.09	0.48	0.39	0.32
VGX.l1	0.65	0.22	0.25	0.09	0.67	0.13	0.32	0.55	0.26	0.37	0.40	0.35	0.18	0.94	0.38	0.99	0.47	0.76	0.38	0.88	0.94	0.77	0.38	0.19	0.45	0.58	0.64	0.68	0.84	0.89	0.52	0.67	0.54	0.94	0.61	0.47	0.91	**0.00**	0.24	0.47	0.29	0.73	0.52	0.65	0.21	0.53	0.99	0.97
WAVES.l1	0.68	0.52	0.65	0.23	0.50	0.86	0.68	0.29	0.12	0.55	0.94	0.33	0.94	0.33	0.43	0.31	0.16	0.61	0.81	0.90	0.41	0.97	0.69	0.51	0.84	0.77	0.43	0.71	0.52	0.45	0.99	0.73	0.40	0.84	0.08	0.97	0.55	0.14	**0.00**	0.59	0.97	0.41	0.41	0.42	0.49	0.30	0.19	0.24
XEM.l1	0.41	0.57	0.82	0.38	0.14	0.44	0.66	0.57	0.98	0.12	0.76	0.82	0.83	0.29	0.39	0.48	0.69	0.42	0.13	0.37	0.50	0.59	0.94	0.53	**0.03**	0.44	0.73	0.72	0.33	0.81	0.99	0.65	0.24	0.79	0.35	0.37	0.47	0.48	0.73	**0.00**	0.88	**0.05**	0.98	0.25	0.18	0.56	0.91	0.99
XLM.l1	0.56	0.41	0.09	**0.03**	**0.01**	0.23	0.61	0.25	0.98	0.22	0.38	0.73	0.31	0.92	0.76	0.86	0.33	0.23	0.18	0.36	0.83	0.48	0.09	0.75	0.95	0.09	0.18	0.25	0.95	0.79	**0.05**	0.13	0.88	0.50	0.84	0.81	0.64	0.39	0.52	0.93	**0.00**	0.15	0.98	0.35	1.00	0.80	0.81	0.33
XMR.l1	0.85	0.21	0.11	**0.02**	0.23	**0.02**	0.36	0.83	0.36	**0.01**	0.18	0.22	0.66	0.60	0.41	0.76	0.09	0.33	**0.02**	0.06	0.86	**0.05**	0.07	0.12	0.14	0.18	0.21	0.47	0.11	0.16	0.44	0.43	0.60	0.71	0.15	0.34	0.40	0.66	0.10	0.15	0.16	0.08	0.40	**0.03**	0.34	0.23	0.86	0.12
XNO.l1	0.38	0.72	0.49	0.70	0.94	0.72	0.45	0.50	0.53	0.74	0.58	0.55	0.93	0.26	0.49	0.82	0.92	0.30	0.36	0.42	0.38	0.23	0.82	0.73	0.76	0.58	0.44	0.40	0.97	0.89	0.75	0.08	0.84	0.69	0.64	0.85	0.62	**0.01**	0.51	0.86	0.92	0.73	**0.00**	0.10	0.32	0.88	0.94	0.50
XRP.l1	0.39	0.42	0.77	0.85	0.97	0.06	0.38	0.37	0.61	0.13	0.72	0.77	0.33	0.25	0.36	0.75	0.38	0.37	0.72	0.16	0.55	0.28	0.76	0.10	0.47	0.49	0.13	0.13	0.92	0.24	0.85	0.77	0.82	0.82	0.34	0.65	0.44	0.09	0.22	0.22	0.93	0.21	0.36	**0.00**	0.14	0.07	0.59	0.11
XTZ.l1	0.88	**0.02**	0.60	0.34	0.14	0.81	0.07	0.43	0.67	0.48	0.54	0.28	0.30	0.92	0.36	0.99	0.11	0.58	0.67	0.40	0.48	0.67	0.11	0.90	0.16	0.26	0.18	0.32	0.95	0.84	0.57	0.54	0.25	0.76	0.79	0.68	0.86	0.98	0.36	0.11	0.30	0.45	0.68	0.91	**0.00**	0.96	0.68	**0.03**
ZEC.l1	0.94	**0.02**	0.54	0.23	0.62	0.62	0.91	0.73	0.99	0.54	0.50	0.77	0.10	0.33	0.36	0.58	0.85	0.83	0.81	0.87	0.82	0.49	0.87	0.35	0.52	0.84	0.67	0.13	0.66	0.17	0.41	0.59	0.36	0.46	0.43	0.64	0.18	0.98	0.85	0.98	0.93	**0.00**	0.31	0.70	0.89	**0.00**	0.26	0.36
ZEN.l1	0.22	0.11	0.94	0.59	0.15	**0.01**	0.25	0.49	0.41	0.90	0.44	0.57	**0.05**	0.11	0.68	0.20	0.61	0.80	0.64	0.29	0.28	0.75	0.86	0.49	0.47	0.55	0.61	0.31	0.64	0.16	0.82	0.55	0.33	0.81	0.92	0.74	0.45	**0.02**	0.43	0.75	0.18	0.54	0.08	0.16	0.54	0.81	**0.00**	0.22
ZRX.l1	0.47	0.81	0.09	0.38	0.54	0.20	0.52	0.11	0.75	**0.04**	**0.04**	0.55	0.80	0.41	0.81	0.08	0.86	**0.00**	0.42	0.47	**0.01**	0.06	0.42	0.34	0.55	0.55	0.19	**0.01**	0.09	0.06	0.28	**0.03**	0.58	0.32	0.60	0.86	0.92	0.56	0.11	0.38	0.78	0.10	0.33	0.22	0.35	0.06	0.08	**0.00**

P-values for Vector Autoregression model of volatility (Part 2/4)

ADA.l2	0.69	0.19	0.35	0.20	0.94	0.57	0.27	0.32	0.39	0.63	0.26	0.41	0.43	0.45	0.57	0.11	**0.00**	0.20	**0.02**	0.66	0.94	0.74	0.73	0.33	0.18	0.28	0.08	0.17	0.95	0.42	0.89	0.14	0.87	0.44	0.65	0.18	0.60	0.80	0.93	**0.02**	0.20	0.53	0.52	0.15	0.31	0.40	0.63	0.19
ANT.l2	**0.02**	**0.00**	0.80	0.56	0.98	0.72	0.34	0.34	0.52	0.23	0.12	0.43	0.57	0.83	0.34	0.41	0.95	0.29	0.23	0.95	0.16	0.14	0.48	0.57	0.64	0.64	0.95	0.23	0.69	0.51	0.72	0.32	0.21	0.50	0.42	0.42	0.11	0.40	0.27	**0.04**	0.17	0.51	0.32	0.33	0.54	0.53	0.63	0.41
BAT.l2	0.83	0.47	0.70	0.79	0.56	0.52	0.81	0.82	0.23	0.57	0.71	0.30	0.71	0.70	0.36	0.22	0.70	0.07	0.23	0.26	0.78	0.88	0.79	0.49	0.90	0.63	0.06	0.33	**0.05**	0.66	0.36	0.73	0.79	0.66	0.58	0.54	0.74	0.12	0.79	0.15	0.50	0.57	0.70	0.86	0.36	0.84	0.61	0.53
BCH.l2	0.20	0.20	0.28	**0.00**	0.75	0.30	0.40	0.44	0.42	0.28	1.00	0.73	0.45	0.19	0.83	0.84	0.72	0.17	0.52	1.00	0.19	0.98	0.87	0.47	0.99	0.70	0.18	0.80	0.42	**0.03**	0.37	0.71	0.70	0.23	0.50	0.43	0.89	0.27	0.13	0.69	0.26	0.17	0.10	0.79	0.63	0.08	0.62	0.08
BNB.l2	0.27	0.69	**0.01**	0.11	**0.00**	0.98	**0.03**	0.28	0.26	0.12	0.59	0.52	0.41	0.10	0.98	0.29	0.45	0.99	0.19	0.98	0.18	0.31	0.43	0.97	0.89	0.30	0.43	0.35	0.23	0.13	0.81	0.28	0.92	0.91	0.12	0.50	0.66	0.17	0.21	0.09	0.74	0.51	0.83	0.79	0.77	0.56	0.32	0.06
BTC.l2	**0.05**	0.13	**0.00**	**0.00**	**0.01**	**0.00**	**0.00**	0.13	**0.00**	0.29	**0.00**	0.23	**0.00**	**0.00**	0.89	**0.03**	**0.00**	0.73	**0.00**	**0.00**	0.47	**0.02**	**0.01**	**0.01**	0.25	**0.02**	0.99	0.64	**0.01**	**0.05**	**0.00**	0.10	**0.00**	0.13	**0.03**	**0.01**	**0.00**	0.09	**0.05**	0.36	**0.00**	**0.04**	**0.02**	**0.00**	**0.02**	**0.03**	0.08	**0.00**
BTG.l2	0.51	**0.05**	0.68	0.83	0.82	0.83	**0.00**	0.18	**0.04**	0.59	0.55	0.49	0.14	0.49	0.38	**0.01**	**0.02**	0.62	0.49	0.43	0.94	0.41	0.44	0.73	**0.01**	0.70	0.73	0.13	0.19	0.50	0.25	0.42	0.84	0.71	0.86	0.65	0.37	0.25	0.83	0.11	0.40	0.24	0.86	0.46	0.35	0.57	0.66	0.56
CVC.l2	0.47	0.11	0.35	0.44	0.26	0.78	0.82	**0.00**	0.59	0.92	0.07	0.56	0.54	0.72	0.64	0.43	0.41	0.26	0.71	0.24	0.38	0.88	0.71	0.77	0.54	0.49	0.41	0.89	0.84	0.55	0.32	0.27	0.90	0.94	0.68	0.11	0.45	0.39	0.41	0.23	0.67	0.38	0.99	0.86	0.31	0.34	0.40	0.37
DASH.l2	0.56	0.20	0.65	0.60	0.90	0.93	0.36	0.89	**0.04**	0.12	0.26	0.54	0.64	0.26	0.49	0.79	0.58	0.60	0.56	0.49	0.55	0.82	0.27	0.86	0.34	0.18	**0.03**	0.35	0.87	0.21	0.24	0.84	0.71	**0.05**	0.52	0.77	0.98	0.39	0.16	0.58	0.17	0.20	0.96	0.35	0.57	**0.00**	**0.00**	0.97
DCR.l2	0.43	0.36	0.95	0.42	0.67	0.74	0.38	0.72	0.84	0.12	0.61	0.48	0.35	0.11	0.98	0.71	0.08	0.56	0.70	0.91	0.56	0.86	**0.00**	0.60	**0.03**	0.94	0.62	0.45	0.13	0.69	0.69	0.59	0.76	0.82	0.27	0.44	0.29	0.74	0.92	0.75	0.43	0.45	0.51	0.78	0.23	0.57	0.90	0.60
DGB.l2	0.09	0.28	0.65	**0.05**	0.44	0.78	0.07	0.19	0.28	0.75	**0.00**	0.86	0.64	0.50	0.66	0.20	0.32	0.23	0.75	0.43	**0.01**	0.23	0.97	0.35	0.26	0.43	0.45	0.24	0.31	0.09	0.28	0.45	0.73	0.14	0.40	0.29	0.15	0.78	0.31	0.24	0.50	0.96	0.31	0.69	0.58	0.43	0.42	0.55
DOGE.l2	0.89	0.74	0.93	0.92	0.97	0.11	0.28	0.98	0.58	0.34	0.71	0.29	0.44	0.99	0.51	0.62	0.78	0.82	0.79	0.90	0.93	0.38	0.61	0.54	0.65	0.88	0.86	0.99	0.57	0.78	0.46	0.82	0.66	0.94	0.21	0.83	0.39	0.66	0.99	0.54	0.32	0.94	0.89	**0.00**	0.84	0.34	0.54	0.59
ENJ.l2	**0.05**	0.07	0.17	0.50	0.56	0.08	0.12	0.97	0.62	0.09	0.42	0.32	**0.00**	0.64	0.55	0.46	0.83	0.06	0.10	0.29	0.65	0.89	0.80	0.51	0.28	0.13	0.64	0.21	0.45	0.67	0.21	0.24	0.36	0.96	0.69	0.16	0.24	0.70	0.90	**0.02**	0.96	0.83	0.93	0.58	0.68	0.12	0.92	0.54
EOS.l2	0.14	0.33	0.11	0.21	0.68	0.14	0.50	0.17	0.68	0.89	0.59	0.34	0.51	**0.01**	0.79	0.18	0.14	0.20	0.78	0.55	0.25	0.87	0.74	**0.02**	0.49	0.39	0.87	0.82	0.96	0.32	0.74	0.90	0.15	0.58	0.25	0.99	0.70	0.51	0.55	0.91	**0.05**	0.76	0.47	0.60	0.58	**0.02**	0.95	0.83
ERG.l2	0.73	0.60	0.07	0.76	0.82	0.87	0.45	0.99	0.68	0.38	0.57	0.55	0.48	0.79	0.58	0.80	0.93	0.94	0.73	0.40	0.99	0.09	0.76	0.08	0.91	0.12	0.80	0.65	0.95	0.70	0.95	0.13	0.26	0.44	0.63	0.93	0.74	0.64	0.48	0.40	0.75	0.34	0.75	0.89	0.44	**0.03**	0.71	0.06
ETC.l2	0.63	0.83	0.94	0.32	**0.05**	0.09	0.81	0.52	0.65	0.68	0.95	0.42	0.24	0.92	0.40	**0.00**	0.23	0.79	0.99	0.88	0.38	0.12	**0.03**	0.44	0.95	0.99	**0.00**	0.69	0.80	0.53	0.33	0.53	**0.02**	0.83	0.18	0.12	0.60	0.76	0.58	0.55	0.88	0.31	0.58	0.79	0.86	0.43	0.08	0.52
ETH.l2	0.85	**0.00**	0.23	0.23	0.92	0.18	0.20	0.44	0.50	0.41	0.62	0.51	0.27	0.57	0.34	**0.01**	**0.00**	0.07	0.55	0.26	0.88	0.90	0.66	0.37	0.13	0.31	0.45	**0.00**	**0.04**	**0.01**	0.47	0.91	**0.03**	0.64	0.17	0.62	**0.00**	0.83	0.18	**0.02**	0.90	0.38	0.34	0.49	0.77	0.58	0.79	0.57
GLM.l2	0.61	0.90	0.66	0.92	0.32	0.18	0.59	0.12	0.85	0.48	0.22	0.32	0.81	0.40	0.43	0.80	0.78	**0.00**	0.99	0.33	0.27	0.22	0.96	0.91	0.50	0.37	0.20	0.07	0.17	0.27	0.58	0.50	0.41	0.86	0.10	0.20	0.25	0.73	0.67	0.65	0.83	0.54	0.77	0.85	0.31	0.15	0.41	**0.05**
GNO.l2	0.75	0.81	0.96	0.43	0.88	0.17	0.21	0.85	0.95	0.44	0.91	0.95	0.94	0.37	0.45	**0.01**	**0.03**	0.63	0.17	0.37	0.84	0.87	0.36	0.89	0.26	0.45	0.41	0.56	0.27	0.88	0.51	0.08	0.69	0.83	0.31	0.10	0.80	0.44	0.92	0.30	0.77	0.19	0.29	0.86	0.12	0.72	0.37	0.60
ICX.l2	0.07	0.07	0.78	0.69	0.79	0.41	0.06	0.47	0.08	0.16	0.58	0.49	0.84	0.07	0.79	0.06	0.06	0.89	0.62	0.56	0.13	0.30	0.26	0.09	0.59	0.20	**0.04**	**0.04**	0.53	**0.01**	0.52	1.00	0.31	0.15	0.50	0.36	0.23	0.82	0.65	0.30	0.52	0.42	0.63	0.52	0.85	0.69	**0.01**	**0.04**
KCS.l2	0.91	0.91	0.56	0.61	0.48	0.38	0.86	0.61	0.48	**0.04**	0.58	0.70	0.34	0.15	0.30	0.18	0.35	0.74	0.90	0.65	**0.00**	**0.01**	0.52	0.31	0.56	0.24	0.63	0.34	0.24	0.23	1.00	0.31	0.93	0.97	0.88	0.80	0.17	0.82	0.59	0.56	0.49	0.70	0.27	0.35	0.59	0.34	0.74	0.67
LINK.l2	0.24	0.38	0.91	0.65	0.49	0.73	0.78	0.53	0.25	0.69	0.11	0.91	0.44	0.97	0.84	0.85	0.45	0.55	0.83	0.18	0.38	0.66	0.42	0.85	0.87	0.24	0.47	0.65	0.54	0.61	0.74	0.50	0.72	0.17	0.74	0.38	0.49	0.45	0.63	0.40	0.70	0.72	0.09	0.46	0.46	0.91	0.35	0.75
LRC.l2	0.84	0.25	0.32	0.45	0.76	0.37	0.39	0.17	0.21	0.84	0.48	0.64	0.87	0.55	0.35	0.92	0.92	0.43	0.54	0.54	0.78	0.73	**0.05**	0.44	0.18	0.97	0.17	0.19	0.53	0.82	0.44	0.80	0.19	0.69	0.23	0.47	0.74	0.81	0.53	0.90	0.91	0.79	0.92	0.17	0.18	0.55	0.33	0.69
LSK.l2	0.22	0.78	0.38	0.46	0.90	0.99	0.40	0.09	0.68	0.70	0.06	0.93	0.81	0.37	0.46	0.49	0.53	0.38	0.94	0.93	0.47	0.26	0.65	0.49	0.99	0.70	0.66	0.28	0.32	0.63	0.65	0.89	0.29	0.27	0.61	0.18	0.48	0.20	0.46	0.15	0.27	0.73	0.80	0.75	0.44	0.10	0.09	0.21
LTC.l2	0.92	0.14	**0.01**	0.12	0.45	**0.00**	0.16	0.58	0.17	0.32	0.80	0.39	0.06	0.58	0.27	0.44	**0.05**	0.21	0.76	0.16	**0.05**	0.78	0.32	0.22	**0.00**	0.69	0.36	**0.02**	0.22	0.36	0.58	0.42	**0.03**	0.13	0.83	0.69	0.18	0.58	0.99	**0.00**	0.26	0.19	0.16	0.61	0.37	0.56	0.65	0.12
MANA.l2	0.64	0.56	0.51	0.85	0.19	0.71	0.65	0.29	0.33	0.46	0.62	0.50	0.20	0.85	0.59	0.37	0.17	0.72	0.82	0.78	0.43	0.37	0.06	0.85	0.23	**0.01**	0.56	0.95	0.72	0.74	0.13	**0.04**	0.63	0.45	0.38	0.47	0.26	0.39	0.89	0.24	0.27	0.16	0.41	0.55	0.29	0.27	0.71	0.99
MIOTA.l2	0.77	0.66	0.80	0.43	0.34	0.86	0.67	0.25	0.79	0.54	0.45	0.61	0.63	0.74	0.39	0.68	0.64	0.95	0.90	0.93	0.30	0.75	0.45	0.30	0.64	0.46	**0.00**	0.11	0.44	0.93	0.36	0.59	0.23	0.85	0.41	0.58	0.52	0.88	0.73	0.53	0.09	0.66	0.33	0.26	0.99	0.46	0.47	0.99
NEO.l2	0.71	1.00	0.17	0.52	0.28	0.94	0.41	0.80	0.38	0.89	0.96	0.30	0.33	0.91	0.42	0.27	0.30	0.08	0.20	**0.03**	0.49	0.11	0.07	0.47	0.11	0.55	0.46	**0.00**	0.31	0.97	0.51	0.48	0.40	0.79	0.72	0.64	0.51	0.53	0.28	**0.02**	0.18	0.73	0.95	**0.01**	0.68	0.51	0.90	0.82
OMG.l2	0.68	**0.01**	0.79	0.55	0.10	0.28	0.44	0.55	0.41	0.43	0.42	0.70	0.56	**0.00**	0.62	0.25	**0.05**	0.45	0.86	0.46	0.18	0.49	0.75	0.24	0.37	0.89	**0.00**	0.27	0.06	0.56	0.59	0.96	0.23	0.39	0.63	0.70	0.69	0.75	0.63	0.96	0.43	**0.02**	0.57	0.70	0.41	0.60	0.83	**0.00**
QTUM.l2	0.56	0.07	0.36	0.76	0.79	0.61	0.83	0.18	0.43	0.40	0.06	0.75	0.84	0.29	0.90	0.56	0.35	0.96	0.35	0.27	0.22	0.49	0.68	0.19	0.99	0.71	0.09	0.69	0.95	**0.00**	0.52	0.74	0.29	0.10	0.64	0.55	0.10	0.09	0.26	0.72	0.33	0.28	0.29	0.34	0.21	0.66	0.39	0.15
REQ.l2	0.85	0.83	0.45	0.85	0.86	0.43	0.83	0.85	0.82	0.98	0.38	0.67	0.76	0.70	0.36	0.68	0.91	0.47	0.35	0.25	0.53	0.54	0.30	0.81	0.61	0.41	**0.04**	0.94	0.49	0.28	0.16	0.32	0.47	0.18	0.18	0.15	0.41	0.65	0.64	0.20	0.77	0.98	0.38	0.75	0.81	**0.03**	**0.05**	0.39
RLC.l2	0.17	0.10	0.18	0.70	0.60	0.37	0.50	0.30	0.69	0.19	0.15	0.63	0.67	0.41	0.94	0.56	0.24	**0.02**	0.14	0.10	0.52	0.93	0.27	0.81	0.38	0.62	**0.02**	0.37	0.54	0.81	**0.05**	**0.00**	0.17	0.76	0.09	**0.02**	0.84	0.87	0.51	0.58	0.39	0.42	0.92	0.15	0.39	0.93	0.31	0.67
SC.l2	0.39	0.24	0.26	0.41	0.33	0.19	0.08	0.46	0.66	0.68	0.64	0.67	0.38	0.46	0.60	0.32	0.23	0.87	0.20	0.94	0.32	0.95	0.58	0.40	0.61	**0.03**	0.63	0.09	0.21	0.79	0.50	0.42	**0.05**	0.79	0.17	0.25	0.89	0.40	0.18	0.39	0.29	0.16	0.54	0.36	0.75	0.97	0.47	0.80
SNT.l2	**0.02**	0.67	0.83	0.60	0.79	0.77	0.26	0.19	0.59	0.91	0.30	0.83	0.17	0.46	0.26	0.53	0.98	0.37	0.42	0.48	0.94	0.14	0.34	0.69	0.29	0.64	0.90	0.46	**0.03**	0.71	0.84	0.35	0.23	**0.00**	0.38	0.17	0.91	0.49	0.41	0.09	0.10	0.52	0.06	0.85	0.79	0.68	0.62	0.95
STORJ.l2	0.46	0.96	0.53	0.18	0.57	**0.01**	0.21	0.27	**0.02**	0.52	0.22	0.46	0.94	0.69	0.94	0.56	0.89	0.62	0.24	0.50	0.27	0.95	0.90	0.71	**0.03**	0.66	**0.05**	0.40	0.90	0.91	0.75	0.85	0.37	0.74	**0.01**	0.13	0.90	0.74	0.87	0.75	1.00	**0.05**	0.47	0.74	0.35	0.78	0.67	0.54
SYS.l2	0.47	0.64	0.87	0.10	0.24	0.62	0.77	0.11	0.24	0.92	0.22	0.30	0.78	0.13	0.52	0.36	0.32	0.45	0.98	0.37	0.33	0.53	0.65	0.50	0.13	0.59	0.55	0.79	0.75	0.31	0.80	0.27	0.93	0.47	0.17	**0.00**	0.94	0.35	0.16	0.13	0.85	0.55	0.47	0.61	0.59	0.91	0.36	0.55
TRX.l2	**0.04**	0.18	0.58	0.56	0.56	0.36	0.91	**0.01**	0.46	0.31	0.32	0.42	0.73	0.15	0.40	0.28	0.63	0.75	0.91	0.08	**0.05**	0.41	0.24	0.25	**0.03**	0.16	0.54	0.64	0.31	**0.02**	0.13	0.35	1.00	0.59	0.48	0.78	**0.00**	0.77	0.65	0.10	0.74	0.48	0.26	0.90	0.14	0.15	0.54	0.74
VGX.l2	0.37	0.42	0.39	0.96	0.86	0.43	0.88	0.50	0.98	0.12	0.98	0.41	0.52	0.75	0.42	0.70	0.42	0.47	0.72	0.62	0.47	0.49	0.88	0.99	0.29	0.17	0.45	0.81	0.29	**0.04**	0.64	0.75	0.12	0.82	0.66	0.28	0.76	**0.00**	0.95	0.65	0.75	0.37	0.33	0.17	0.21	0.84	0.40	0.29
WAVES.l2	0.07	0.98	0.60	0.09	0.37	0.75	0.25	0.68	0.11	0.61	0.38	0.59	0.25	0.13	0.31	0.27	0.35	0.41	0.15	0.58	0.61	0.33	0.50	0.92	0.36	0.78	0.31	0.39	0.32	0.07	0.19	0.34	0.80	0.29	0.20	0.42	0.48	0.30	**0.00**	0.30	**0.05**	0.99	0.72	**0.04**	0.82	0.28	0.58	0.97
XEM.l2	0.23	0.83	0.38	0.29	0.66	0.92	0.55	0.68	0.49	0.44	0.44	0.39	0.39	0.86	0.49	0.10	0.06	0.80	0.41	0.13	**0.01**	0.65	0.07	0.18	0.27	0.33	0.72	0.24	0.23	0.64	0.46	0.51	0.89	0.81	0.17	0.17	0.87	0.63	0.74	0.88	0.15	0.88	0.96	0.42	0.77	0.77	0.20	0.76
XLM.l2	0.65	0.36	**0.02**	0.20	0.08	0.42	0.60	0.43	0.26	0.22	0.89	0.47	**0.02**	0.35	0.28	0.08	0.56	0.18	0.21	0.73	0.90	0.98	0.22	0.14	0.56	0.26	0.81	**0.00**	0.76	0.09	0.14	0.09	0.56	0.35	0.84	0.15	0.16	0.99	0.40	0.16	**0.00**	0.54	0.11	0.75	0.84	**0.03**	0.21	0.08
XMR.l2	**0.04**	0.21	0.25	0.35	0.57	0.49	0.29	0.45	0.99	0.83	0.57	0.32	0.59	**0.05**	0.30	0.23	0.41	0.89	0.26	0.06	0.63	0.17	0.41	0.16	0.60	0.81	**0.03**	0.61	0.17	0.07	0.59	0.94	0.49	0.21	0.98	0.32	0.82	0.51	0.56	0.38	0.11	**0.00**	0.79	0.39	0.25	0.40	0.87	0.80
XNO.l2	0.33	0.33	0.34	0.28	0.37	0.86	0.37	0.50	0.36	0.83	0.84	0.14	0.46	0.96	0.54	0.28	0.51	0.91	0.07	0.56	0.64	0.64	0.72	0.55	0.75	0.43	1.00	0.57	0.32	0.51	0.33	0.69	0.88	0.39	0.58	0.38	0.41	0.53	0.61	0.28	0.45	0.44	**0.01**	0.93	0.67	0.88	0.31	0.40
XRP.l2	0.06	0.86	0.49	**0.04**	0.46	0.06	0.82	0.58	0.31	0.44	0.62	0.77	0.87	0.28	0.30	0.30	0.54	0.06	0.21	0.34	0.66	0.52	0.81	0.41	0.90	0.84	0.85	0.84	0.96	0.31	0.75	0.82	0.46	0.15	0.20	0.34	0.38	0.53	0.83	0.48	0.41	0.14	0.39	**0.00**	0.52	0.40	0.40	0.53
XTZ.l2	**0.02**	**0.00**	0.14	**0.05**	0.63	0.08	0.45	0.12	0.11	0.07	0.71	0.31	0.10	0.07	0.98	0.16	**0.03**	0.15	0.33	**0.00**	**0.02**	0.99	0.78	0.71	**0.04**	0.18	0.12	0.16	0.71	0.80	0.46	0.71	0.41	**0.01**	0.93	0.60	**0.02**	0.50	0.45	0.14	**0.05**	0.88	0.88	**0.00**	**0.00**	0.36	0.55	**0.00**
ZEC.l2	0.42	0.14	0.14	**0.02**	0.26	**0.00**	0.22	0.09	0.61	0.10	0.79	0.16	0.13	0.23	0.63	0.54	0.83	0.65	0.26	**0.02**	0.10	0.80	0.93	**0.01**	**0.01**	0.44	0.10	0.59	0.65	0.36	0.38	0.39	0.42	0.48	0.24	0.11	0.26	0.17	0.83	0.16	**0.02**	**0.02**	0.11	0.46	0.80	**0.00**	0.45	0.63
ZEN.l2	0.54	0.54	0.42	0.95	0.85	0.13	0.38	0.39	0.16	0.38	0.66	0.37	0.62	0.83	0.83	0.58	0.18	0.67	0.37	0.82	0.55	0.59	0.19	0.87	0.43	0.96	0.81	**0.05**	0.28	0.31	0.29	0.45	0.45	0.44	0.26	0.71	0.35	0.67	0.90	0.06	0.07	0.45	0.60	0.85	0.84	0.58	**0.00**	0.42
ZRX.l2	0.92	0.53	0.79	0.16	0.86	0.48	0.63	0.78	0.65	0.92	**0.01**	0.31	**0.02**	0.13	0.78	0.93	0.38	0.09	0.94	0.62	0.17	0.10	0.16	0.87	0.57	0.83	0.14	**0.01**	0.49	0.57	0.24	**0.04**	0.55	0.12	0.58	0.87	0.27	1.00	0.07	0.51	0.29	**0.01**	0.36	0.81	0.63	**0.00**	0.17	0.93

P-values for Vector Autoregression model of volatility (Part 3/4)

ADA.l3	0.27	0.11	0.76	0.06	0.86	0.38	0.25	0.22	0.32	0.92	0.28	0.51	0.57	0.06	0.59	0.19	**0.02**	0.63	0.35	0.44	0.17	0.98	0.18	0.28	**0.02**	0.15	0.22	0.78	0.08	0.65	0.40	0.50	0.77	0.73	0.64	0.57	0.45	0.74	0.25	**0.03**	0.28	0.69	0.98	0.24	0.31	0.58	0.37	0.58
ANT.l3	0.73	**0.00**	0.57	0.28	0.43	0.57	0.32	0.20	0.99	1.00	0.85	0.45	0.11	0.11	0.38	0.97	0.46	0.97	0.56	0.19	0.24	0.97	0.99	0.75	**0.05**	0.25	0.53	0.16	0.38	0.60	0.59	**0.05**	0.90	0.53	0.44	0.63	0.59	0.45	0.27	0.29	0.42	0.94	0.37	0.36	0.31	0.37	**0.04**	0.24
BAT.l3	0.93	0.85	0.72	0.41	0.95	0.99	0.93	0.36	0.06	0.91	0.78	0.68	0.99	0.97	0.29	0.06	0.20	0.28	0.95	0.52	0.74	0.68	0.48	0.44	**0.01**	0.53	0.89	**0.01**	0.10	0.85	0.17	0.94	0.60	0.82	0.80	0.27	0.17	0.96	0.90	0.42	0.26	0.28	0.13	0.97	**0.01**	0.73	0.60	0.40
BCH.l3	0.37	0.85	0.22	**0.00**	0.53	0.47	0.57	0.27	0.23	**0.02**	0.93	0.63	0.21	0.82	0.26	0.59	**0.00**	0.98	0.68	0.25	0.66	0.29	0.77	0.80	0.85	0.23	0.70	0.94	**0.05**	0.81	0.83	0.54	0.06	0.57	0.48	0.41	0.96	0.70	0.91	0.46	0.08	0.10	0.42	0.09	**0.05**	0.47	0.87	0.84
BNB.l3	0.72	0.35	0.07	0.36	**0.00**	0.95	0.12	0.75	0.45	0.15	0.51	0.67	0.43	0.78	0.72	0.26	0.11	0.19	0.25	0.17	**0.01**	0.83	0.36	0.28	0.87	0.21	0.45	0.93	0.17	0.22	0.72	0.67	0.94	0.71	0.51	0.17	0.84	0.44	0.11	0.78	0.48	0.45	0.12	0.51	0.82	0.41	0.78	0.40
BTC.l3	0.92	0.99	0.72	0.58	0.95	**0.00**	**0.04**	0.48	**0.04**	0.31	0.07	0.30	0.58	0.57	0.90	0.78	0.78	0.97	0.06	0.45	0.09	0.18	0.98	0.89	0.06	0.38	0.11	0.41	0.85	0.44	0.74	0.18	**0.01**	0.87	0.51	0.73	**0.04**	0.81	0.69	0.22	**0.02**	0.45	0.15	0.73	0.72	0.39	0.64	0.69
BTG.l3	**0.02**	0.11	0.45	**0.03**	0.14	0.74	0.19	0.75	0.69	0.37	0.48	0.24	0.26	0.29	0.53	**0.01**	0.40	0.61	0.55	0.26	0.12	0.10	0.39	0.13	0.36	0.99	0.71	0.12	0.53	0.41	0.73	0.51	0.27	0.22	0.62	0.72	0.10	0.37	0.17	0.71	0.16	0.26	0.13	0.39	0.99	0.72	**0.00**	0.55
CVC.l3	0.07	**0.00**	0.39	0.38	0.23	0.55	0.38	0.61	**0.04**	0.18	0.34	0.40	0.33	0.41	0.95	0.07	0.28	**0.01**	0.22	0.18	0.39	0.40	0.12	0.30	0.44	0.09	0.45	0.25	0.58	0.51	0.57	0.33	0.27	0.24	0.12	0.93	0.60	0.85	0.59	0.58	0.31	0.10	0.29	**0.04**	**0.02**	0.15	**0.00**	0.19
DASH.l3	0.46	0.99	0.20	0.95	0.85	0.29	0.82	0.57	**0.00**	0.84	0.59	0.84	0.57	0.78	0.50	0.73	0.17	0.25	0.18	0.59	0.73	0.56	0.90	0.95	0.37	0.31	0.61	0.29	0.44	0.88	0.31	**0.04**	0.93	0.25	0.84	0.49	0.08	0.92	0.71	0.36	0.35	0.58	0.37	0.94	0.92	**0.00**	**0.03**	0.59
DCR.l3	0.51	0.59	0.49	0.74	0.75	0.38	0.73	0.78	0.28	**0.00**	0.38	0.44	0.97	0.61	0.58	0.57	0.59	0.59	0.52	0.46	0.59	0.30	0.32	0.29	0.99	0.53	0.84	0.89	0.70	0.52	0.45	0.57	0.48	0.82	0.43	0.74	0.83	0.87	0.31	0.77	0.53	0.39	0.40	0.81	0.99	0.53	0.91	0.75
DGB.l3	**0.03**	0.42	0.44	0.10	0.79	0.56	**0.01**	0.59	0.67	0.68	0.41	0.87	0.99	0.85	0.69	0.43	0.85	0.35	0.34	0.21	0.83	0.36	0.16	0.65	0.10	0.90	0.47	0.72	0.97	0.91	0.87	0.29	0.28	0.38	0.55	0.82	0.72	0.57	0.46	0.65	**0.02**	0.44	0.16	0.53	0.60	0.99	0.75	0.16
DOGE.l3	0.55	0.84	0.52	0.83	0.22	0.26	0.42	0.59	0.68	0.22	0.84	0.63	0.92	0.99	0.62	0.92	0.74	0.53	0.94	0.41	0.68	0.89	0.46	0.78	0.81	0.24	0.83	0.61	0.77	0.72	0.95	0.29	0.92	0.38	0.62	0.42	0.39	0.47	0.40	0.73	0.49	0.84	0.62	0.56	0.82	0.41	0.75	0.44
ENJ.l3	0.93	1.00	0.73	0.77	0.99	0.91	0.15	0.45	0.31	0.33	0.67	0.54	0.31	0.68	0.32	0.58	0.85	0.90	0.41	0.80	0.69	0.43	0.36	0.31	0.57	0.31	0.57	0.12	0.91	0.65	0.67	0.73	0.33	0.16	0.82	0.86	0.49	0.43	0.85	0.09	0.80	0.57	0.57	0.93	0.30	0.16	0.30	0.60
EOS.l3	0.36	0.32	0.97	0.23	0.52	0.99	0.22	0.39	0.25	0.57	0.94	0.76	0.53	0.72	0.50	**0.04**	**0.03**	0.37	0.13	0.82	0.32	0.80	0.26	0.91	0.21	0.53	0.85	0.59	0.95	0.88	0.48	0.28	0.33	0.24	0.91	0.68	**0.05**	0.64	0.90	0.99	0.96	0.80	0.50	0.31	0.33	0.67	0.12	0.71
ERG.l3	0.89	0.76	0.91	0.89	0.73	0.91	**0.04**	0.95	0.50	0.35	0.47	0.75	0.84	0.19	0.75	0.82	0.10	0.94	0.73	0.49	0.67	0.88	0.06	0.94	0.80	0.89	0.83	0.73	0.82	0.89	0.44	0.54	0.37	0.43	0.98	0.87	0.91	0.97	0.64	0.86	0.65	0.93	0.61	**0.00**	0.52	0.95	0.83	0.96
ETC.l3	0.55	0.08	0.24	**0.02**	0.17	0.23	0.43	0.60	0.13	0.19	0.72	0.30	0.81	0.28	0.58	**0.00**	**0.00**	0.21	0.39	0.48	0.24	0.24	0.52	0.69	0.25	0.89	0.96	0.84	0.62	0.66	0.45	**0.04**	0.92	0.74	0.91	0.36	0.83	0.89	0.45	0.43	0.10	0.58	0.22	0.23	0.29	0.34	0.64	0.40
ETH.l3	0.21	0.62	0.61	**0.05**	0.43	0.66	**0.02**	0.67	0.33	0.07	0.80	0.31	0.54	**0.00**	0.23	0.65	**0.00**	0.38	0.75	0.13	0.19	0.09	0.24	0.08	0.18	0.22	0.40	**0.00**	**0.00**	0.36	**0.03**	0.95	0.95	0.89	0.62	0.30	0.71	0.27	0.14	0.06	0.99	0.51	0.34	0.38	**0.02**	0.22	0.85	0.89
GLM.l3	0.75	0.92	0.93	0.32	0.83	0.46	0.85	0.19	0.38	0.90	0.58	0.62	0.36	0.51	0.34	0.97	1.00	**0.00**	0.71	0.31	0.95	0.35	0.17	0.84	0.70	0.60	0.10	0.52	0.46	0.53	0.68	0.63	0.85	0.83	0.38	0.63	0.23	0.73	0.43	0.33	0.18	0.67	0.42	0.74	0.98	0.62	0.74	0.83
GNO.l3	0.77	0.42	0.44	0.74	0.46	0.08	0.22	0.56	0.89	0.37	0.82	0.33	0.70	0.30	0.42	**0.02**	**0.04**	0.74	0.78	0.96	0.78	**0.05**	0.51	0.48	0.30	0.92	0.51	0.34	0.39	0.17	0.76	0.64	0.84	0.91	0.25	0.22	0.41	0.73	0.74	0.36	0.85	0.21	0.42	0.90	0.06	0.92	0.63	0.67
ICX.l3	0.67	0.96	0.56	0.24	0.78	0.58	0.24	0.78	0.37	0.63	0.15	0.33	0.65	0.68	0.60	0.42	0.22	0.87	0.73	**0.00**	0.30	0.51	0.84	**0.02**	0.42	0.87	0.77	0.13	0.38	0.29	0.43	0.75	0.87	0.36	0.94	0.41	0.43	0.60	0.39	0.74	0.78	0.29	0.34	0.67	0.64	0.96	0.13	0.95
KCS.l3	0.66	0.32	0.38	0.32	0.39	0.69	0.85	0.22	0.75	0.17	0.60	0.45	0.32	0.98	0.27	0.24	0.83	0.64	0.74	0.85	**0.00**	**0.01**	0.92	0.56	0.35	**0.05**	0.93	0.91	0.63	0.36	0.37	0.13	0.26	0.84	0.78	0.81	0.28	0.28	0.15	0.89	0.23	0.65	0.54	0.36	0.60	0.62	0.79	0.84
LINK.l3	**0.05**	0.52	**0.01**	0.18	0.07	0.62	0.24	0.90	0.15	0.18	**0.03**	0.80	0.22	**0.04**	0.32	0.06	0.58	0.12	0.22	**0.01**	0.08	0.65	**0.04**	**0.01**	**0.05**	0.17	0.34	**0.02**	**0.01**	**0.02**	0.10	0.53	0.64	0.13	**0.04**	0.89	0.59	0.82	0.19	0.76	0.71	0.23	0.58	**0.04**	0.96	0.54	0.16	0.09
LRC.l3	0.06	0.18	0.94	0.38	0.30	0.59	0.72	0.23	0.69	0.08	0.15	0.86	0.55	0.90	0.40	0.66	0.52	0.26	0.48	0.17	0.71	0.87	**0.00**	0.64	0.80	0.38	0.51	0.69	0.95	0.51	0.26	0.16	**0.02**	0.19	0.77	0.83	0.73	0.88	0.69	0.50	0.25	0.32	0.06	0.30	0.40	0.30	0.93	0.11
LSK.l3	0.08	0.43	0.06	0.58	0.20	0.38	0.17	0.56	0.15	0.37	0.19	0.29	0.14	0.44	0.37	0.62	0.11	0.51	0.33	0.09	0.74	0.62	0.23	**0.00**	0.86	0.17	**0.01**	0.68	0.24	0.30	0.24	0.20	0.16	**0.02**	0.54	0.84	0.26	0.66	0.29	0.19	0.09	0.98	0.23	0.68	0.21	0.69	0.43	0.17
LTC.l3	0.30	0.70	0.95	0.47	0.57	0.61	0.49	0.71	0.91	0.43	0.81	0.29	**0.04**	0.31	0.35	0.82	0.75	0.16	0.59	0.84	0.29	0.87	0.43	0.58	**0.00**	0.76	0.23	0.90	0.93	0.15	0.71	0.90	0.32	0.30	0.35	0.73	0.38	0.20	0.45	**0.04**	0.64	0.46	0.82	0.91	0.16	0.53	0.40	0.09
MANA.l3	0.82	0.35	0.94	0.41	0.70	0.70	0.21	0.35	0.08	0.21	0.66	0.82	0.48	0.64	0.92	**0.05**	0.41	0.89	0.69	0.86	0.90	0.28	0.80	0.63	0.54	0.06	0.99	0.89	0.53	0.71	0.81	0.23	0.64	0.67	0.91	0.36	0.10	0.74	0.56	0.50	0.76	0.08	0.91	0.09	0.65	0.14	0.62	0.17
MIOTA.l3	0.79	0.67	0.90	0.71	0.96	0.18	0.11	0.42	**0.00**	0.16	0.28	0.26	0.56	0.11	0.70	0.97	0.07	0.10	0.16	0.72	0.47	0.86	0.90	0.51	0.32	0.46	**0.00**	0.22	0.16	0.35	0.49	0.29	0.86	0.36	0.58	0.20	0.56	0.95	0.61	0.99	0.06	0.23	0.41	0.92	**0.05**	0.14	0.67	0.71
NEO.l3	0.94	0.89	0.78	0.13	0.18	0.43	0.87	0.33	**0.01**	0.08	0.81	0.30	0.38	0.16	0.25	0.10	0.53	0.95	0.30	0.51	0.14	0.52	0.72	0.09	**0.00**	0.21	0.33	**0.00**	0.21	0.99	0.86	0.27	**0.02**	0.24	0.13	**0.05**	0.75	0.93	0.71	0.84	0.71	0.40	0.08	0.75	**0.05**	**0.01**	0.09	0.85
OMG.l3	0.95	0.07	0.32	0.80	0.55	0.81	0.56	0.47	0.64	0.89	0.96	0.24	0.35	**0.00**	0.22	0.66	0.68	**0.03**	0.49	0.21	0.22	0.16	0.49	0.38	0.61	0.85	0.35	0.92	0.23	0.46	0.09	0.26	0.47	0.65	0.91	0.13	0.67	0.61	0.07	0.78	0.98	0.89	0.72	0.74	0.12	0.81	0.69	0.08
QTUM.l3	0.48	0.18	0.50	0.69	0.91	0.06	0.71	0.13	0.63	0.81	0.78	0.70	0.63	0.36	0.62	0.57	0.52	0.41	0.31	0.31	0.12	0.67	0.48	0.12	0.70	0.22	0.39	0.16	0.09	**0.00**	0.76	0.19	0.12	0.71	0.50	0.23	0.65	0.77	0.70	0.80	0.64	0.50	0.82	0.59	0.30	0.74	0.56	0.97
REQ.l3	0.57	**0.00**	0.46	0.67	0.37	0.79	0.69	**0.04**	0.21	0.32	0.37	0.49	0.50	0.49	0.93	0.55	0.64	0.77	0.38	0.37	0.78	0.60	0.95	0.06	0.62	0.25	0.17	0.36	0.96	0.48	0.97	**0.05**	0.84	**0.04**	0.78	0.08	0.54	0.92	0.68	0.57	0.42	0.69	0.88	0.92	0.30	0.08	0.82	**0.05**
RLC.l3	0.67	0.52	0.47	0.58	0.65	0.43	0.38	0.42	0.43	0.93	0.26	0.56	0.94	0.42	0.77	0.92	0.35	0.53	0.37	0.71	0.85	0.07	0.63	0.66	0.35	0.35	0.37	0.64	**0.04**	0.76	**0.02**	**0.00**	0.62	0.09	0.44	0.06	0.36	0.06	0.72	0.42	0.96	0.74	0.41	0.32	0.09	0.55	0.28	0.35
SC.l3	0.26	0.76	0.12	0.50	0.54	0.83	0.47	0.91	0.19	0.67	0.99	0.51	0.38	0.40	0.27	0.69	0.10	0.40	0.80	0.71	**0.02**	0.18	**0.05**	0.19	0.29	0.93	0.11	0.45	0.11	0.89	0.42	0.77	**0.04**	0.17	**0.04**	0.55	0.96	0.75	0.24	0.92	0.52	0.76	0.96	0.29	0.32	0.35	0.09	0.66
SNT.l3	0.12	0.13	0.93	0.97	0.96	0.18	0.48	0.59	0.46	0.54	0.98	0.65	0.83	0.20	0.35	0.71	0.89	0.62	0.73	0.48	**0.03**	0.60	0.45	0.93	0.69	0.21	0.21	0.21	0.61	0.33	0.78	0.67	0.78	**0.00**	**0.04**	0.20	0.29	0.27	0.90	0.51	0.27	0.39	0.41	0.16	0.21	0.38	0.33	0.82
STORJ.l3	0.21	0.76	0.91	0.16	**0.00**	0.53	0.83	0.74	**0.03**	0.85	0.99	0.62	0.97	0.06	0.76	1.00	0.57	0.92	0.96	0.65	0.67	0.81	0.92	0.67	0.37	0.25	0.18	0.49	0.45	0.71	0.29	0.83	0.75	0.83	**0.03**	0.89	0.85	0.52	0.88	0.65	0.19	0.25	0.32	0.17	0.84	0.99	0.28	0.83
SYS.l3	0.13	0.80	0.25	0.54	0.62	0.54	0.95	0.74	0.72	0.78	0.48	0.60	0.50	0.97	0.47	0.45	0.97	0.86	0.68	0.81	0.42	0.38	0.45	0.24	0.64	0.53	0.10	0.50	0.35	**0.02**	0.55	0.63	0.60	**0.04**	0.57	**0.00**	0.40	0.21	0.92	0.59	0.07	0.35	0.32	0.12	0.65	0.77	0.07	0.22
TRX.l3	0.85	0.17	0.61	0.44	0.06	0.71	0.56	0.69	0.33	0.74	0.34	0.38	0.65	0.45	0.98	0.27	**0.01**	0.34	0.80	0.16	0.76	0.25	0.80	0.15	0.22	0.63	0.85	0.40	0.27	0.21	0.43	0.29	0.27	0.45	0.72	0.90	**0.01**	0.85	0.20	0.97	0.80	0.96	0.70	0.76	0.22	0.66	0.14	0.98
VGX.l3	0.51	0.35	0.08	0.92	0.57	0.76	0.57	0.11	0.96	0.61	0.47	0.51	0.80	0.40	0.48	0.92	0.80	0.35	0.10	0.10	0.30	0.18	0.12	0.13	0.40	0.09	0.31	0.49	0.09	0.69	0.53	0.76	0.52	0.77	0.63	0.80	0.56	**0.00**	0.16	1.00	**0.03**	0.98	0.99	0.37	0.86	0.95	**0.05**	0.43
WAVES.l3	**0.04**	0.83	0.92	0.10	0.57	0.81	0.92	0.55	**0.01**	0.75	0.75	0.23	0.20	0.16	0.36	0.11	0.07	0.67	0.55	0.65	0.29	0.23	0.70	0.88	0.42	0.98	0.90	0.38	0.77	0.32	0.25	0.77	0.09	0.81	0.23	0.09	0.32	0.71	**0.00**	0.20	0.11	0.69	0.86	0.72	0.51	0.40	0.69	0.30
XEM.l3	0.17	0.40	**0.03**	0.13	0.83	0.63	**0.02**	0.72	**0.02**	0.49	0.25	0.49	0.20	0.90	0.64	0.10	0.46	0.10	0.52	0.47	**0.04**	0.44	0.11	0.63	0.17	0.10	0.59	**0.04**	0.46	0.10	0.69	0.36	0.36	0.40	0.68	0.76	0.86	0.97	0.42	0.82	0.67	0.49	0.61	0.71	0.16	0.11	0.63	0.66
XLM.l3	0.69	0.99	0.82	**0.01**	0.21	0.17	0.24	0.20	0.82	1.00	0.67	0.67	0.29	0.89	0.37	0.70	0.52	0.93	0.23	0.24	0.78	0.34	0.71	0.93	0.87	0.12	0.34	**0.04**	0.89	0.28	0.18	0.12	0.70	**0.04**	0.59	0.93	0.91	0.38	0.73	0.42	**0.05**	0.27	0.34	0.46	0.78	**0.05**	0.44	0.19
XMR.l3	0.14	0.93	0.71	0.49	0.69	0.28	0.90	0.41	0.80	0.78	0.42	0.27	0.28	0.56	0.99	0.21	0.48	0.85	0.47	0.51	0.59	0.48	0.86	0.35	0.84	0.66	0.49	0.59	0.29	0.68	**0.04**	0.29	0.97	0.30	0.46	0.50	0.86	0.69	0.99	0.07	0.89	**0.00**	0.83	0.89	0.35	0.58	0.82	**0.04**
XNO.l3	0.49	0.67	0.43	0.55	0.94	0.38	0.86	0.43	0.58	0.79	0.37	0.48	0.96	0.65	0.57	0.75	0.22	0.41	0.91	0.92	0.34	0.74	0.96	0.92	0.43	0.46	0.72	0.54	0.64	0.62	0.29	0.93	0.88	0.52	0.96	0.61	0.68	0.39	0.94	0.59	0.43	0.72	0.06	0.78	0.83	0.84	0.64	0.21
XRP.l3	0.11	0.49	0.47	**0.02**	0.43	0.90	0.54	0.56	0.77	0.49	0.79	0.66	0.88	0.73	0.36	0.48	0.76	**0.02**	0.42	0.34	0.51	0.20	0.13	0.71	0.23	0.16	0.16	**0.02**	0.42	0.96	0.56	0.51	0.61	0.61	0.54	0.83	0.89	0.36	0.40	0.43	0.51	0.17	0.21	**0.00**	0.65	0.80	0.60	0.20
XTZ.l3	0.06	0.14	0.30	**0.04**	**0.01**	**0.02**	0.38	0.23	0.25	0.63	**0.03**	0.27	0.06	0.26	0.53	0.17	**0.04**	0.26	0.50	0.60	0.13	0.18	0.36	0.17	**0.04**	0.36	0.07	0.91	0.62	0.87	0.61	0.62	**0.00**	0.44	0.73	0.58	0.45	0.20	0.07	0.75	0.31	0.19	0.49	0.10	**0.00**	0.21	0.11	0.62
ZEC.l3	0.72	0.61	0.50	0.18	0.93	0.56	0.40	0.26	0.27	0.32	0.70	0.79	0.60	0.38	0.29	0.22	0.38	0.88	0.72	0.84	0.77	0.78	0.91	0.69	0.88	0.97	0.52	0.24	0.59	0.30	0.12	0.23	0.90	0.07	0.40	0.24	0.37	0.45	0.22	0.14	0.66	0.19	0.79	0.77	0.28	**0.00**	0.66	0.13
ZEN.l3	0.87	0.23	0.39	0.49	0.72	0.83	0.97	0.17	0.54	0.54	0.33	0.32	0.61	0.75	0.32	0.65	1.00	0.57	0.16	0.33	0.60	0.12	0.41	0.64	0.87	0.42	0.54	0.34	0.71	0.42	0.79	0.58	0.66	0.48	0.32	0.33	0.16	0.59	0.79	0.57	0.58	0.06	0.81	0.50	0.65	0.63	**0.00**	1.00
ZRX.l3	0.82	0.41	0.58	0.56	0.56	0.17	0.88	0.89	0.50	0.32	**0.05**	0.34	**0.05**	**0.03**	0.39	0.15	0.94	0.84	0.40	0.53	0.85	0.70	0.67	0.88	0.74	0.17	0.15	0.12	0.84	0.35	0.57	0.52	0.68	0.15	0.70	0.97	0.20	0.41	0.11	0.52	0.21	0.80	0.72	0.17	0.09	0.51	0.91	0.40

P-values for Vector Autoregression model of volatility (Part 4/4)

ADA.l4	0.82	0.62	0.93	0.75	0.63	0.75	0.68	0.38	0.21	0.72	0.23	0.99	0.92	0.84	0.34	0.34	0.25	0.66	0.76	0.09	0.27	0.80	0.39	0.84	0.31	0.88	0.28	0.98	0.38	0.20	0.88	0.85	0.08	0.72	0.63	0.78	0.23	0.63	0.37	0.86	0.78	0.29	**0.02**	0.46	0.60	0.63	0.96	0.46
ANT.l4	0.06	**0.00**	**0.01**	1.00	0.15	0.06	0.13	0.62	0.12	**0.01**	**0.02**	0.44	0.15	**0.01**	0.72	**0.05**	**0.01**	0.11	0.47	0.10	0.14	0.13	0.82	0.45	0.25	0.48	0.50	**0.00**	**0.00**	**0.05**	**0.05**	0.13	0.34	0.39	0.09	**0.03**	0.12	0.17	**0.00**	0.08	**0.01**	**0.04**	0.96	0.10	**0.00**	**0.03**	0.47	**0.05**
BAT.l4	0.96	0.73	0.07	0.29	0.51	0.90	0.97	0.19	**0.03**	0.70	0.53	0.24	0.19	0.73	0.36	**0.03**	0.12	0.82	0.88	0.66	0.66	0.09	0.72	0.12	**0.05**	**0.03**	0.11	0.13	**0.03**	0.61	0.06	0.84	0.18	0.66	0.39	0.89	0.14	0.06	0.99	0.95	0.24	0.50	0.11	0.47	**0.02**	0.35	0.88	0.82
BCH.l4	0.69	0.07	0.31	0.26	0.06	0.64	0.71	0.10	0.12	0.87	0.47	0.61	0.46	0.24	0.39	0.55	0.87	0.11	0.79	0.09	0.09	0.31	0.45	0.21	0.37	0.23	0.18	0.36	0.66	0.54	0.86	0.11	0.47	0.39	0.77	0.44	0.66	**0.04**	0.58	0.45	0.22	0.80	0.88	0.74	0.39	0.60	0.20	0.21
BNB.l4	0.57	0.73	0.30	0.09	0.28	0.27	0.32	0.17	0.19	0.24	0.33	0.93	0.66	0.80	0.87	0.48	**0.01**	**0.01**	**0.03**	**0.05**	0.13	0.09	0.55	0.13	0.30	0.34	0.40	0.33	0.14	0.61	0.98	0.06	0.16	0.38	0.15	**0.04**	0.87	0.18	0.07	0.22	0.71	0.13	0.16	0.89	0.45	0.80	**0.01**	0.36
BTC.l4	0.18	0.38	**0.01**	**0.01**	**0.03**	**0.00**	**0.00**	0.32	**0.00**	0.14	**0.00**	0.24	**0.03**	**0.00**	0.68	0.15	**0.01**	0.33	**0.00**	**0.01**	0.64	0.31	**0.02**	**0.01**	0.95	**0.02**	0.52	0.44	0.06	**0.02**	0.15	0.59	**0.00**	0.12	0.22	0.10	**0.00**	0.43	0.08	0.24	**0.00**	**0.01**	**0.02**	0.08	**0.02**	0.20	**0.03**	**0.00**
BTG.l4	0.68	0.24	**0.05**	0.36	0.15	0.77	0.78	1.00	0.64	0.61	0.40	0.47	**0.04**	0.29	0.38	0.61	0.29	0.40	0.76	0.63	0.12	0.54	0.73	0.85	0.22	0.50	0.34	0.80	0.33	0.10	0.63	0.66	0.32	0.73	0.96	0.24	0.32	0.86	0.51	0.38	0.68	0.69	0.68	0.68	0.37	0.88	0.30	0.98
CVC.l4	0.20	0.80	0.99	0.86	0.56	0.87	0.53	0.13	0.52	0.85	0.13	0.28	0.92	0.65	0.57	0.90	0.75	0.68	0.74	0.96	0.48	0.40	1.00	0.28	0.90	0.10	0.46	0.23	0.82	0.31	0.53	0.32	0.89	0.54	0.41	0.78	0.72	0.96	0.67	0.23	0.59	0.77	0.43	0.71	0.55	0.93	0.22	0.31
DASH.l4	0.40	0.77	0.37	0.57	0.45	0.84	0.47	0.19	0.52	0.34	0.80	0.53	0.26	0.37	0.55	**0.04**	0.61	0.97	0.15	0.29	0.70	0.61	0.58	0.42	0.89	0.44	0.97	0.27	0.51	0.48	0.40	0.48	0.58	0.18	0.26	0.82	0.61	0.79	0.34	0.08	0.49	0.25	0.98	0.44	0.68	**0.00**	0.60	0.25
DCR.l4	0.64	0.18	0.63	0.72	0.32	0.39	0.55	0.67	0.75	0.19	0.26	0.46	0.91	0.71	0.57	0.58	0.52	0.55	0.43	0.74	0.33	0.14	0.89	0.85	0.44	0.77	0.61	0.53	0.67	0.59	0.36	0.14	0.84	0.82	0.74	0.92	0.90	0.53	0.46	0.92	0.70	0.89	0.74	0.62	0.85	0.65	0.10	0.76
DGB.l4	0.22	**0.04**	0.84	0.39	0.24	0.72	**0.00**	0.72	0.89	0.25	0.50	0.65	0.29	0.41	0.86	0.79	0.76	0.46	0.51	0.47	0.78	0.36	0.49	0.24	0.18	0.89	0.38	0.13	0.49	**0.02**	0.89	0.12	0.93	0.47	0.18	0.74	**0.03**	0.38	0.92	0.27	**0.01**	0.84	0.14	0.14	0.93	0.85	0.35	0.48
DOGE.l4	0.56	0.30	0.90	0.35	**0.00**	0.25	0.99	0.97	0.76	0.79	0.72	0.16	0.69	0.85	0.46	0.30	0.89	0.54	0.61	0.83	0.83	0.95	0.89	0.36	0.96	0.57	0.67	0.99	0.10	0.75	0.72	0.61	0.66	0.50	0.84	0.66	0.76	0.70	0.59	0.20	0.78	0.94	0.78	0.07	0.31	0.95	0.71	0.88
ENJ.l4	0.18	0.38	0.76	0.60	0.70	0.79	0.40	0.47	0.45	0.32	0.92	0.57	0.72	0.83	0.21	0.60	0.60	0.10	0.61	0.42	**0.02**	**0.03**	0.44	0.41	0.95	0.30	0.54	0.59	0.51	0.59	0.95	0.50	0.45	0.17	0.84	0.58	0.42	0.60	0.97	0.12	0.92	0.76	0.69	0.89	0.59	0.21	0.39	0.69
EOS.l4	0.57	0.30	0.83	0.78	0.85	0.36	0.65	0.71	0.34	0.50	0.41	0.31	0.11	**0.03**	0.29	0.61	0.98	0.58	0.36	0.79	0.93	0.49	0.48	0.56	0.63	0.17	0.19	0.89	0.74	0.29	0.39	0.75	0.55	0.16	0.38	0.34	0.97	0.29	0.95	**0.04**	0.14	0.83	0.36	0.64	0.90	0.72	0.79	0.12
ERG.l4	0.35	0.93	0.87	0.75	**0.02**	0.83	0.41	0.67	0.94	0.37	0.46	0.72	0.52	0.88	0.82	0.71	0.26	0.13	**0.00**	0.72	0.69	0.94	0.72	0.95	0.64	0.58	0.50	0.81	0.34	0.85	0.98	0.59	0.40	0.80	0.62	0.96	0.86	0.62	0.33	0.90	0.87	0.95	0.24	0.51	0.69	0.54	0.75	0.46
ETC.l4	0.51	0.37	0.12	0.15	0.28	0.10	0.38	0.18	0.29	0.66	0.70	0.54	0.78	0.59	0.47	**0.00**	0.19	0.16	0.66	0.49	0.20	0.11	0.08	0.66	0.23	0.64	0.67	0.97	0.63	0.41	0.45	0.50	**0.04**	0.31	0.90	0.38	0.61	0.57	0.55	0.60	0.99	0.16	0.33	0.16	0.13	0.15	0.43	0.42
ETH.l4	**0.00**	0.77	0.36	**0.01**	0.15	0.67	**0.05**	0.33	0.31	0.87	0.93	0.21	0.30	**0.04**	0.72	**0.04**	0.14	**0.01**	0.38	0.15	0.12	0.13	0.24	**0.05**	0.62	0.71	0.78	**0.00**	**0.01**	**0.02**	**0.00**	0.94	0.28	0.53	0.38	**0.02**	1.00	0.42	0.15	0.56	0.08	0.29	**0.05**	0.09	**0.00**	0.55	0.28	0.21
GLM.l4	0.27	0.29	0.70	0.17	0.07	0.10	0.09	0.09	0.32	0.22	0.20	0.35	0.09	0.77	0.46	0.65	0.78	**0.00**	0.98	0.51	0.53	0.83	0.86	0.88	**0.02**	0.85	0.48	0.14	0.37	0.78	0.46	0.16	0.26	0.80	0.43	0.46	0.10	0.75	0.36	0.73	0.30	0.26	0.87	0.58	0.19	0.49	0.55	0.35
GNO.l4	0.71	0.13	0.93	0.72	0.76	0.47	0.32	0.53	0.39	0.29	0.84	0.35	0.57	0.07	0.84	0.99	0.19	0.77	0.67	0.46	0.18	0.49	0.72	0.84	1.00	0.46	0.52	0.98	0.89	0.18	0.67	0.57	0.52	0.82	0.21	0.25	0.69	0.71	0.65	0.61	0.62	0.76	0.94	0.70	0.29	0.72	0.40	0.28
ICX.l4	0.45	0.90	0.95	0.12	0.79	0.70	0.67	0.45	0.28	0.16	0.09	0.55	0.27	0.69	0.32	0.19	0.53	0.98	0.58	0.47	0.55	0.48	0.84	0.91	0.59	0.48	0.93	0.44	0.83	0.94	0.13	0.49	0.41	0.96	0.92	0.94	0.98	0.24	0.57	0.47	0.20	0.98	0.31	0.73	0.49	0.47	0.61	0.49
KCS.l4	0.39	0.95	0.35	0.38	0.12	0.65	0.71	**0.00**	0.21	0.66	0.24	0.22	0.34	0.29	0.88	0.56	**0.05**	**0.04**	0.71	0.16	0.92	0.82	0.40	0.75	0.70	0.19	**0.04**	0.53	0.15	0.70	0.11	0.15	**0.03**	0.35	0.47	0.08	0.82	**0.02**	**0.01**	0.49	0.99	**0.04**	0.94	0.47	0.44	0.56	0.47	0.66
LINK.l4	0.18	0.56	**0.02**	0.22	0.06	0.25	0.79	0.62	0.17	0.45	0.58	0.22	0.89	0.12	0.62	0.31	0.37	0.07	0.20	**0.00**	0.77	0.91	**0.01**	**0.04**	0.07	0.23	0.72	**0.02**	**0.02**	**0.01**	**0.02**	0.39	0.58	0.51	**0.00**	0.98	0.46	0.36	0.75	0.53	0.47	0.10	0.61	**0.01**	0.97	0.65	0.37	0.36
LRC.l4	0.40	0.75	0.98	0.40	0.24	0.66	0.96	0.22	0.72	0.46	0.74	0.36	0.55	0.43	0.34	0.38	0.46	0.44	0.95	0.89	0.43	0.54	0.07	0.42	0.42	1.00	0.38	0.89	0.42	0.69	0.17	0.60	0.13	0.06	0.15	0.11	0.91	0.29	0.15	0.38	0.13	0.55	0.98	0.06	0.80	0.69	0.92	0.75
LSK.l4	0.22	0.70	0.15	0.24	0.06	0.35	0.67	0.56	0.76	0.98	0.87	0.49	0.70	0.49	0.49	0.13	0.86	0.71	0.72	**0.05**	0.21	0.38	0.17	0.28	0.12	0.47	**0.04**	0.89	0.93	0.41	0.90	0.76	0.16	0.14	0.54	0.71	0.71	0.95	0.48	0.77	**0.01**	0.50	0.94	0.52	0.19	0.70	0.12	0.07
LTC.l4	0.64	0.69	0.11	0.17	0.25	**0.02**	0.47	0.72	0.06	0.60	0.56	0.28	**0.05**	0.66	0.28	0.95	0.69	0.25	0.65	0.21	0.37	0.74	0.43	**0.05**	**0.00**	0.59	0.85	0.78	0.47	0.23	0.72	0.28	0.43	0.29	0.18	0.42	0.77	0.52	0.78	**0.03**	0.17	0.79	0.48	0.67	**0.00**	0.43	**0.04**	0.81
MANA.l4	0.14	0.24	0.33	0.10	0.69	0.64	1.00	0.87	0.98	0.83	0.43	0.48	0.35	0.15	0.68	0.41	0.54	0.95	0.83	0.86	0.58	0.57	0.83	0.74	0.24	0.07	0.42	0.42	0.49	0.80	0.89	0.86	0.95	0.53	0.72	0.49	0.16	0.63	0.27	0.66	0.16	0.95	0.99	0.50	0.68	0.90	0.29	0.88
MIOTA.l4	0.85	0.36	0.08	0.77	0.50	0.36	0.47	0.27	**0.01**	0.17	0.27	0.44	0.29	0.80	0.73	0.81	**0.03**	0.37	0.26	0.67	0.55	0.39	0.90	**0.01**	0.40	0.09	**0.00**	0.28	0.06	0.22	0.45	0.31	0.59	0.84	0.11	**0.03**	0.78	0.46	0.52	0.83	**0.04**	0.34	0.32	0.13	**0.04**	0.17	**0.04**	0.59
NEO.l4	0.30	0.48	0.77	0.65	0.34	0.06	0.34	1.00	0.11	**0.02**	0.36	0.21	0.18	0.19	0.55	**0.03**	0.80	0.06	0.74	0.10	**0.01**	0.84	0.86	0.33	**0.00**	0.92	0.36	**0.00**	0.63	0.16	0.16	0.39	0.09	0.18	0.15	0.20	0.15	0.98	0.98	0.28	0.35	**0.02**	0.92	0.21	0.24	0.12	**0.00**	0.96
OMG.l4	0.95	0.36	0.22	0.40	0.06	0.91	0.90	0.28	0.98	0.55	0.85	0.24	0.20	0.20	0.88	0.88	0.79	**0.01**	0.44	0.78	0.78	0.78	0.12	0.41	0.33	0.75	0.55	0.69	0.09	0.71	0.18	0.87	0.14	0.69	0.37	0.27	0.96	0.81	0.26	0.41	0.10	0.49	0.75	0.90	0.13	0.09	0.84	0.31
QTUM.l4	0.66	0.23	0.57	0.76	0.48	0.99	0.47	0.20	0.28	0.51	0.10	0.29	0.54	0.96	0.94	0.97	0.09	0.43	0.91	0.57	0.08	0.46	0.51	0.08	0.50	0.33	0.40	0.77	0.94	**0.00**	0.38	0.94	0.28	1.00	0.72	0.17	0.98	0.15	0.33	0.73	0.15	0.10	**0.04**	0.30	0.77	0.49	0.28	0.95
REQ.l4	0.39	0.51	0.96	0.84	0.82	0.52	0.77	0.84	0.86	0.55	0.15	0.71	0.66	0.89	0.81	0.85	0.95	0.94	0.33	0.30	0.53	0.86	0.31	0.32	0.72	0.36	0.96	0.30	0.91	0.91	0.53	0.64	0.57	0.61	0.97	0.09	0.55	0.82	0.70	0.58	0.40	0.60	0.66	0.41	0.66	0.39	0.91	0.37
RLC.l4	0.62	0.12	0.70	0.76	0.15	0.86	0.35	0.28	0.74	0.33	0.86	0.45	0.31	0.15	0.34	0.74	0.98	0.33	**0.05**	0.83	0.96	0.98	0.46	0.87	0.58	0.33	0.69	**0.05**	0.83	0.77	0.27	0.55	0.52	0.89	0.51	0.91	0.13	0.47	0.61	1.00	0.69	0.52	0.55	0.86	0.81	0.34	0.18	0.66
SC.l4	0.34	0.26	0.49	0.13	0.30	**0.05**	0.15	0.57	0.69	0.96	0.82	0.42	0.94	0.77	0.54	0.33	0.46	0.60	0.55	0.17	0.50	0.08	0.07	0.39	0.31	0.48	0.82	0.83	0.61	0.25	0.85	0.72	0.11	**0.04**	0.26	0.65	0.58	0.78	0.57	0.27	0.46	0.95	0.17	0.53	0.06	0.58	0.12	0.91
SNT.l4	0.30	0.63	0.23	0.75	0.73	0.62	0.94	0.94	0.81	0.81	0.58	0.74	0.65	0.06	0.84	0.26	0.91	0.08	0.16	0.55	0.33	0.06	0.33	0.68	0.54	0.48	0.10	0.11	0.56	0.07	0.40	0.61	0.88	**0.00**	0.34	0.39	0.21	0.57	0.28	0.51	0.06	0.98	0.85	0.15	0.91	0.21	0.97	0.06
STORJ.l4	0.76	0.29	0.55	0.78	0.22	0.15	0.58	0.82	0.96	0.33	0.86	0.72	0.45	0.49	0.48	0.66	0.52	0.61	0.19	0.83	0.75	0.52	0.97	0.21	0.65	0.58	0.69	0.40	0.51	0.66	0.57	0.18	0.27	0.68	0.13	0.12	0.58	0.66	0.20	0.27	0.89	0.20	0.96	0.76	0.46	0.13	0.97	0.50
SYS.l4	0.30	0.28	0.45	0.48	0.24	0.87	0.71	0.17	0.09	0.17	0.47	0.28	0.50	0.10	0.76	0.49	0.09	0.92	0.88	0.60	0.60	**0.05**	0.06	0.07	0.12	0.63	0.75	0.28	0.43	**0.04**	0.52	0.24	0.49	0.47	**0.03**	**0.00**	0.60	0.45	0.28	0.17	0.46	0.83	0.14	0.87	0.85	0.60	0.21	0.14
TRX.l4	0.77	0.33	0.87	0.87	0.23	0.17	**0.02**	0.30	0.28	0.51	0.83	0.27	0.27	0.85	0.38	0.26	0.07	0.82	0.07	0.13	0.16	0.48	0.76	0.89	0.53	0.68	0.81	0.44	0.96	**0.01**	0.62	0.24	0.87	0.71	0.24	0.78	0.79	0.81	0.56	0.09	**0.05**	0.71	0.84	0.90	0.37	0.24	0.35	0.24
VGX.l4	0.57	0.86	0.66	0.94	0.67	0.84	0.15	0.75	0.92	0.57	0.45	0.36	0.52	0.60	0.32	**0.02**	0.06	0.08	0.07	0.20	0.61	0.50	**0.03**	0.77	0.14	0.34	0.42	0.49	0.07	0.32	0.28	0.19	0.40	0.30	0.35	0.20	0.76	**0.04**	0.48	0.71	0.82	0.95	0.21	0.13	0.42	0.06	0.90	0.12
WAVES.l4	0.86	**0.04**	0.29	0.40	0.23	0.37	0.08	0.32	0.73	0.96	0.44	0.28	0.47	0.23	0.21	0.77	0.12	0.29	0.65	0.06	0.07	0.89	0.71	0.90	0.92	0.70	0.09	0.80	0.44	0.75	**0.02**	0.11	0.53	0.93	0.42	**0.04**	0.82	**0.03**	0.28	0.68	0.48	0.39	0.92	0.12	0.25	0.22	0.72	0.60
XEM.l4	0.85	0.75	0.43	0.98	0.11	0.64	0.06	0.87	0.39	0.48	1.00	0.29	0.80	0.12	0.24	0.17	**0.02**	0.84	0.72	0.99	0.30	0.10	0.72	0.39	0.88	0.09	0.98	0.32	0.98	0.99	0.54	0.58	0.61	0.13	0.57	0.24	**0.05**	0.85	0.39	0.64	0.64	0.42	0.84	**0.01**	0.12	0.76	0.50	0.12
XLM.l4	0.92	0.29	0.97	0.39	0.85	0.70	**0.03**	0.82	0.15	0.27	1.00	0.19	0.77	0.53	0.53	0.58	0.40	0.78	0.29	0.86	0.48	0.44	0.88	0.70	0.75	0.41	0.19	0.29	0.77	0.08	0.45	0.19	0.30	0.21	0.40	0.26	0.94	0.96	0.17	**0.04**	0.37	0.88	0.08	**0.05**	0.55	0.59	0.67	0.27
XMR.l4	0.09	0.36	0.95	0.18	0.54	0.28	0.66	0.85	0.90	0.30	0.46	0.28	0.31	0.38	0.30	0.28	0.90	0.50	0.15	0.11	0.43	0.39	0.63	0.76	0.85	0.49	**0.03**	0.54	0.77	0.80	0.14	0.99	0.71	0.66	0.74	0.32	0.85	0.68	0.30	0.59	0.43	**0.00**	0.93	0.20	0.68	0.83	0.96	0.31
XNO.l4	0.31	**0.05**	0.95	0.31	0.89	0.76	0.91	0.51	0.72	0.87	0.19	0.32	0.60	0.79	0.91	0.36	0.27	0.45	0.17	0.39	0.40	0.66	0.44	0.42	0.43	0.99	0.35	0.42	0.98	0.37	0.53	0.87	0.57	0.15	0.90	0.93	0.36	0.44	0.47	0.45	0.30	0.97	0.06	0.64	0.16	0.77	0.97	0.87
XRP.l4	0.28	0.73	0.44	0.38	0.68	0.93	0.84	0.24	0.75	0.36	0.58	0.52	0.36	0.96	0.32	0.53	0.72	0.13	0.86	0.88	0.37	0.28	0.43	0.53	0.22	0.67	0.28	0.18	0.40	0.79	0.74	0.53	0.16	0.50	0.12	0.71	0.81	0.28	0.14	0.47	0.83	0.50	**0.00**	0.49	0.57	0.26	0.21	0.38
XTZ.l4	0.60	0.30	0.95	0.09	**0.04**	0.75	0.07	0.88	0.20	0.91	**0.03**	0.38	0.44	0.65	0.56	0.30	0.14	0.48	0.19	0.29	0.82	0.06	0.07	0.18	**0.01**	0.86	**0.01**	0.09	0.25	0.68	**0.04**	0.78	**0.02**	0.77	**0.02**	0.16	0.74	0.56	**0.04**	0.46	0.26	0.23	0.27	0.53	**0.00**	**0.00**	0.31	0.61
ZEC.l4	0.87	0.88	0.12	0.85	0.54	0.34	0.95	0.92	0.92	0.84	0.78	0.58	0.08	0.44	0.87	0.38	0.65	0.87	0.58	0.60	0.70	0.72	0.78	0.97	0.50	0.16	0.42	0.13	0.30	0.45	0.42	0.39	0.23	0.33	0.21	0.15	0.98	0.79	0.22	0.15	0.67	0.93	0.60	0.39	0.95	**0.00**	0.73	0.34
ZEN.l4	0.76	**0.05**	0.61	0.90	0.44	0.09	0.63	0.96	0.23	0.48	0.50	0.42	**0.05**	**0.05**	0.37	0.57	0.50	0.75	0.43	0.98	0.11	0.72	0.93	0.65	0.85	0.82	0.97	0.94	0.89	**0.03**	0.89	0.79	0.29	0.87	0.80	0.76	0.95	0.16	0.62	0.70	0.67	0.62	0.07	**0.04**	0.55	0.14	**0.00**	0.09
ZRX.l4	0.37	0.60	0.20	0.79	0.83	0.31	0.19	0.93	0.54	0.77	0.28	0.31	0.82	0.15	0.34	0.18	0.39	0.67	0.90	0.66	0.70	0.70	0.79	0.91	0.69	**0.05**	0.85	0.97	0.56	0.47	0.25	0.60	0.44	0.25	0.18	0.62	0.91	0.21	0.77	0.28	0.92	0.11	0.87	**0.04**	**0.03**	0.38	0.27	**0.00**
const	**0.00**	0.75	**0.00**	**0.03**	0.37	0.49	**0.00**	**0.00**	0.07	**0.01**	0.37	0.36	0.86	**0.00**	0.07	**0.01**	**0.00**	**0.00**	0.22	0.10	0.10	0.13	**0.00**	0.25	**0.00**	0.61	0.23	**0.00**	**0.00**	**0.00**	0.06	**0.00**	0.54	0.30	**0.02**	0.14	**0.01**	**0.01**	**0.02**	0.06	0.13	0.53	0.80	**0.02**	**0.02**	**0.01**	0.07	**0.00**
Count < 0.05	11	19	13	17	11	15	17	7	17	9	12	1	9	19	0	18	24	16	10	12	15	5	11	11	23	6	18	24	15	23	12	10	18	12	11	11	12	13	9	16	14	12	7	18	19	20	19	11
Count % < 0.05	*6%*	*10%*	*7%*	*9%*	*6%*	*8%*	*9%*	*4%*	*9%*	*5%*	*6%*	*1%*	*5%*	*10%*	*0%*	*9%*	*12%*	*8%*	*5%*	*6%*	*8%*	*3%*	*6%*	*6%*	*12%*	*3%*	*9%*	*12%*	*8%*	*12%*	*6%*	*5%*	*9%*	*6%*	*6%*	*6%*	*6%*	*7%*	*5%*	*8%*	*7%*	*6%*	*4%*	*9%*	*10%*	*10%*	*10%*	*6%*
Count < 0.1	27	31	25	28	23	29	27	12	26	16	19	1	18	29	1	29	40	28	16	22	24	19	24	22	31	17	29	31	29	36	19	21	23	17	15	20	19	20	17	27	31	19	19	26	29	31	29	30
Count % < 0.1	*14%*	*16%*	*13%*	*15%*	*12%*	*15%*	*14%*	*6%*	*13%*	*8%*	*10%*	*1%*	*9%*	*15%*	*1%*	*15%*	*21%*	*15%*	*8%*	*11%*	*12%*	*10%*	*12%*	*11%*	*16%*	*9%*	*15%*	*16%*	*15%*	*19%*	*10%*	*11%*	*12%*	*9%*	*8%*	*10%*	*10%*	*10%*	*9%*	*14%*	*16%*	*10%*	*10%*	*13%*	*15%*	*16%*	*15%*	*16%*

A.8 Augmented Dicky-Fuller test

The table shows the results from the Augmented Dicky-Fuller test on 48 different cryptocurrencies' return series using lag selection based on the Akaike information criterion (AIC). In addition, we employ the ADF test on the time series containing the latent volatility component extracted from the marginal model. The test statistic for both tests follow a Gaussian distribution, which is commonly used in statistical analysis.

ADF results return				ADF results volatility			
Ticker	Lag order	P-value	Test statistic	Ticker	Lag order	P-value	Test statistic
ADA	3	0.01	-19.1	ADA	3	0.01	-9.8
ANT	1	0.01	-31.9	ANT	9	0.01	-5.3
BAT	1	0.01	-31.3	BAT	9	0.01	-4.7
BCH	7	0.01	-14.9	BCH	4	0.01	-4.9
BNB	10	0.01	-11.0	BNB	10	0.01	-4.9
BTC	2	0.01	-24.8	BTC	10	0.01	-4.2
BTG	1	0.01	-32.7	BTG	3	0.01	-10.1
CVC	1	0.01	-33.3	CVC	8	0.01	-7.8
DASH	2	0.01	-25.3	DASH	9	0.01	-5.8
DCR	1	0.01	-33.0	DCR	7	0.01	-5.7
DGB	7	0.01	-13.9	DGB	8	0.01	-4.6
DOGE	3	0.01	-20.3	DOGE	2	0.01	-20.1
ENJ	6	0.01	-15.1	ENJ	7	0.01	-5.9
EOS	6	0.01	-15.6	EOS	10	0.01	-4.7
ERG	3	0.01	-25.9	ERG	1	0.01	-29.8
ETC	4	0.01	-18.5	ETC	10	0.01	-5.4
ETH	6	0.01	-15.3	ETH	10	0.01	-6.8
GLM	3	0.01	-21.9	GLM	8	0.01	-6.3
GNO	1	0.01	-31.5	GNO	10	0.01	-7.8
ICX	9	0.01	-13.1	ICX	8	0.01	-5.8
KCS	4	0.01	-16.1	KCS	7	0.01	-4.8
LINK	3	0.01	-20.7	LINK	1	0.01	-6.0
LRC	6	0.01	-15.8	LRC	8	0.01	-6.6
LSK	1	0.01	-32.2	LSK	6	0.01	-5.7
LTC	6	0.01	-15.6	LTC	10	0.01	-6.0
MANA	6	0.01	-15.8	MANA	9	0.01	-6.4
MIOTA	2	0.01	-24.0	MIOTA	10	0.01	-5.6
NEO	1	0.01	-31.2	NEO	10	0.01	-5.2
OMG	4	0.01	-18.7	OMG	5	0.01	-6.7
QTUM	6	0.01	-15.3	QTUM	10	0.01	-5.4
REQ	6	0.01	-15.6	REQ	10	0.01	-8.0
RLC	1	0.01	-32.5	RLC	4	0.01	-5.2
SC	7	0.01	-15.2	SC	10	0.01	-4.2
SNT	8	0.01	-15.7	SNT	7	0.01	-5.4
STORJ	8	0.01	-15.1	STORJ	7	0.01	-6.0
SYS	3	0.01	-21.6	SYS	10	0.01	-5.1
TRX	10	0.01	-13.2	TRX	10	0.01	-5.6
VGX	5	0.01	-16.1	VGX	5	0.01	-8.9
WAVES	6	0.01	-15.1	WAVES	4	0.01	-7.2
XEM	3	0.01	-21.2	XEM	10	0.01	-4.9
XLM	3	0.01	-20.2	XLM	10	0.01	-4.8
XMR	2	0.01	-25.6	XMR	7	0.01	-4.8
XNO	9	0.01	-10.9	XNO	7	0.01	-5.1

XRP	2	0.01	-24.3	XRP	7	0.01	-5.2
XTZ	9	0.01	-13.2	XTZ	10	0.01	-5.7
ZEC	7	0.01	-15.7	ZEC	7	0.01	-6.4
ZEN	5	0.01	-17.8	ZEN	10	0.01	-4.9
ZRX	6	0.01	-15.4	ZRX	9	0.01	-4.7

A.9 Ljung-Box test

This table showcase the results of the Ljung-Box test employed on the residuals of the marginal model (i.e., eGARCH model). The purpose of this test is to determine whether the residuals of the marginal model exhibit any autocorrelation, which can indicate that the model is not accurately capturing the time series properties of the data. The lag length for the Ljung-Box test has been selected based on a rule of thumb suggested by Hyndman (2014), which is to use the minimum of 10 and half the number of observations. In this case, the number of observations is 48, so the lag length for the Ljung-Box test is 10. Significant values at a 5% threshold are highlighted in bold.

Nr.	Ticker	Test statistic	P-value	Nr.	Ticker	Test statistic	P-value
1	SNT	23.84	**0.008**	25	NEO	6.21	0.798
2	BCH	22.93	**0.011**	26	EOS	5.59	0.849
3	OMG	20.82	**0.022**	27	ANT	5.05	0.888
4	XMR	14.53	0.150	28	CVC	4.99	0.892
5	BTC	13.61	0.192	29	DGB	4.87	0.899
6	XLM	12.98	0.225	30	ZEN	4.53	0.920
7	SC	12.83	0.233	31	XTZ	4.34	0.931
8	BNB	11.19	0.343	32	XRP	3.71	0.959
9	ICX	10.68	0.383	33	LTC	3.53	0.966
10	QTUM	9.92	0.448	34	WAVES	3.34	0.972
11	GNO	9.86	0.453	35	GLM	3.34	0.972
12	ETH	9.38	0.496	36	ENJ	3.20	0.976
13	BAT	9.27	0.507	37	DASH	2.85	0.985
14	LRC	8.98	0.534	38	RLC	2.72	0.987
15	MIOTA	8.82	0.549	39	VGX	2.40	0.992
16	ZEC	8.36	0.594	40	STORJ	2.34	0.993
17	ZRX	8.27	0.602	41	SYS	1.83	0.997
18	LSK	7.51	0.677	42	LINK	1.75	0.998
19	BTG	7.27	0.700	43	XEM	1.55	0.999
20	MANA	7.26	0.701	44	XNO	1.20	1.000
21	ETC	7.11	0.715	45	DOGE	1.18	1.000
22	TRX	7.06	0.720	46	REQ	1.15	1.000
23	ADA	6.77	0.747	47	DCR	0.49	1.000
24	KCS	6.42	0.779	48	ERG	0.11	1.000

A.10 Shapiro-Wilk Normality test

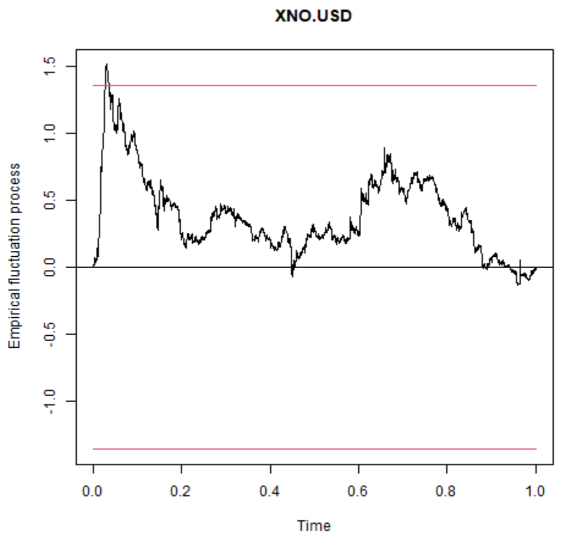
Below are the outcomes of the Shapiro-Wilk Normality test performed on the marginal model.

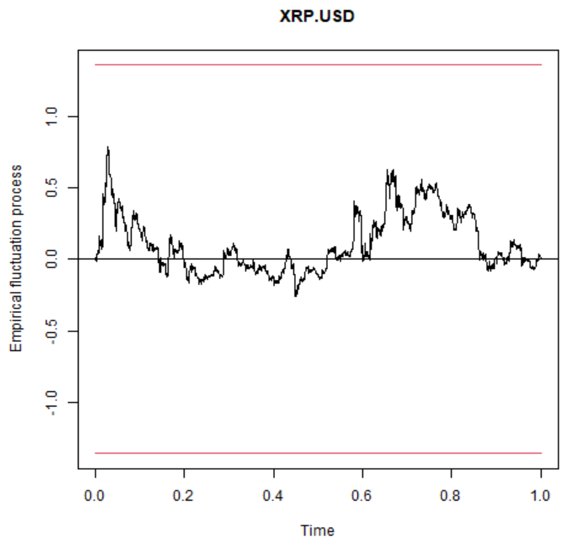
Ticker	Statistic	P.value
ADA	0.944	0.000
ANT	0.936	0.000
BAT	0.953	0.000
BCH	0.888	0.000
BNB	0.932	0.000
BTC	0.871	0.000
BTG	0.860	0.000
CVC	0.892	0.000
DASH	0.928	0.000
DCR	0.862	0.000
DGB	0.919	0.000
DOGE	0.791	0.000
ENJ	0.897	0.000
EOS	0.918	0.000
ERG	0.685	0.000
ETC	0.909	0.000
ETH	0.941	0.000
GLM	0.912	0.000
GNO	0.941	0.000
ICX	0.959	0.000
KCS	0.944	0.000
LINK	0.959	0.000
LRC	0.930	0.000
LSK	0.948	0.000
LTC	0.936	0.000
MANA	0.931	0.000
MIOTA	0.940	0.000
NEO	0.942	0.000
OMG	0.950	0.000
QTUM	0.913	0.000
REQ	0.836	0.000
RLC	0.933	0.000
SC	0.936	0.000
SNT	0.910	0.000
STORJ	0.830	0.000
SYS	0.910	0.000
TRX	0.909	0.000
VGX	0.889	0.000
WAVES	0.925	0.000
XEM	0.916	0.000
XLM	0.948	0.000
XMR	0.948	0.000
XNO	0.828	0.000
XRP	0.888	0.000
XTZ	0.933	0.000
ZEC	0.957	0.000
ZEN	0.945	0.000
ZRX	0.959	0.000

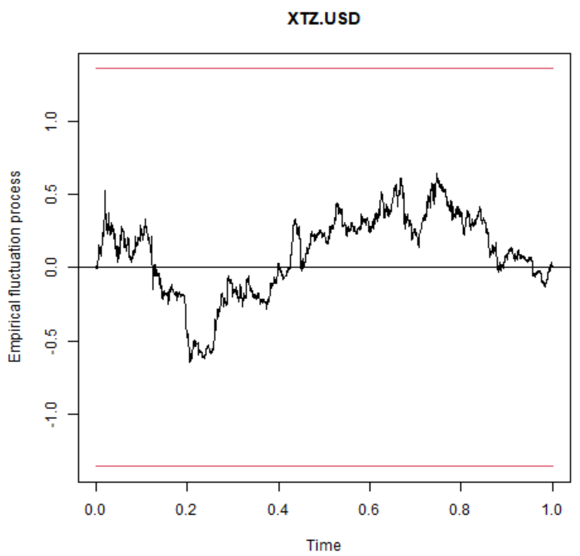
A.11 Empirical fluctuation plots

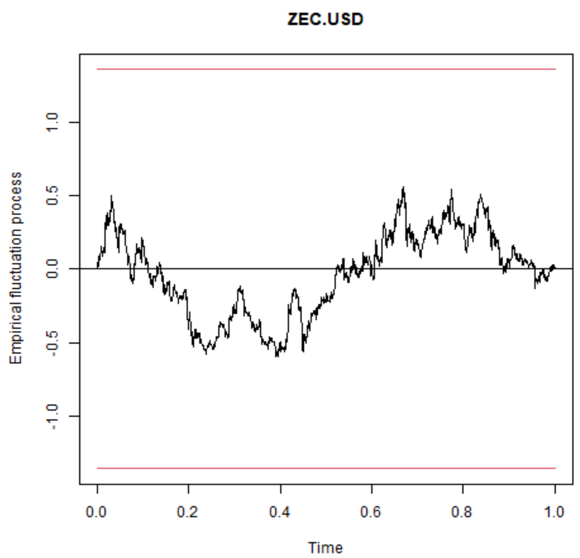
The empirical fluctuation plot through OLS-CUSUM test has been employed on the Vector Autoregression (VAR) model containing return and latent volatility components. This test is used to detect structural breaks in the data that may affect the reliability of the model. The plot displays the cumulative sums of recursive residuals from the OLS regression, which can provide visual evidence of any structural breaks. The red bands displayed on the plot represent the confidence interval for the cumulative sums of recursive residuals, and an observation crossing these bands indicates a potential structural break in the data.

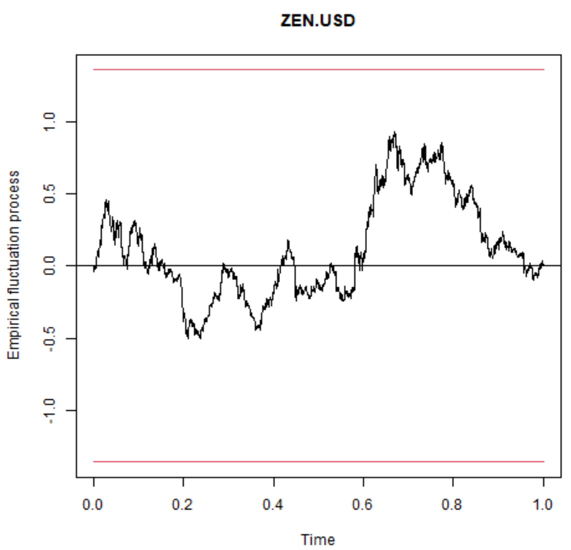
Vector Autoregression (VAR) model of returns

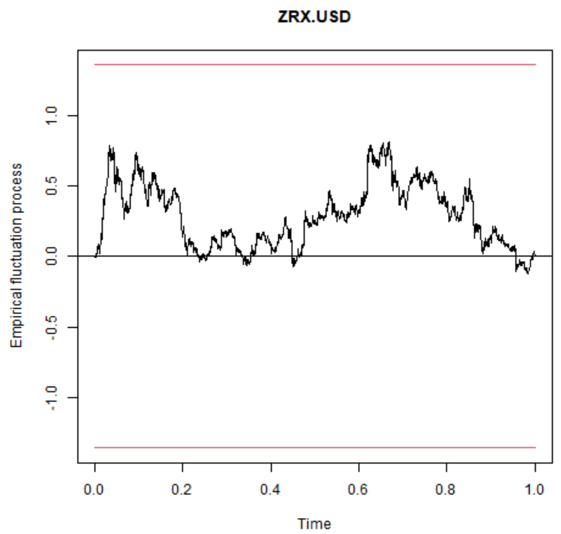


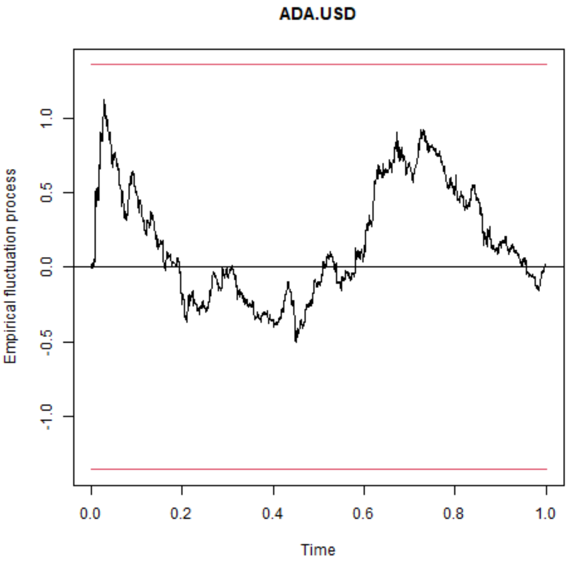











ADA.USD
Empirical fluctuation process
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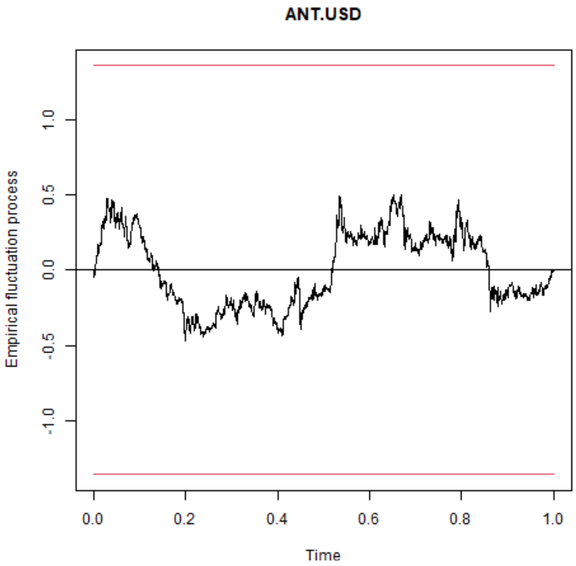
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time


ANT.USD
Empirical fluctuation process
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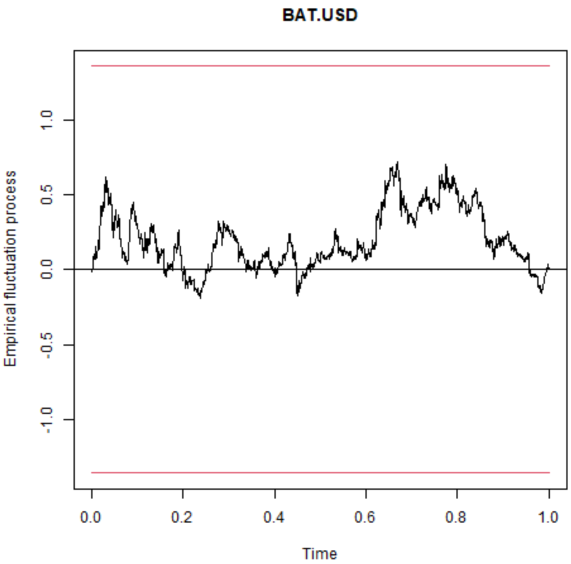
0.8
1.0
Time


BAT.USD
Empirical fluctuation process
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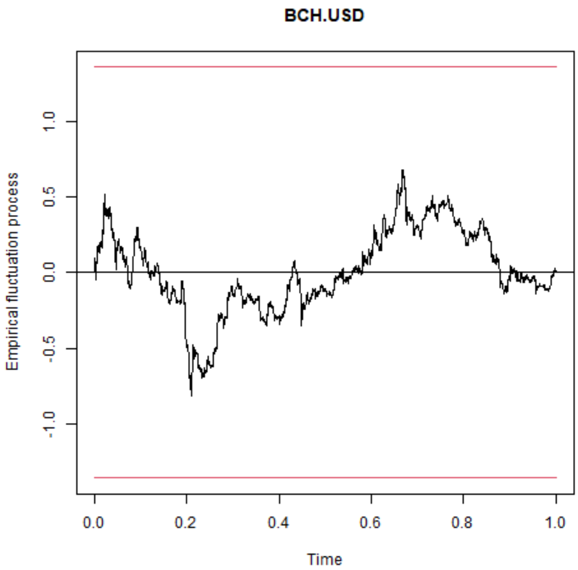
0.0
0.2
0.4
0.6
0.8
1.0
Time


BCH.USD
Empirical fluctuation process
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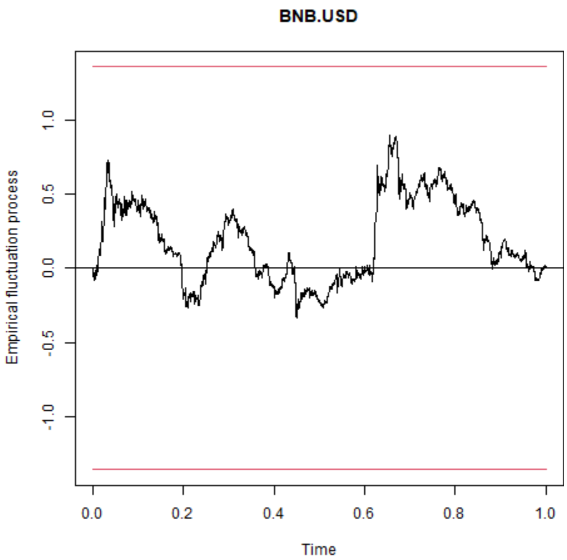
0.0
0.2
0.4
0.6
0.8
1.0
Time


BNB.USD
Empirical fluctuation process
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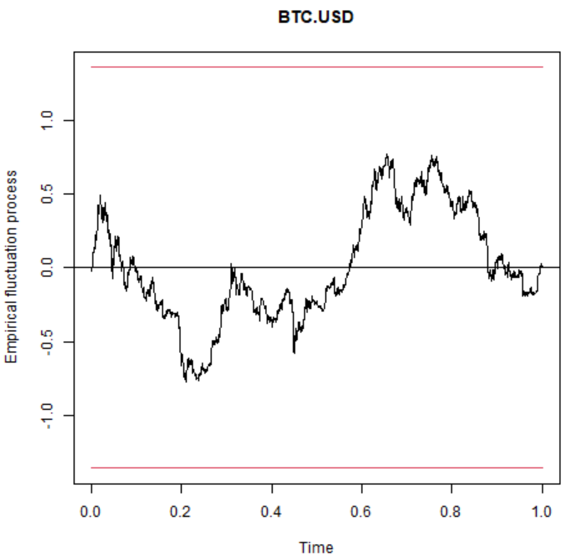
0.0
0.2
0.4
0.6
0.8
1.0
Time


BTC.USD
Empirical fluctuation process
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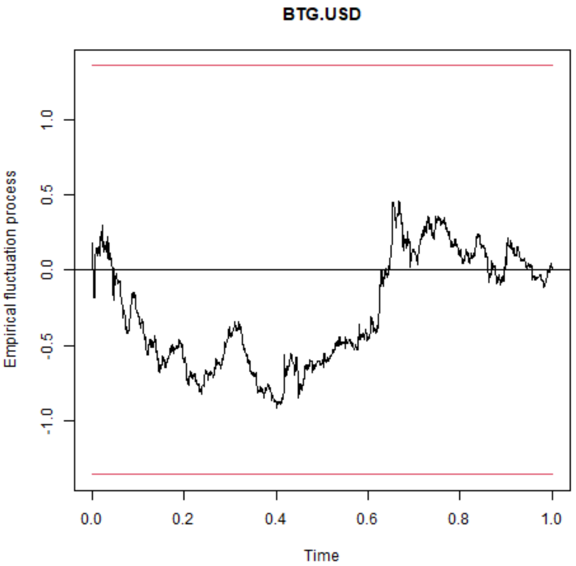
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time


BTG.USD
Empirical fluctuation process
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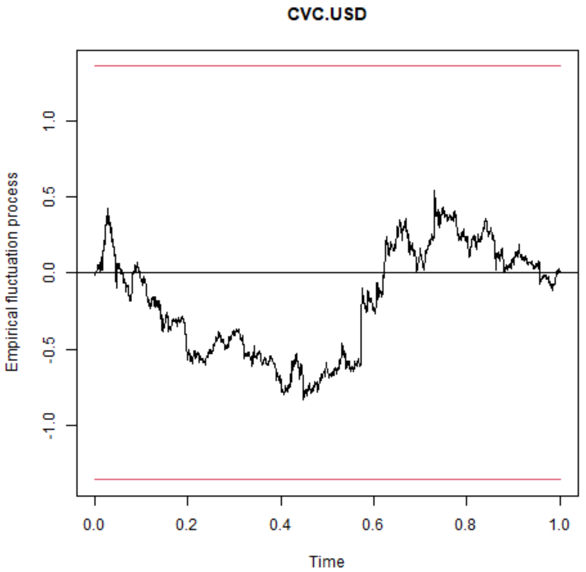
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0


CVC.USD
Empirical fluctuation process
Time
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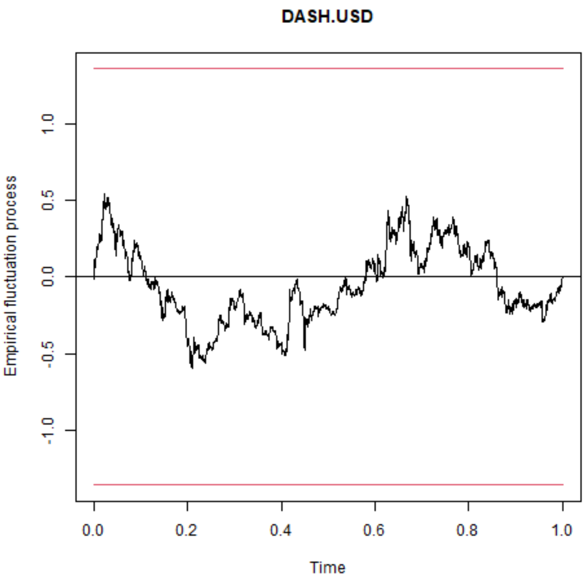
1.0
0.0
0.2
0.4
0.6
0.8
1.0


DASH.USD
Empirical fluctuation process
Time
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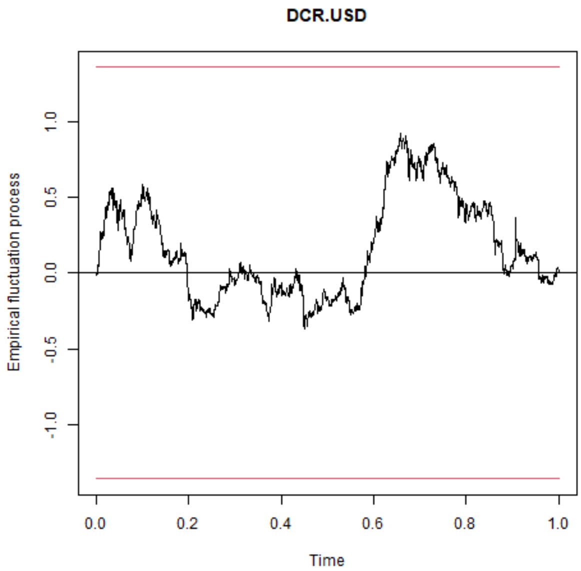
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0


DCR.USD
Empirical fluctuation process
Time
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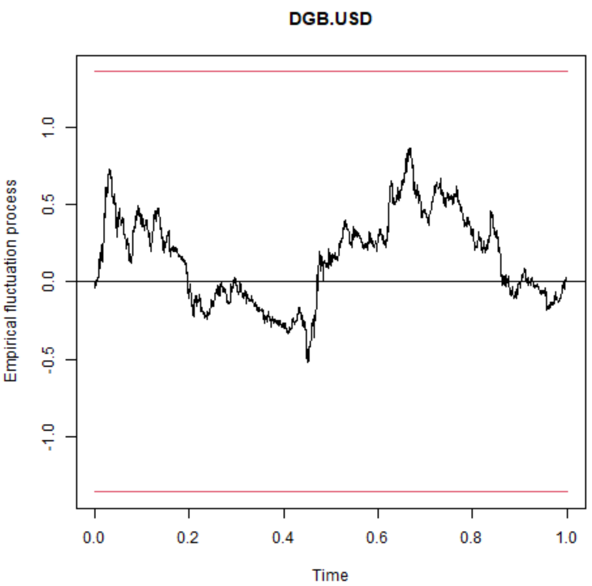
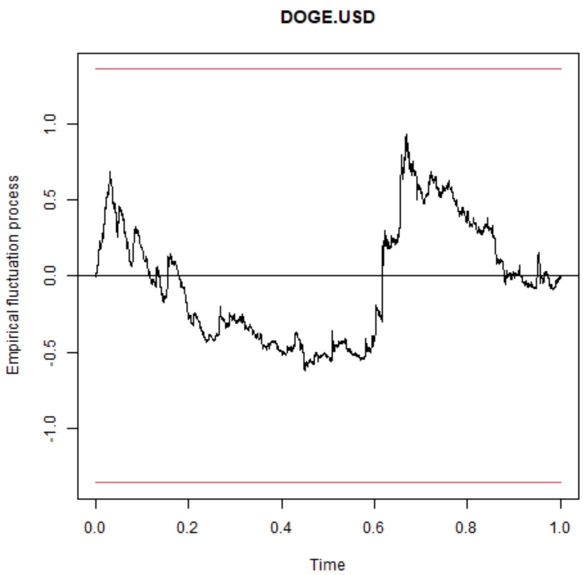
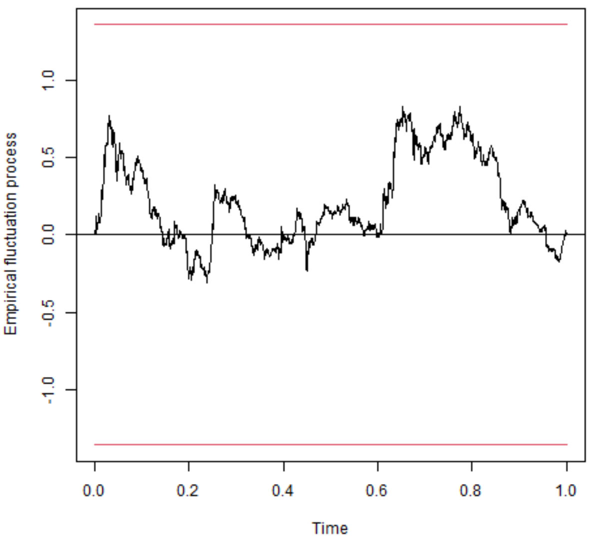
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0

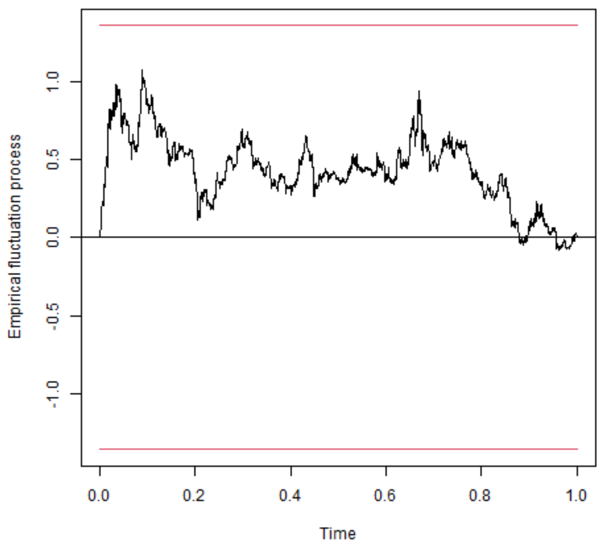

DGB.USD
Empirical fluctuation process
Time
-1.0
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0


DOGE.USD
Empirical fluctuation process
Time
-1.0
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0

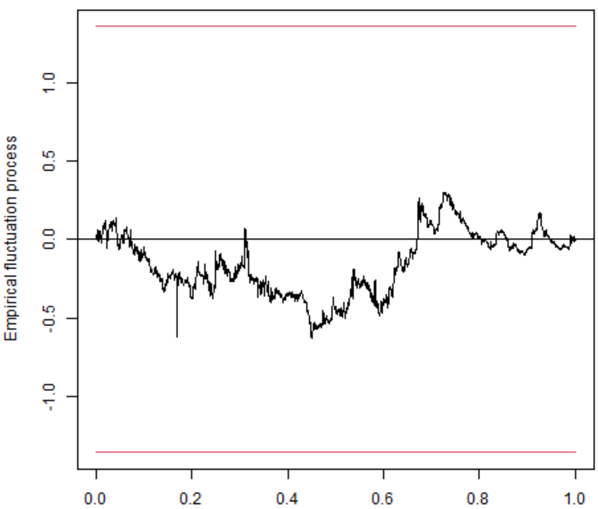
ENJ.USD



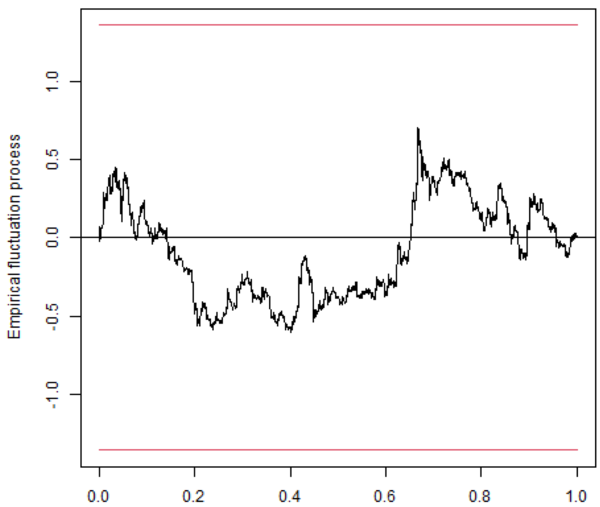
EOS.USD



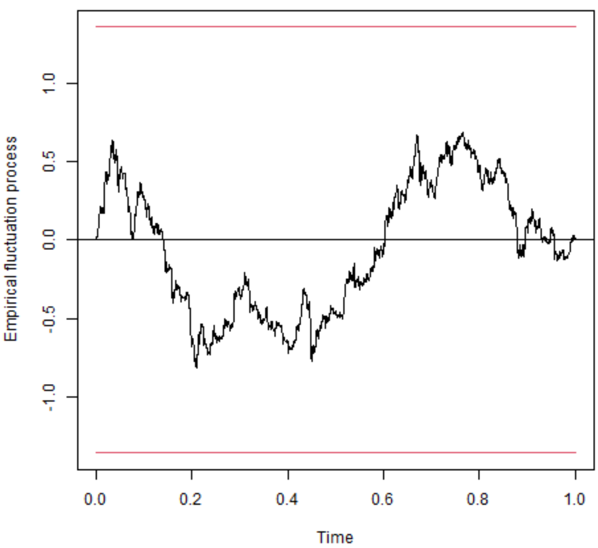
ERG.USD



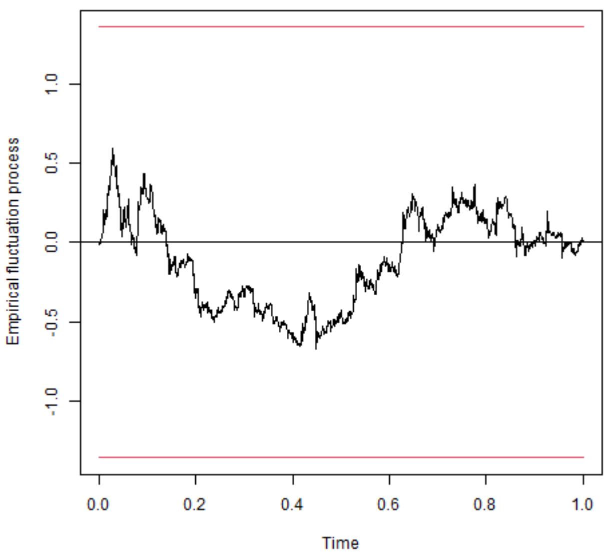
ETC.USD



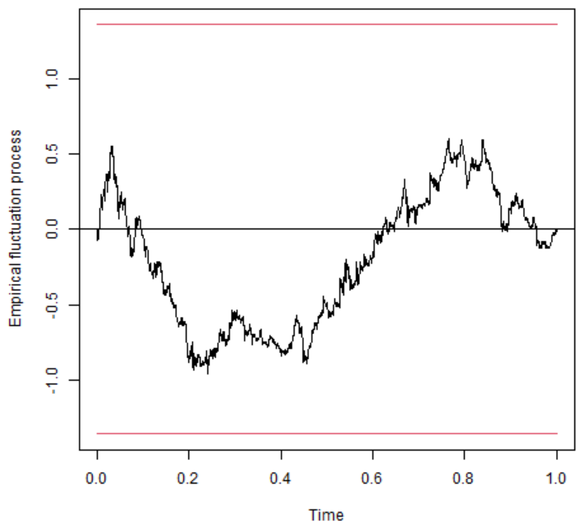
ETH.USD



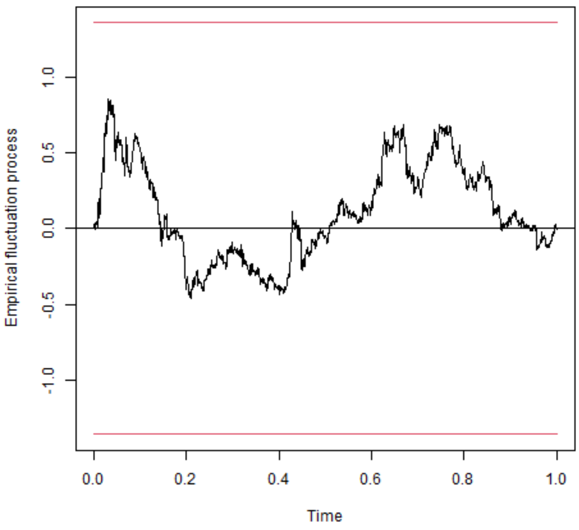
GLM.USD



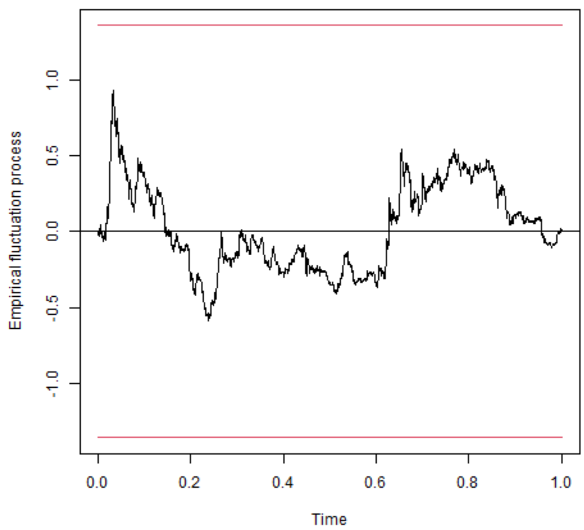
GNO.USD



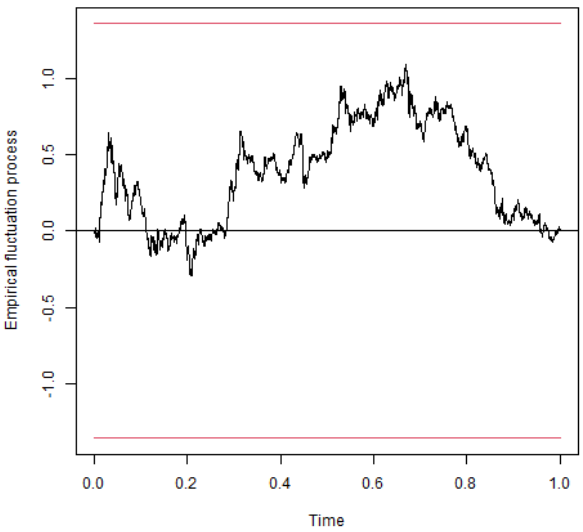
ICX.USD



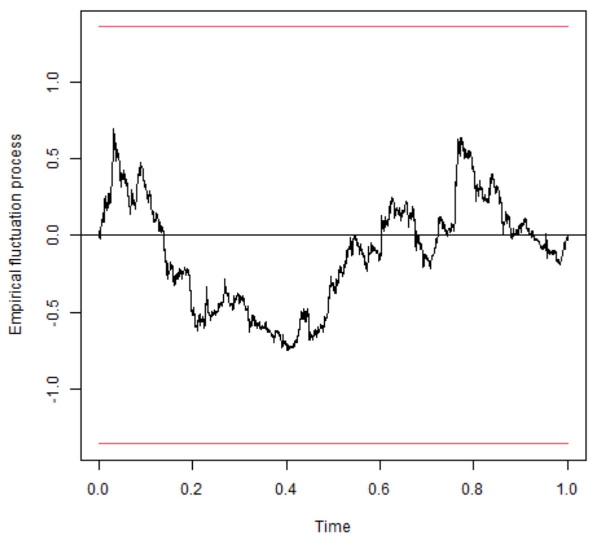
KCS.USD



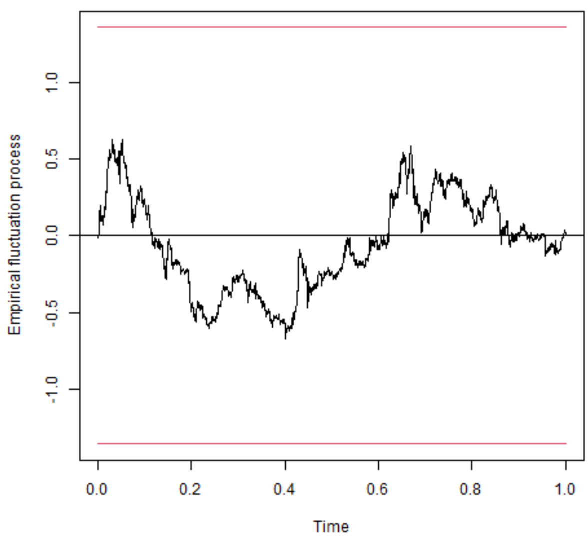
LINK.USD

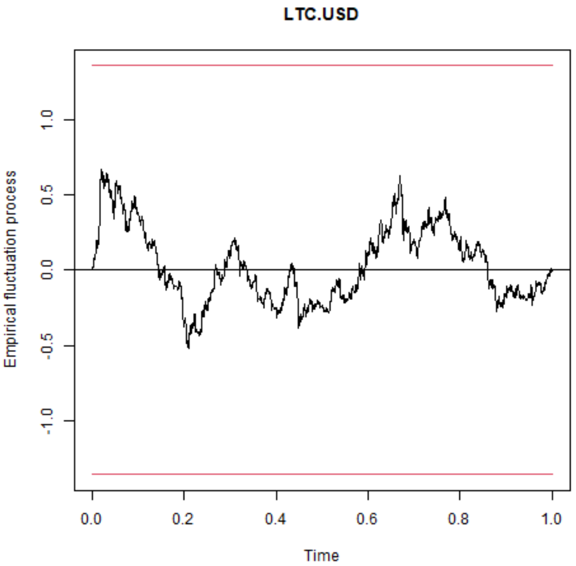


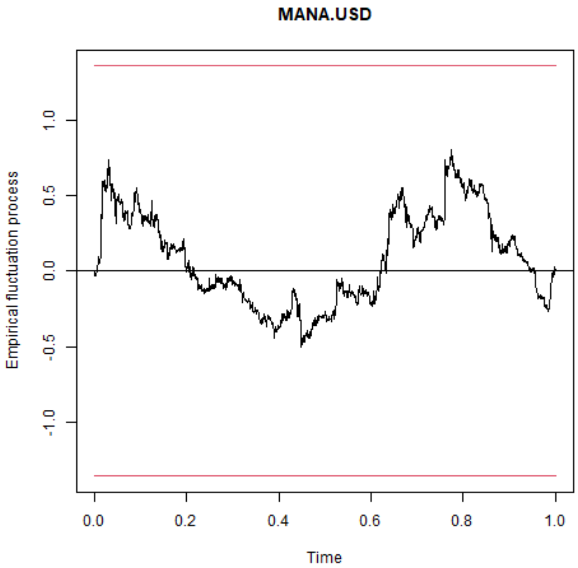
LRC.USD

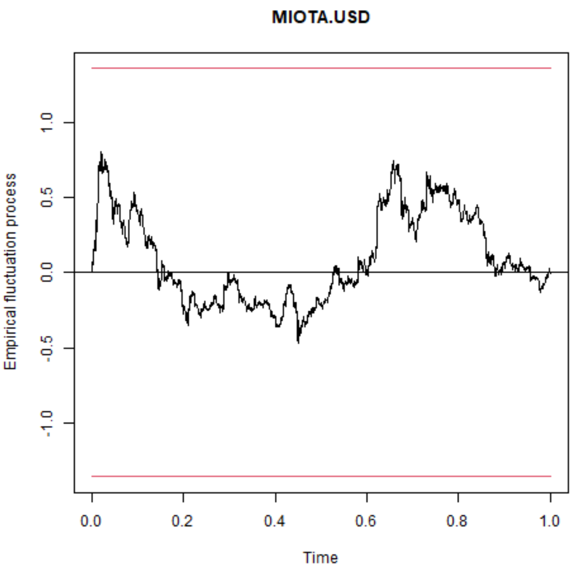


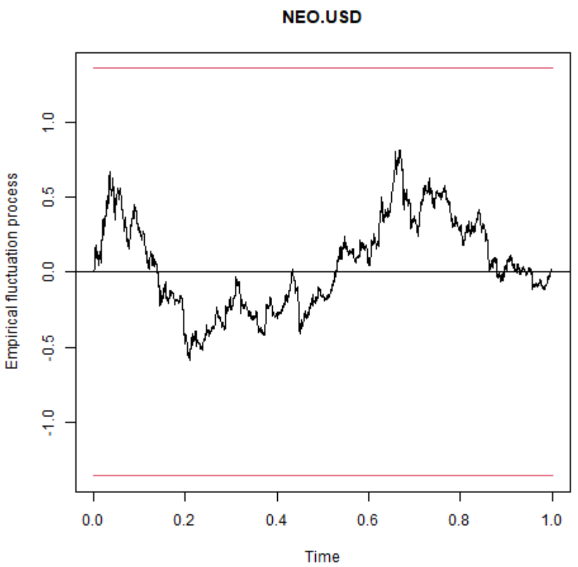
LSK.USD

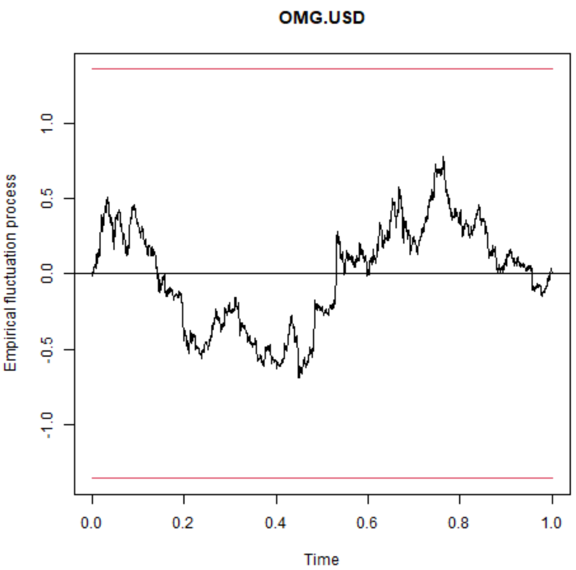


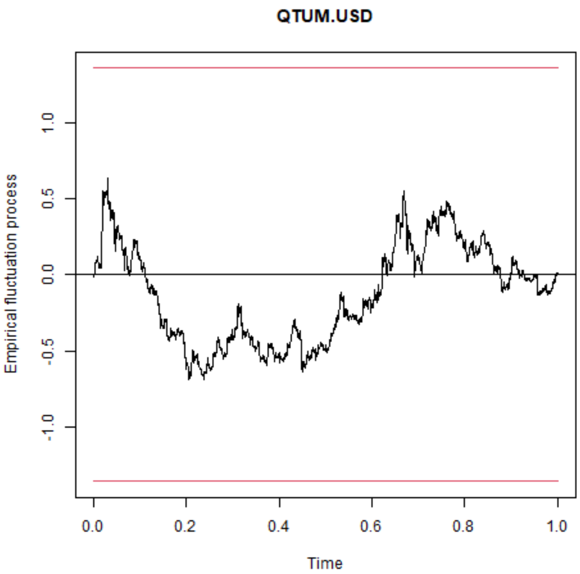

LTC.USD
Empirical fluctuation process
Time
1.0
0.5
0.0
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0

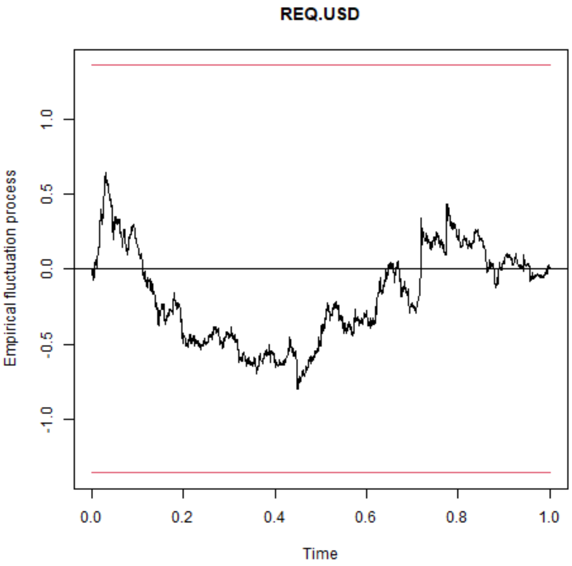

MANA.USD
Empirical fluctuation process
Time
1.0
0.5
0.0
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0


MIOTA.USD
Empirical fluctuation process
Time
1.0
0.5
0.0
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0


NEO.USD
Empirical fluctuation process
Time
1.0
0.5
0.0
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0


OMG.USD
Empirical fluctuation process
Time
1.0
0.5
0.0
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0


QTUM.USD
Empirical fluctuation process
Time
1.0
0.5
0.0
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0


REQ.USD
Empirical fluctuation process
Time
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-0.5
0.0
0.5
1.0
0.0
0.2
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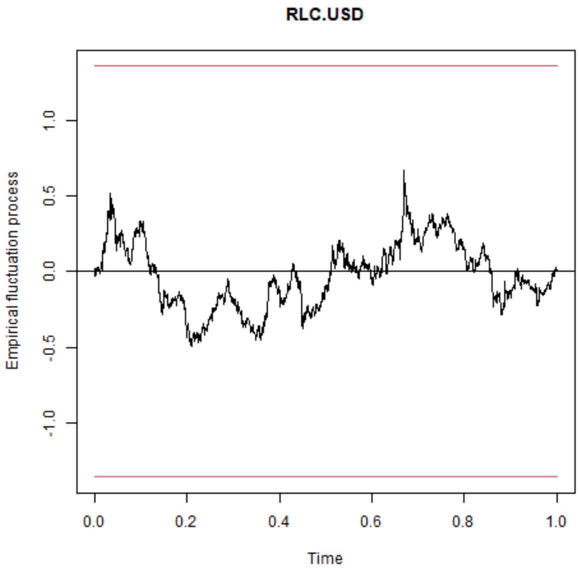
0.6
0.8
1.0


RLC.USD
Empirical fluctuation process
Time
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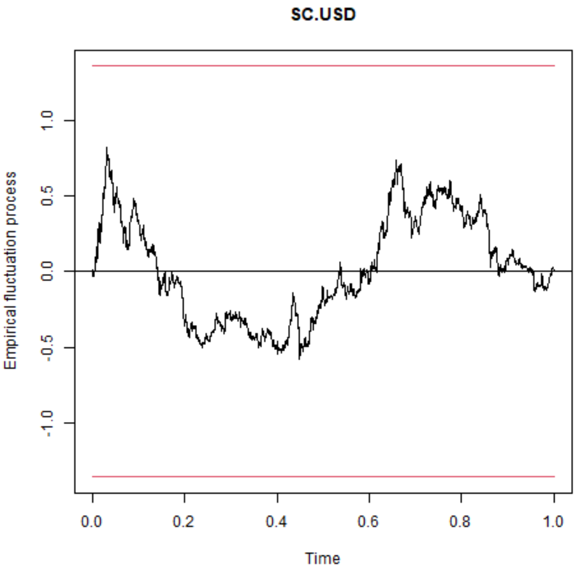
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0


SC.USD
Empirical fluctuation process
Time
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0.5
1.0
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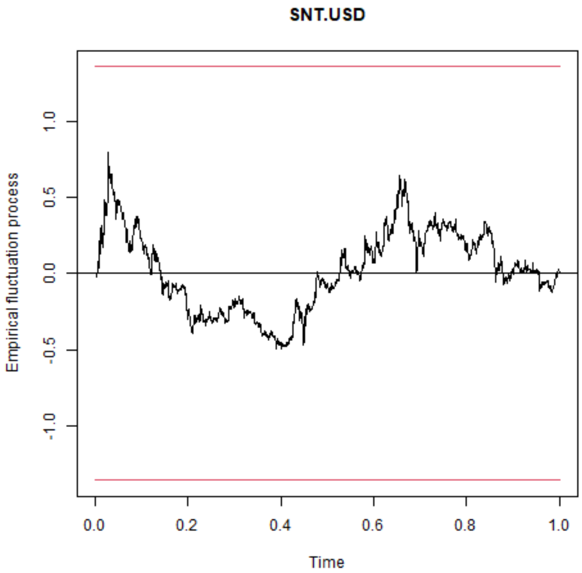
0.2
0.4
0.6
0.8
1.0


SNT.USD
Empirical fluctuation process
Time
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0.0
0.5
1.0
0.0
0.2
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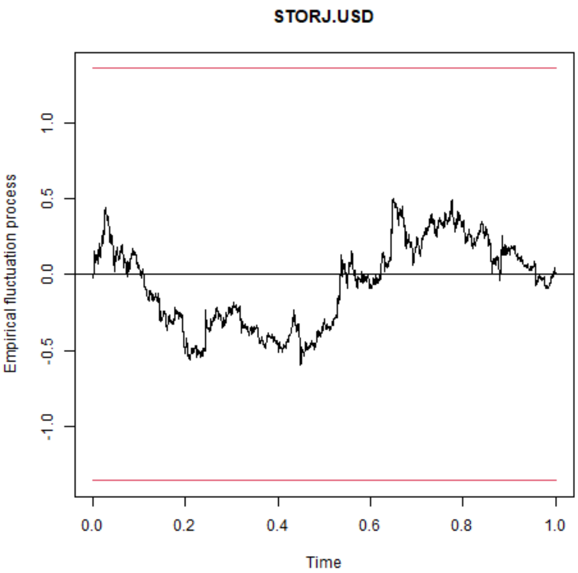
0.6
0.8
1.0


STORJ.USD
Empirical fluctuation process
Time
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-0.5
0.0
0.5
1.0
0.0
0.2
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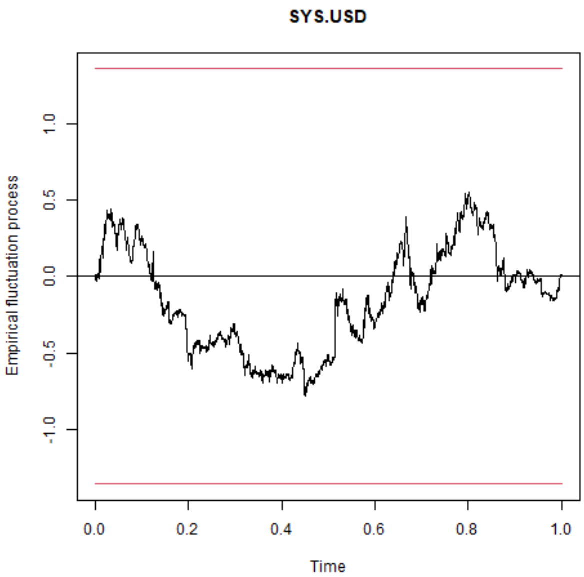
0.6
0.8
1.0


SYS.USD
Empirical fluctuation process
Time
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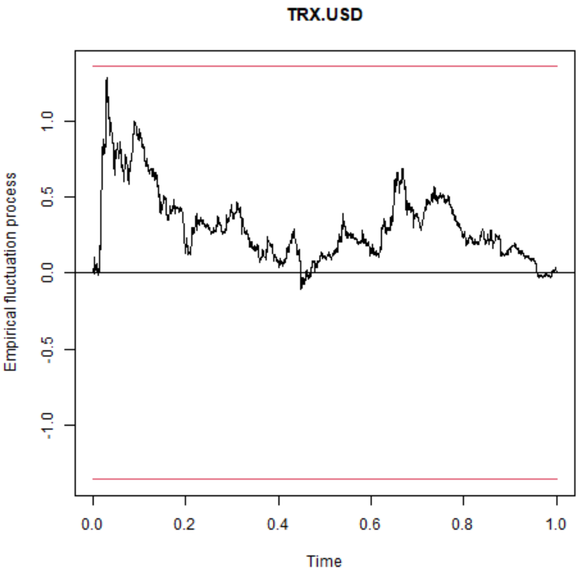
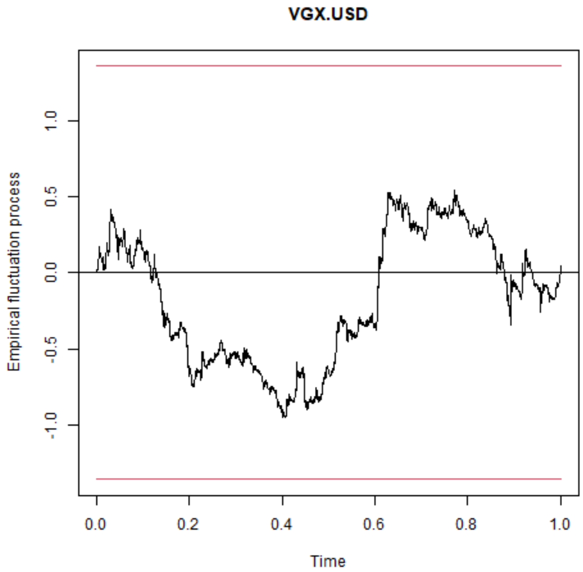
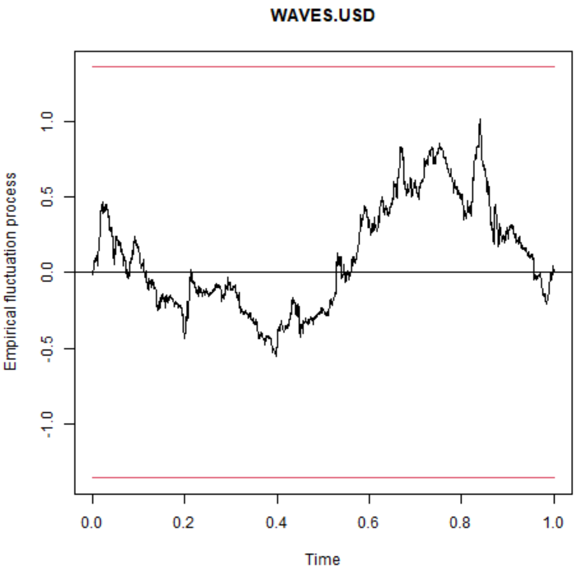
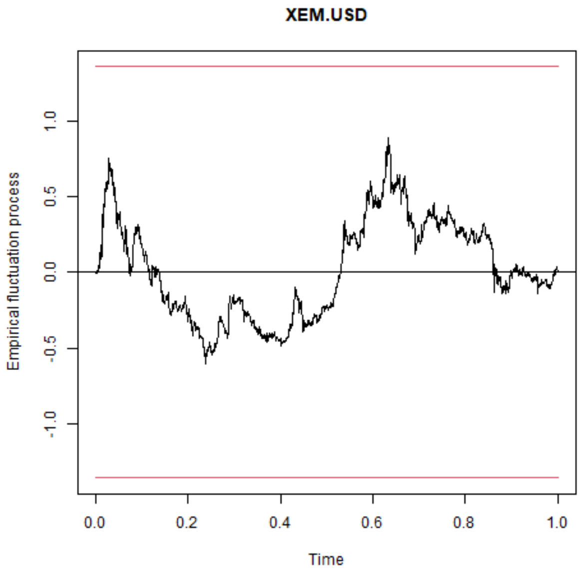
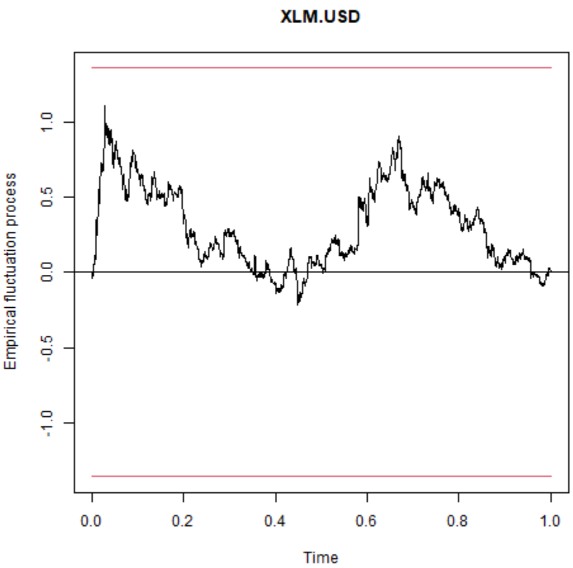
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0

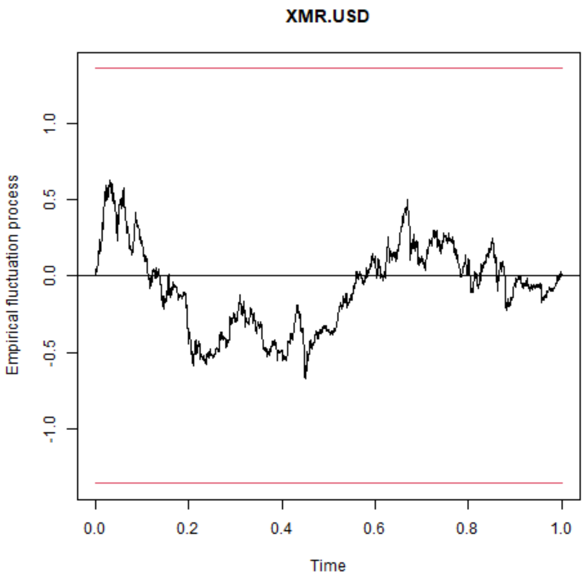

TRX.USD
Empirical fluctuation process
Time


VGX.USD
Empirical fluctuation process
Time

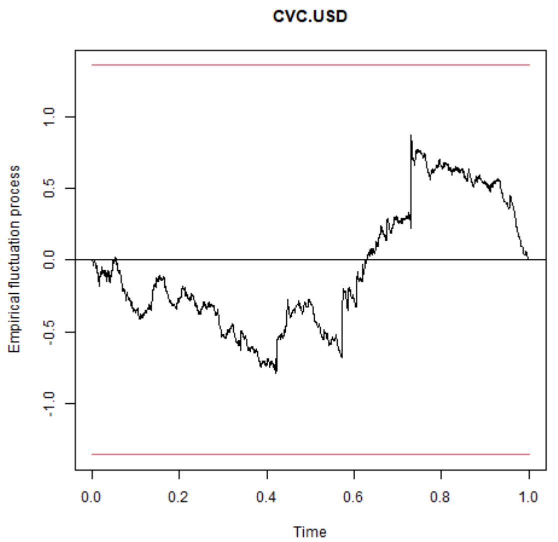

WAVES.USD
Empirical fluctuation process
Time

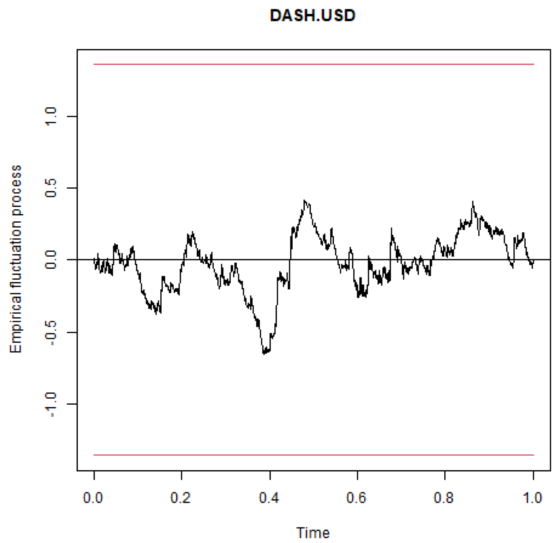

XEM.USD
Empirical fluctuation process
Time

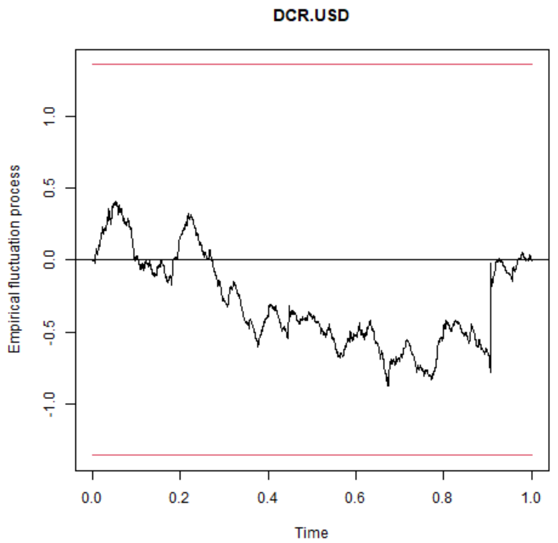

XLM.USD
Empirical fluctuation process
Time

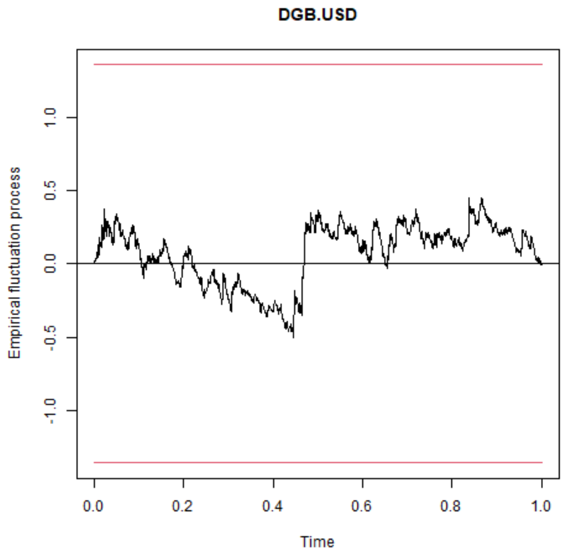

XMR.USD
Empirical fluctuation process
Time

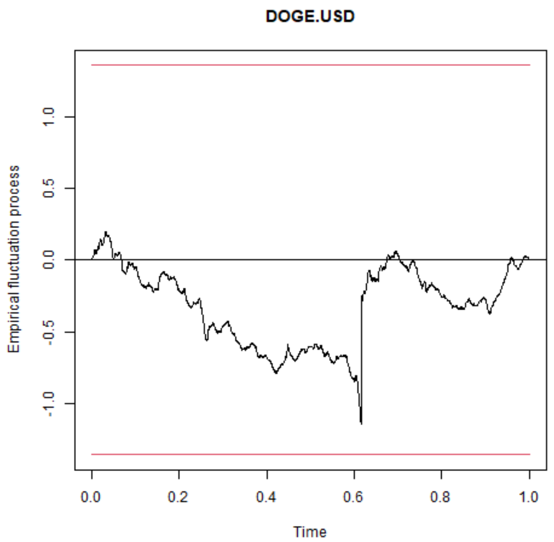
Vector Autoregression (VAR) model of Volatility

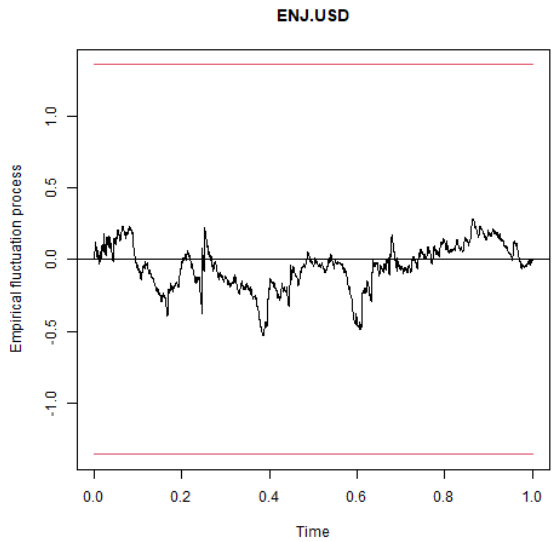


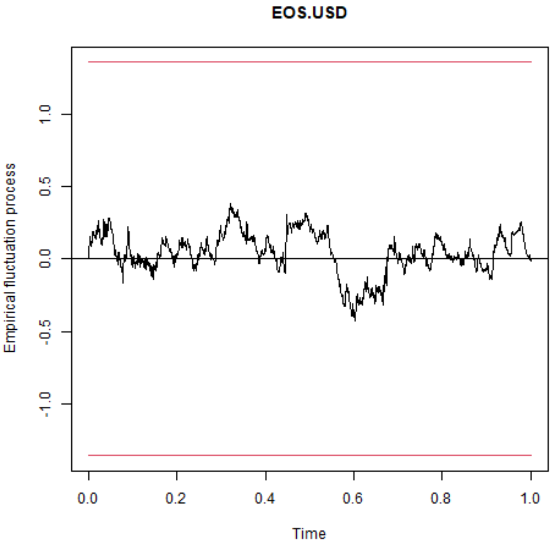


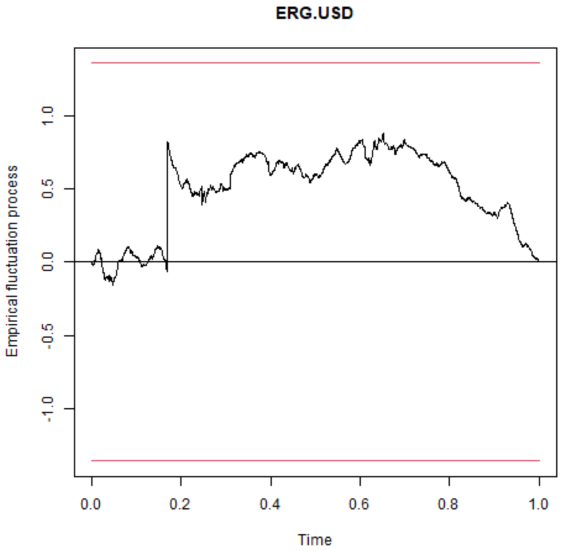









EOS.USD
Empirical fluctuation process
-1.0
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time


ERG.USD
Empirical fluctuation process
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-0.5
0.0
0.5
1.0
0.0
0.2
0.4
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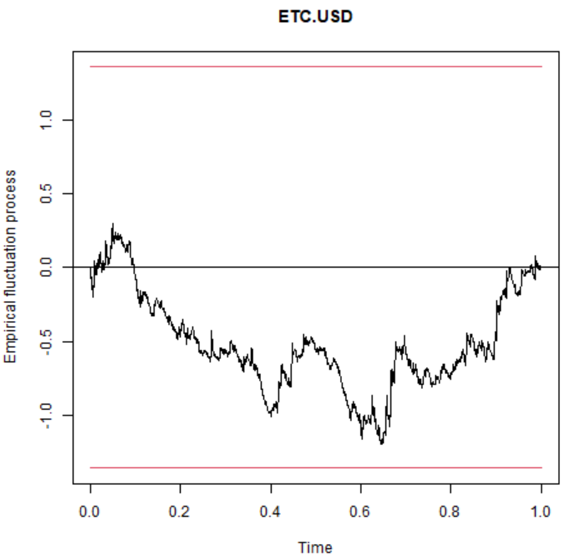
0.8
1.0
Time


ETC.USD
Empirical fluctuation process
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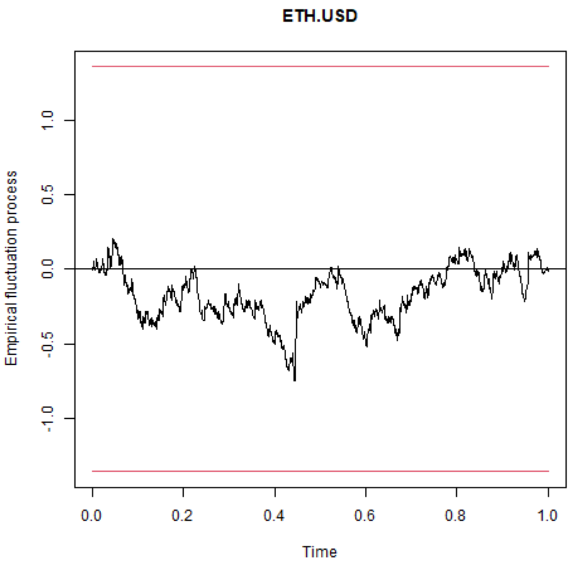
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time


ETH.USD
Empirical fluctuation process
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0.0
0.5
1.0
0.0
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0.4
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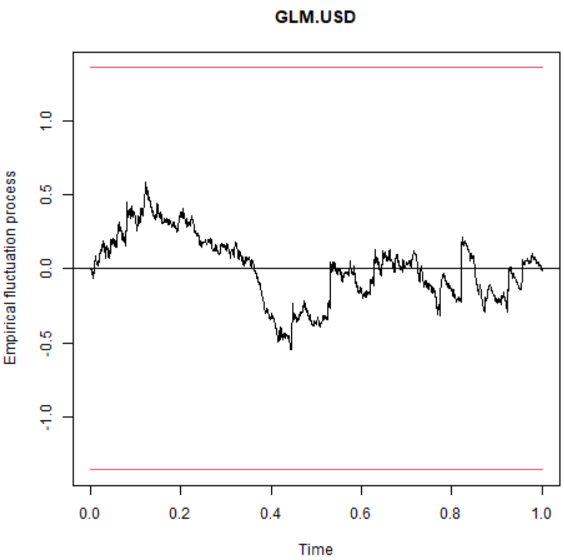
0.8
1.0
Time


GLM.USD
Empirical fluctuation process
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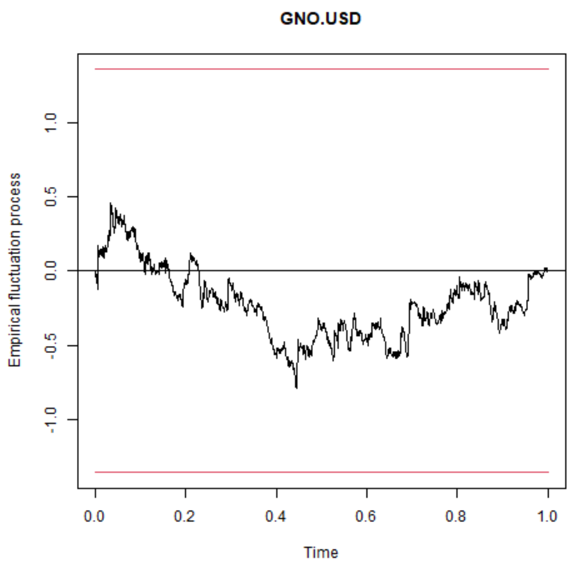
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time


GNO.USD
Empirical fluctuation process
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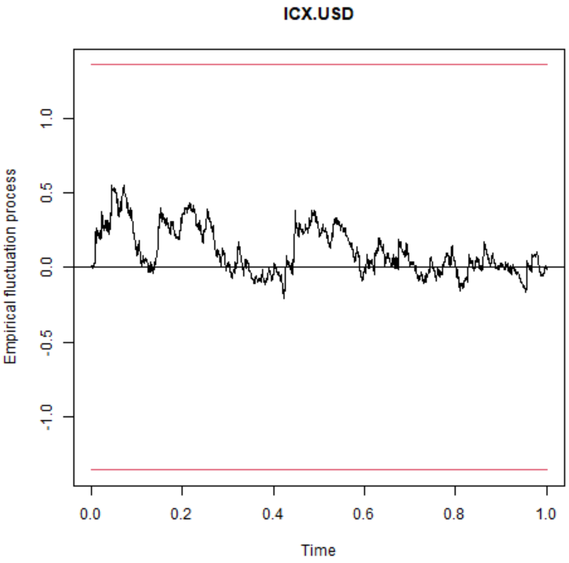
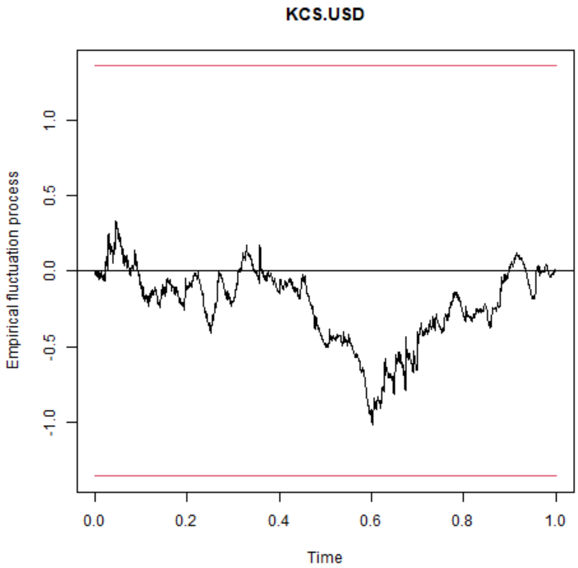
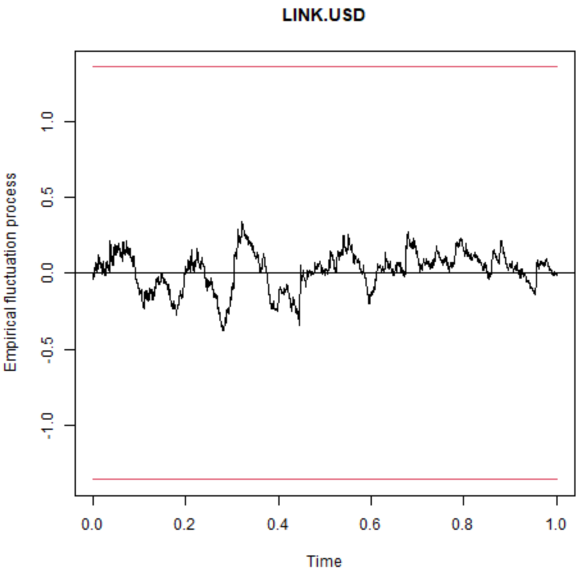
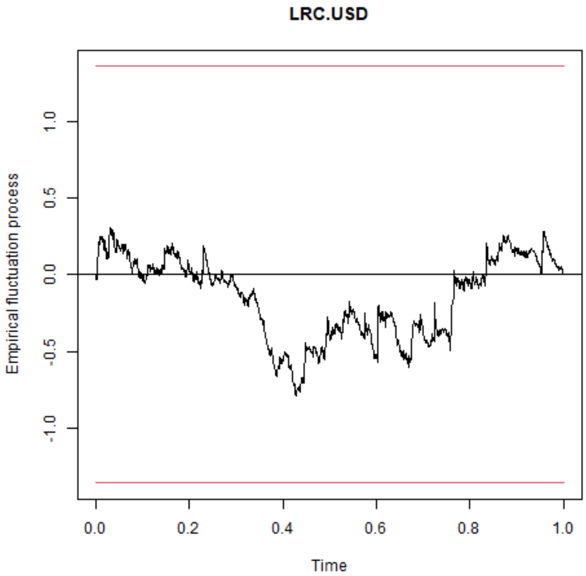
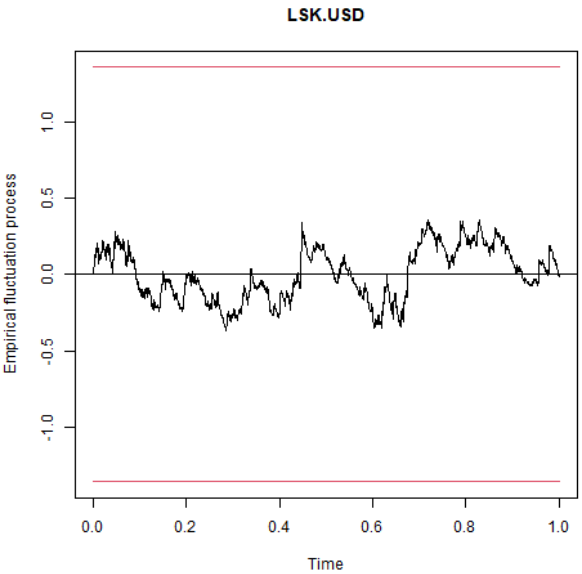
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time

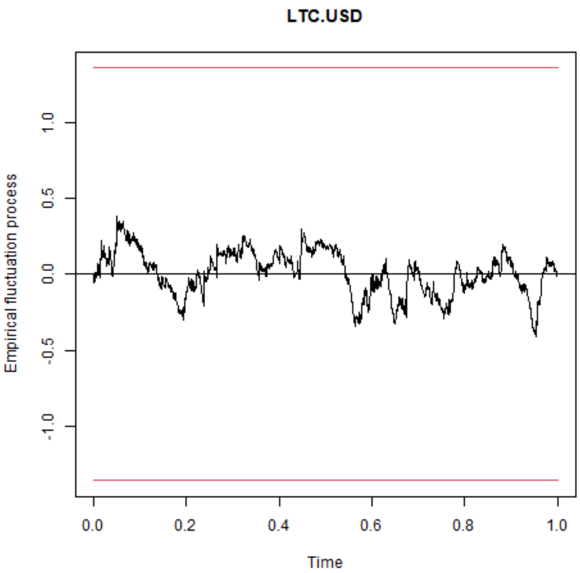

ICX.USD
Empirical fluctuation process
Time

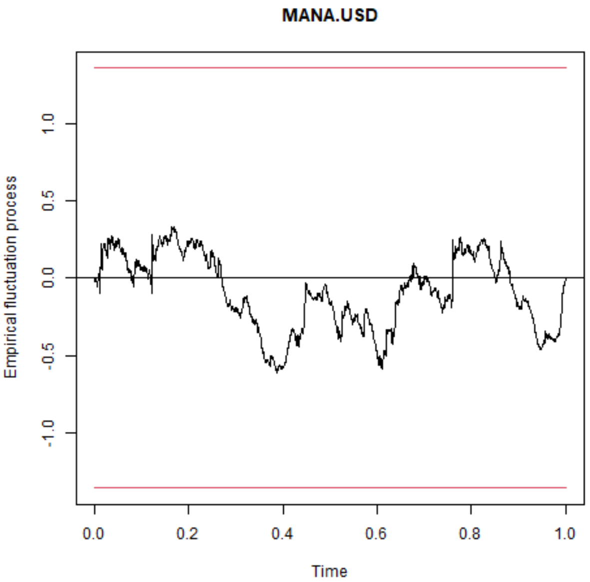

KCS.USD
Empirical fluctuation process
Time

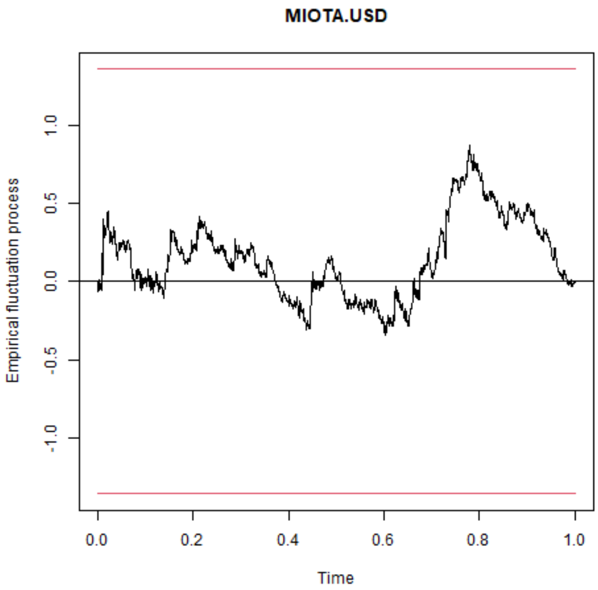

LINK.USD
Empirical fluctuation process
Time


LRC.USD
Empirical fluctuation process
Time


LSK.USD
Empirical fluctuation process
Time


LTC.USD
Empirical fluctuation process
Time


MANA.USD
Empirical fluctuation process
1.0
0.5
0.0
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time


MIOTA.USD
Empirical fluctuation process
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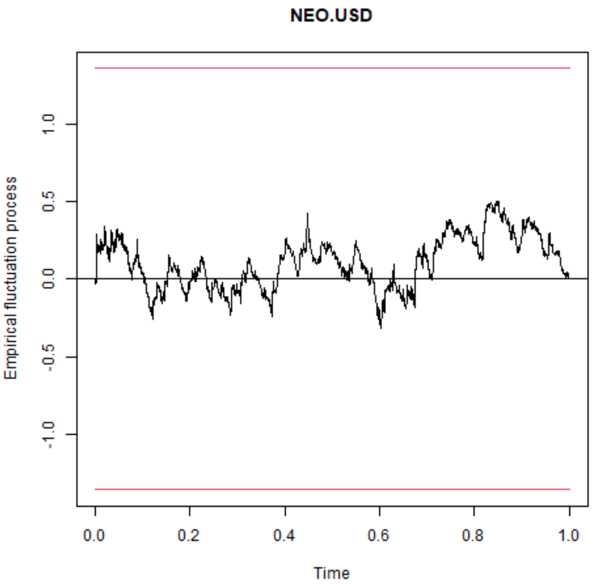
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time


NEO.USD
Empirical fluctuation process
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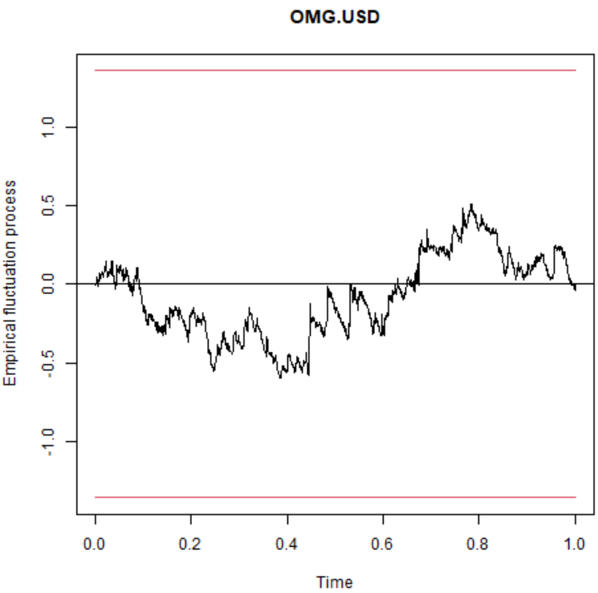
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time


OMG.USD
Empirical fluctuation process
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-0.5
-1.0
0.0
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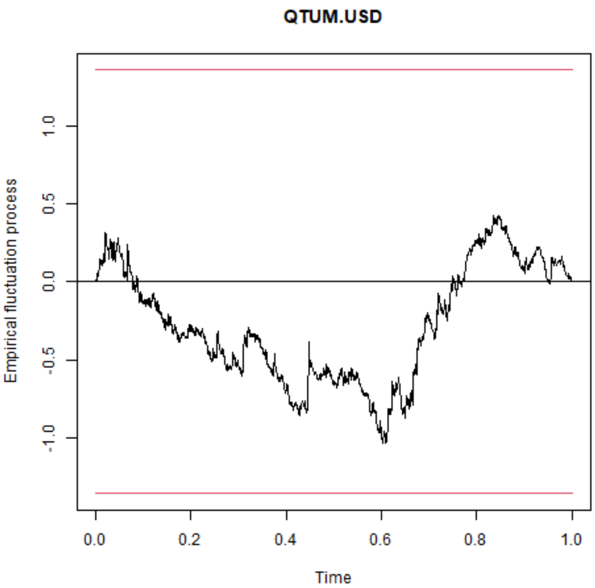
0.4
0.6
0.8
1.0
Time


QTUM.USD
Empirical fluctuation process
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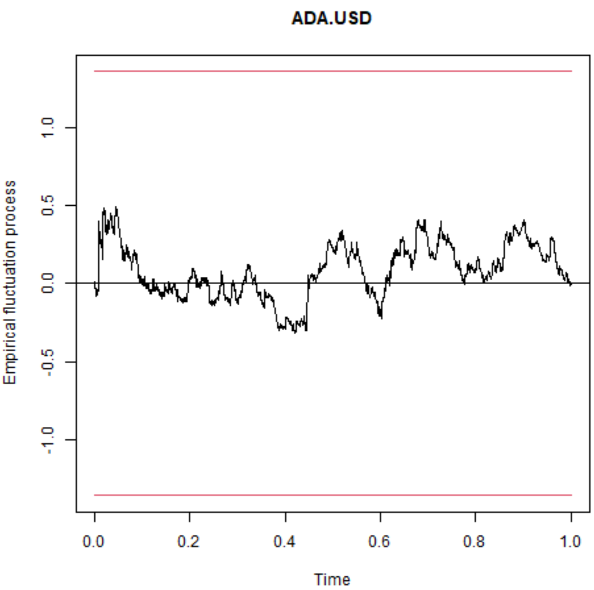
0.0
-0.5
-1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time


ADA.USD
Empirical fluctuation process
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0.0
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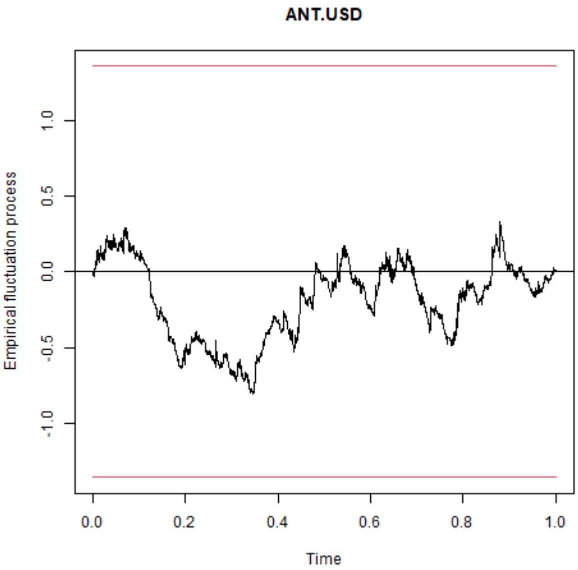
0.4
0.6
0.8
1.0
Time


ANT.USD
Empirical fluctuation process
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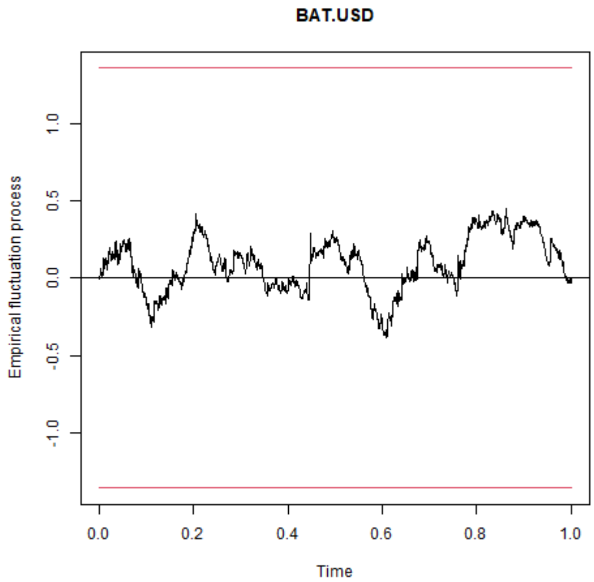
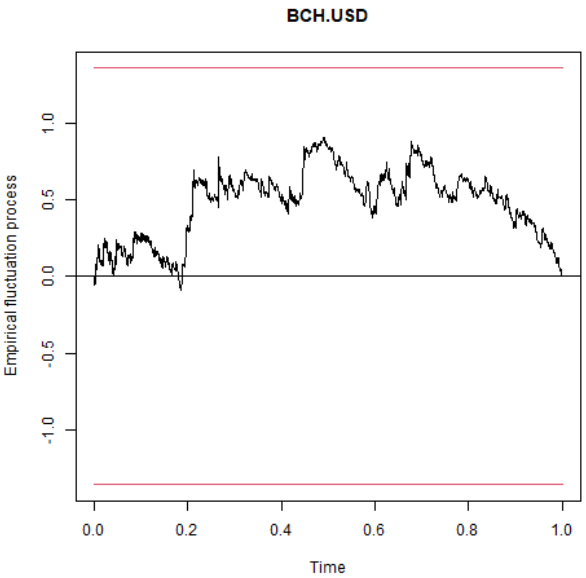
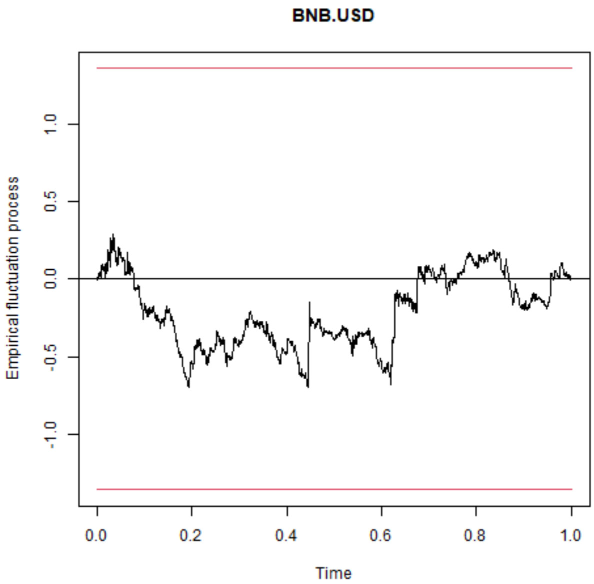
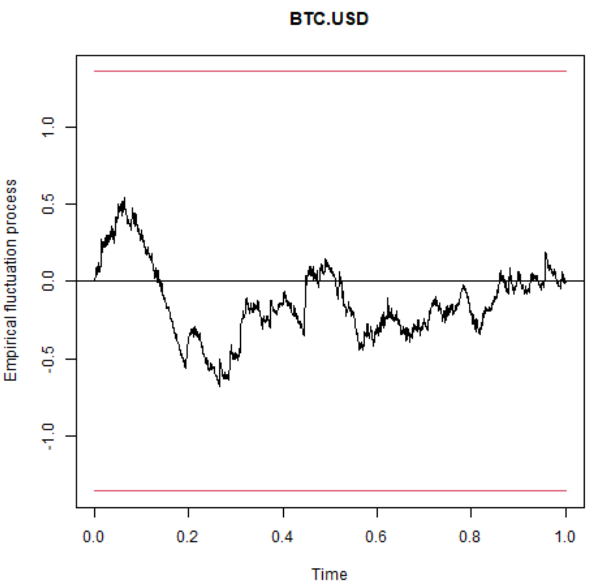
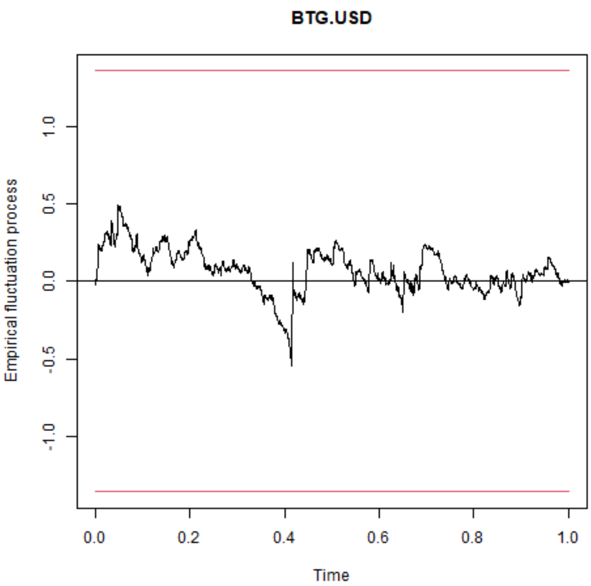
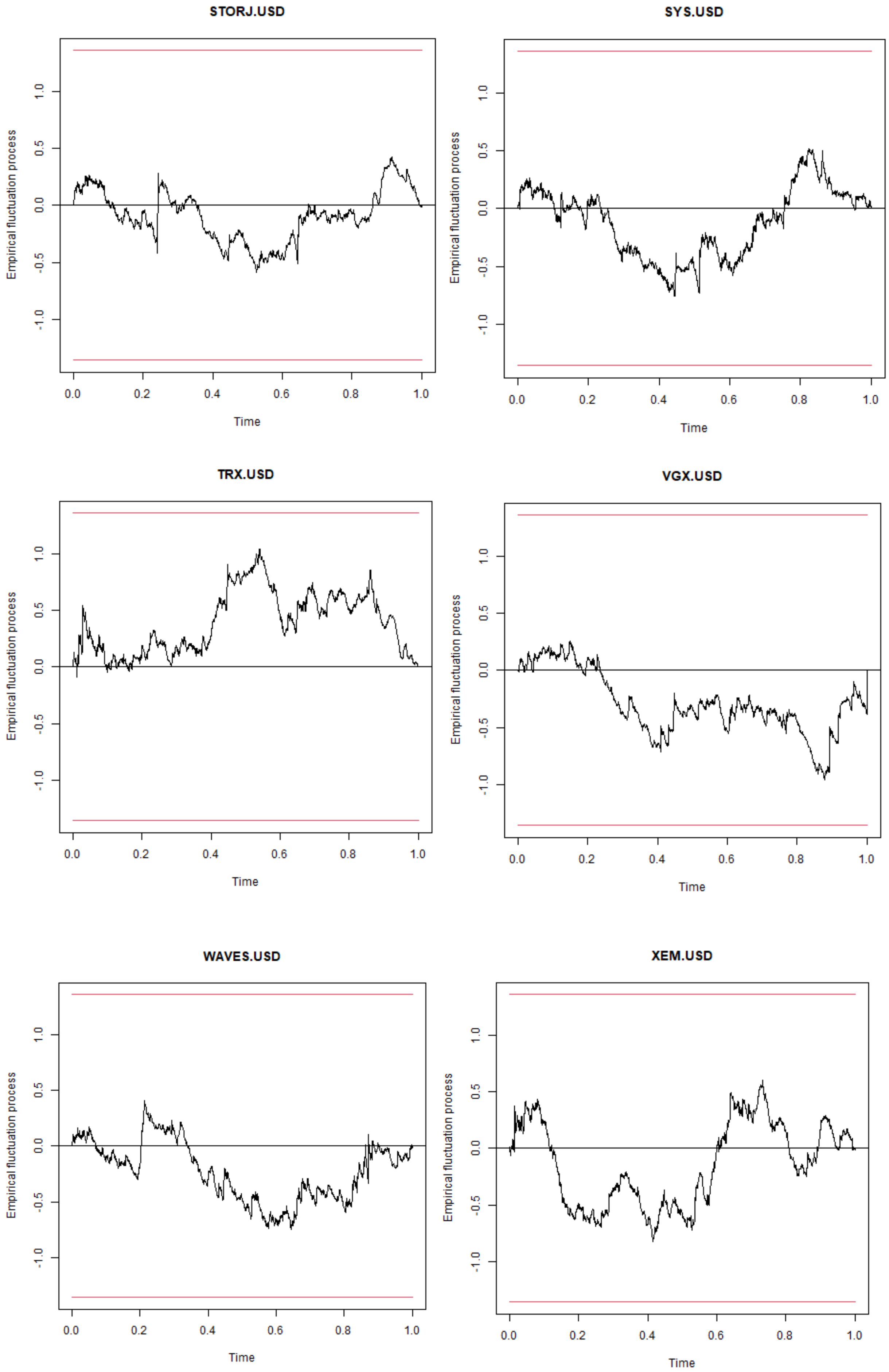
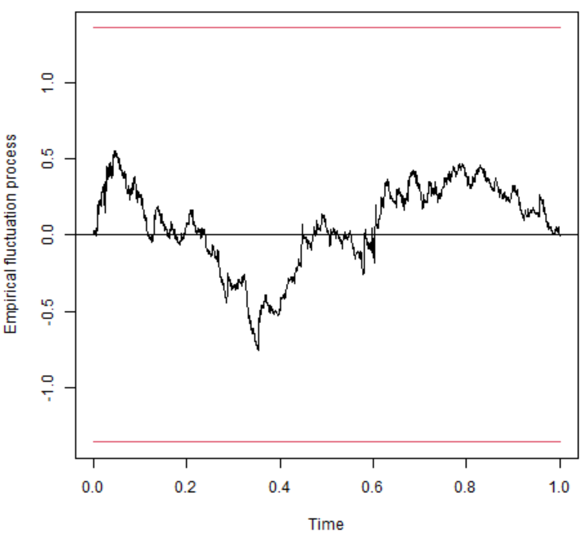
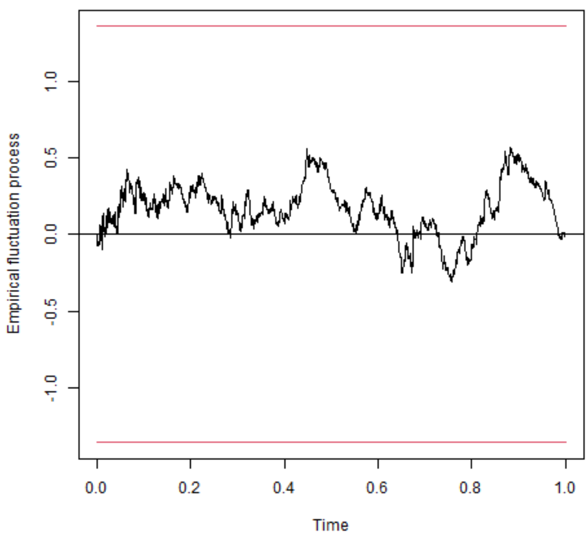
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time

BAT.USD
Empirical fluctuation process
-1.0
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time

BCH.USD
Empirical fluctuation process
-1.0
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time

BNB.USD
Empirical fluctuation process
-1.0
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time

BTC.USD
Empirical fluctuation process
-1.0
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time

BTG.USD
Empirical fluctuation process
-1.0
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0
Time


STORJ.USD
SYS.USD
TRX.USD
VGX.USD
WAVES.USD
XEM.USD
Empirical fluctuation process
Time
-1.0
-0.5
0.0
0.5
1.0
0.0
0.2
0.4
0.6
0.8
1.0

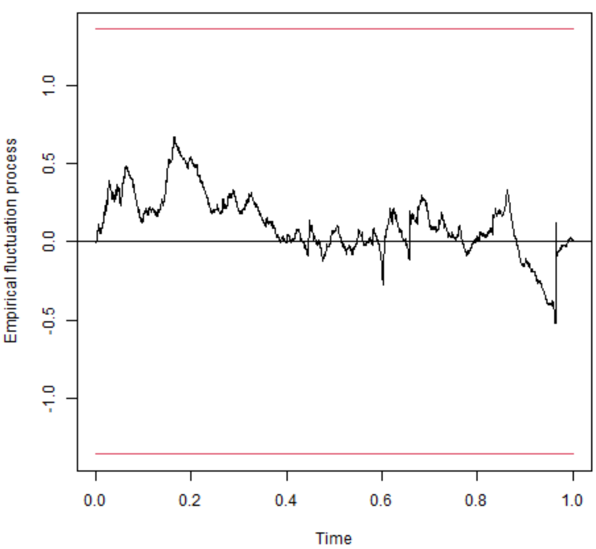
XLM.USD



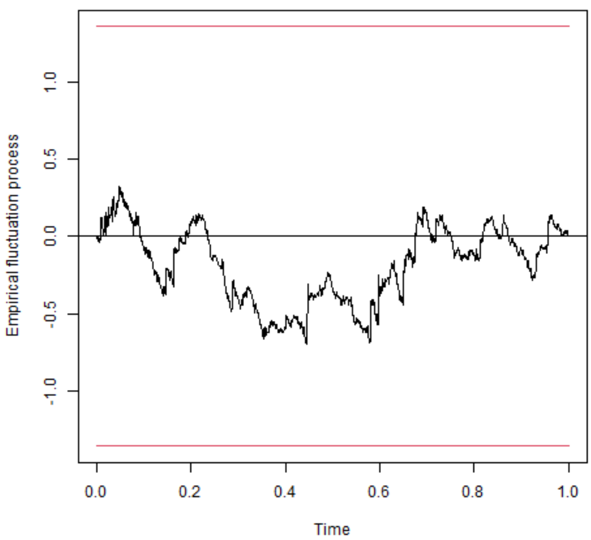
XMR.USD



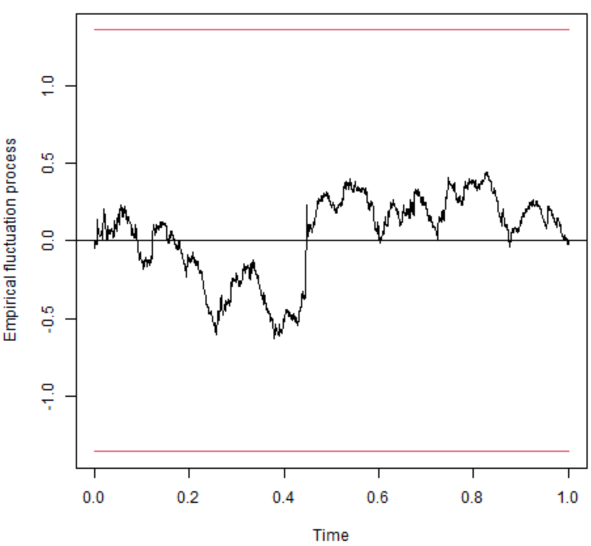
XNO.USD



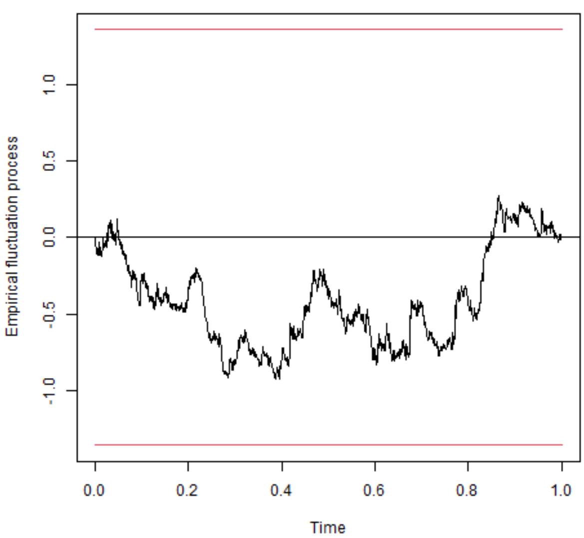
XRP.USD

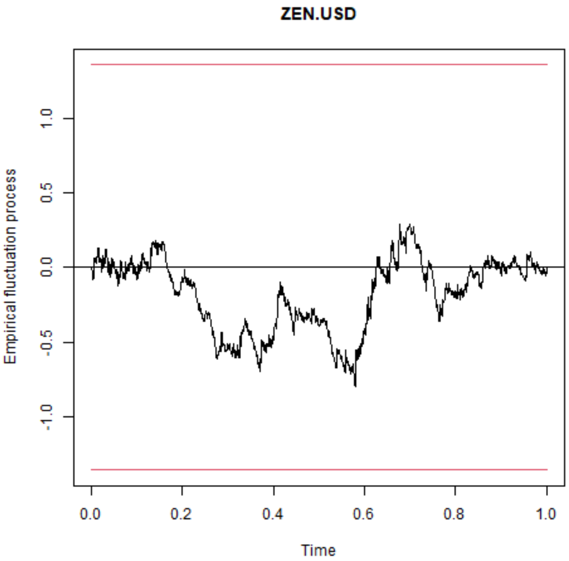


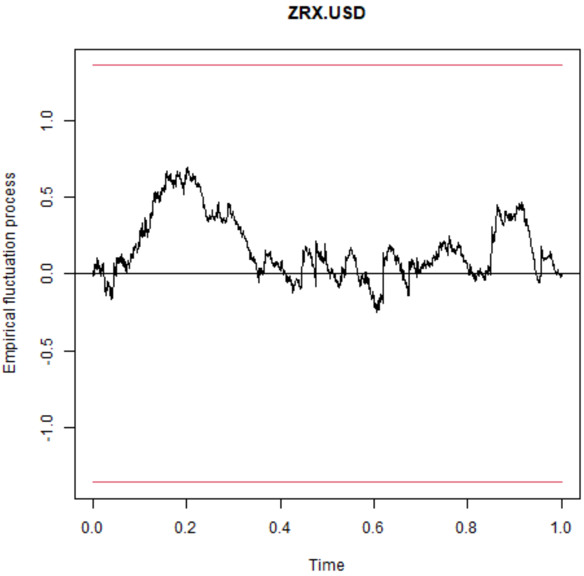
XTZ.USD

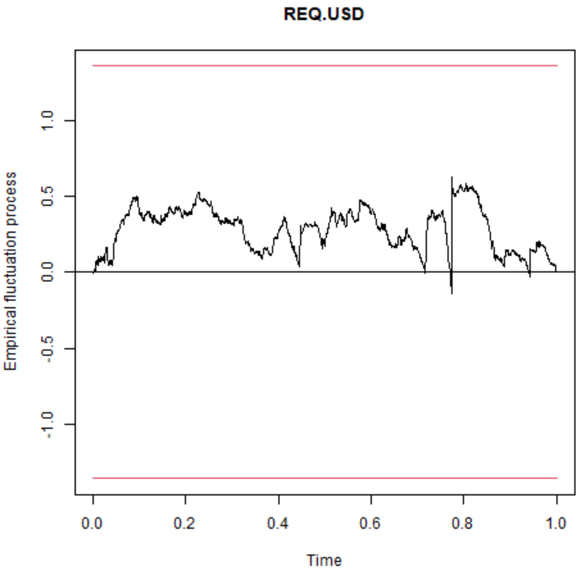


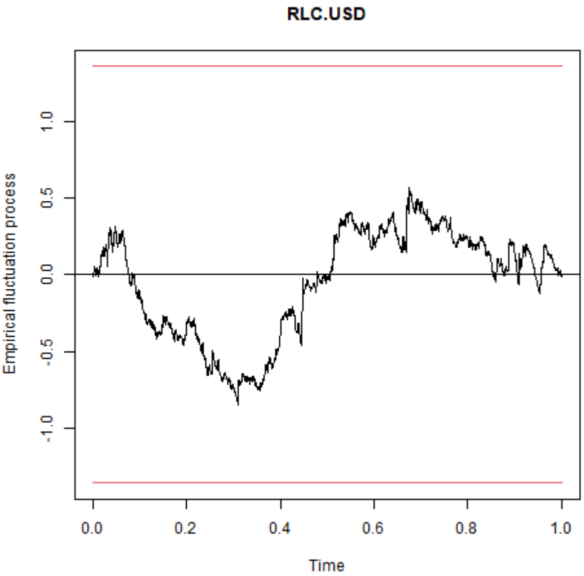
ZEC.USD

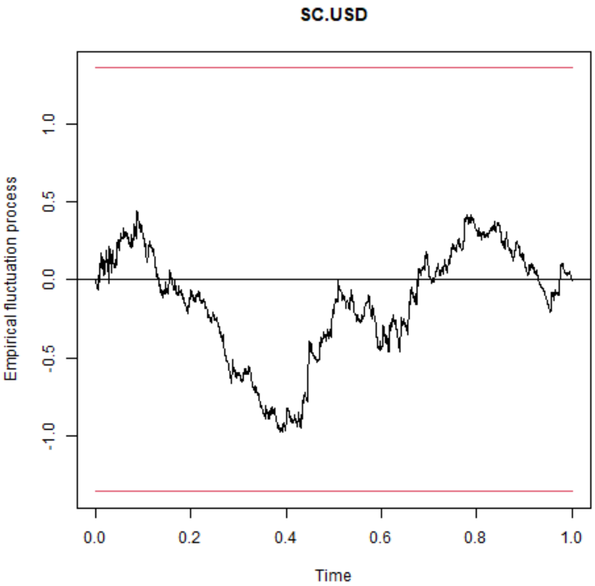


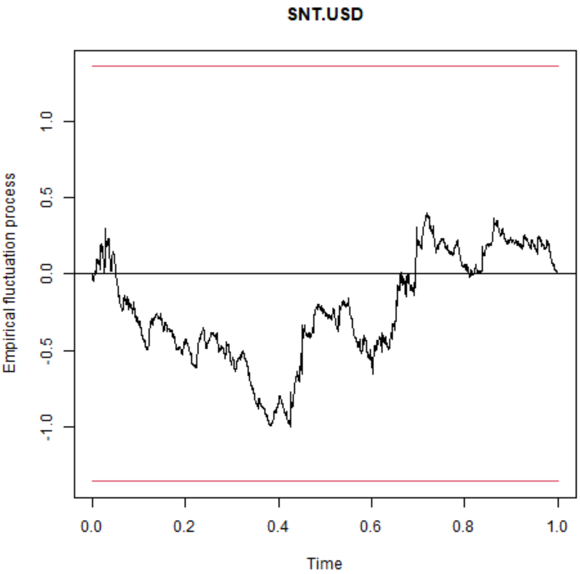

ZEN.USD
Empirical fluctuation process
Time


ZRX.USD
Empirical fluctuation process
Time


REQ.USD
Empirical fluctuation process
Time


RLC.USD
Empirical fluctuation process
Time


SC.USD
Empirical fluctuation process
Time


SNT.USD
Empirical fluctuation process
Time

Appendix 2

B.1 Nakamotos message

The appendix contains the original email sent by Satoshi Nakamoto, the anonymous creator of Bitcoin, on Fri Oct 31 14:10:00 EDT 2008, presenting the concept of Bitcoin to the cryptography mailing list. The email provides a fascinating insight into the early days of the cryptocurrency and the thought process of its creator. It is an essential resource for those interested in the history and evolution of Bitcoin and the broader cryptocurrency market.

Bitcoin P2P e-cash paper

Satoshi Nakamoto satoshi at vistomail.com
Fri Oct 31 14:10:00 EDT 2008

- Previous message: Fw: SHA-3 lounge
- **Messages sorted by:** [date] [thread] [subject] [author]

```
I've been working on a new electronic cash system that's fully
peer-to-peer, with no trusted third party.

The paper is available at:
http://www.bitcoin.org/bitcoin.pdf

The main properties:
 Double-spending is prevented with a peer-to-peer network.
 No mint or other trusted parties.
 Participants can be anonymous.
 New coins are made from Hashcash style proof-of-work.
 The proof-of-work for new coin generation also powers the
    network to prevent double-spending.

Bitcoin: A Peer-to-Peer Electronic Cash System

Abstract.  A purely peer-to-peer version of electronic cash would
allow online payments to be sent directly from one party to another
without the burdens of going through a financial institution.
Digital signatures provide part of the solution, but the main
benefits are lost if a trusted party is still required to prevent
double-spending.  We propose a solution to the double-spending
problem using a peer-to-peer network.  The network timestamps
transactions by hashing them into an ongoing chain of hash-based
proof-of-work, forming a record that cannot be changed without
redoing the proof-of-work.  The longest chain not only serves as
proof of the sequence of events witnessed, but proof that it came
from the largest pool of CPU power.  As long as honest nodes control
the most CPU power on the network, they can generate the longest
chain and outpace any attackers.  The network itself requires
minimal structure.  Messages are broadcasted on a best effort basis,
and nodes can leave and rejoin the network at will, accepting the
longest proof-of-work chain as proof of what happened while they
were gone.

Full paper at:
http://www.bitcoin.org/bitcoin.pdf

Satoshi Nakamoto

---------------------------------------------------------------------
The Cryptography Mailing List
Unsubscribe by sending "unsubscribe cryptography" to majordomo at metzdowd.com
```

B.2 The Yahoo-Finance code

The following code is conducted using Python 3.11.1. It is important to note that the code is provided for reference purposes only, and it is the responsibility of the user to ensure that they fully understand the code before attempting to use it. The authors of this code do not assume any liability for the use of this code or any damage that may result from its use. The code is used to retrieve data on 250 of the largest cryptocurrencies denominated in United States dollars. The code utilises the open-source Python package "yfinance" and the unauthorised Python API "Yahooquery" for retrieving data.

```
import os

# Importing packages
import pandas as pd
import yfinance as yf
from yahooquery import Screener

# Setting the working directory
path = 'D:/New HD 2TR/Python
Directory/Masteroppgave/Getting_all_data_crypto'

os.chdir(path)

# Defining the "Screener" object
s = Screener()

# Retrieving information on 250 cryptocurrencies
data = s.get_screeners('all_cryptocurrencies_us', count=250)

# Storing information needed (Name and tickers stored in quotes)
info = data['all_cryptocurrencies_us']['quotes']

# Retrieving the tickers from "info"
tickers = [d['symbol'] for d in info]
full_name = [d['shortName'] for d in info]

# Retrieving historical data on "tickers"
data = yf.download(tickers, start="2017-09-10")

# Getting the Adjusted close prices
time_series = data['Adj Close']

# Converting the results to panda Data frame
df1 = pd.DataFrame(time_series)
df1.reset_index(inplace=True)
df1['Date'] = df1['Date'].dt.tz_localize(None)

# Print the results to excel
df1.to_excel('Crypto_price15.xlsx',  sheet_name='Prices')
```

Market capitalisation can be retrieved using the following code:

```
# retrieving Market Cap
market_cap = [d['marketCap'] for d in info]

# Tickers, full name and market cap to data frame
df = pd.DataFrame({"Tickers": tickers,
                   "Full name": full_name,
                   "Market cap": market_cap})
```

B.3 The full master thesis code

The following code is conducted using RStudio version 4.2.2 (2022-10-31 ucrt). The code presented uses various packages, several self-made functions, and modified versions of certain packages (such as frequencyConnectedness and vars). Information on packages can be retrived typing "?" before entering the name of a specific package in the R console. The authors of this code do not assume any liability for the use of this code or any damage that may result from its use. Note that the code is provided for reference purposes only, albeit recreation is easy.

Function For loading or installing the required libraries.

```
# Loads or install packages function ----
using <-function(...) {
    libs<-unlist(list(...))
    req<-unlist(lapply(libs,require,character.only=TRUE))
    need<-libs[req==FALSE]
    if(length(need)>0){
        install.packages(need)
        lapply(need,require,character.only=TRUE)
    }
}

# Loading the libraries calling the 'using' function
using("frequencyConnectedness",
      "lubridate",
      "tidyverse",
      "rugarch",
      "vars",
      "xlsx",
      "readxl",
      "tseries",
      "corrplot",
      "latticeExtra",
      "ggrepel",
      "moments"
      )
```

```r
# ===========================================================================
#
# ======================== Loading Data =====================================
#
# ===========================================================================
#

# Setting working directory ----
setwd("~WORKING DIRECTORY")

# Getting market cap info
mcap <- read_excel("MarketCap_250.xlsx", sheet = "Selected")

# Loading the price data ----
data <- read_excel("Crypto_prices.xlsx", sheet = "prices")
# ========================================================================== #

# price sub-samples --
price_18 <- data %>% filter(year(Date) == 2018)
price_19 <- data %>% filter(year(Date) == 2019)
price_20 <- data %>% filter(year(Date) == 2020)
price_21 <- data %>% filter(year(Date) == 2021)
price_22 <- data %>% filter(year(Date) == 2022)

# Computing returns
r_all <- apply(log((cbind(data[,-1]))), 2, diff)

# Computing returns sub periods
# Get a list of unique years from the date column
years <- unique(as.numeric(format(data$Date, "%Y")))

# Create an empty list to store the new tibble objects
yearly_data_list <- list()

# Loop through the years and filter the data for each year
for (year in years) {
  year_data <- data %>% filter(as.numeric(format(Date, "%Y")) == year)
  yearly_data_list[[as.character(year)]] <- year_data
}

# Creating sub periods of the data set
r_18 <- apply(log((cbind(yearly_data_list$`2018`[,-1]))), 2, diff)
r_19 <- apply(log((cbind(yearly_data_list$`2019`[,-1]))), 2, diff)
r_20 <- apply(log((cbind(yearly_data_list$`2020`[,-1]))), 2, diff)
r_21 <- apply(log((cbind(yearly_data_list$`2021`[,-1]))), 2, diff)
r_22 <- apply(log((cbind(yearly_data_list$`2022`[,-1]))), 2, diff)
```

```
# ======================================================================
#
# ===================== Creating functions ==============================
#
# ======================================================================
#


# ===================================================================== #
# ================ Descriptive statistics ============================== #
# ===================================================================== #

descriptive_table <- function(data = r_all){
  descriptive_table_all <- tibble(
  Mean = colMeans(data)*365,
  StdDev = apply(data, 2, sd)*sqrt(365),
  Min = apply(data, 2, min),
  Max = apply(data, 2, max),
  Kurtosis = apply(data, 2, kurtosis),
  Skewness = apply(data, 2, skewness)
  ) %>%
  mutate(
    Sharpe = round(Mean/StdDev,5)
    )
  return(descriptive_table_all)
}
#=======================================================================#
# ----

# ===================================================================== #
# ===================== Graph functions =============================== #
# ===================================================================== #

# Making a template for line graphs ----
line_graph <- function(data,
                       x,
                       y,
                       Title="",
                       ylab="",
                       xlab="",
                       isDate=FALSE,
                       xmax = 10,
                       xmin = 0,
                       len = 6) {

  if(isDate == TRUE){
      data %>%
    ggplot(aes(x = as.Date(x), y = y)) +
    geom_line(size = 0.6,color = "#45BCCA") +
    labs(
     title = Title,
    # subtitle = "Monthly spot price observations",
     x = xlab,
     y = ylab
```

```
    ) +
    # General theme
    theme_base(base_size = 14) +
    # Setting the theme details
    theme(
     axis.title = element_text(size = 11),
     title = element_text(colour = "Black", size = 12, family = "sans"),
     plot.subtitle = element_text(size = 10, hjust = 0.5),
     plot.title = element_text(hjust = 0.5),
     panel.grid.major = element_blank(),
     panel.grid.minor = element_blank(),
     panel.background = element_blank(),
     panel.border =  element_rect(colour = "gray", fill=NA, size=0.5)
        ) +
      scale_x_date(date_labels =  "%Y", date_breaks = "1 year") +
      scale_y_continuous(breaks = seq(xmin, xmax, len = len))
  } else{
    data %>%
    ggplot(aes(x = x, y = y)) +
    geom_line(size = 0.6,color = "#45BCCA") +
    labs(
     title = Title,
    # subtitle = "Monthly spot price observations",
     x = xlab,
     y = ylab
     ) +
    # General theme
    theme_base(base_size = 14) +
    # Setting the theme details
    theme(
     axis.title = element_text(size = 11),
     title = element_text(colour = "Black", size = 12, family = "sans"),
     plot.subtitle = element_text(size = 10, hjust = 0.5),
     plot.title = element_text(hjust = 0.5),
     panel.grid.major = element_blank(),
     panel.grid.minor = element_blank(),
     panel.background = element_blank(),
     panel.border =  element_rect(colour = "gray", fill=NA, size=0.5)
        )

    }
}

#==========================================================================#
# ----

# Correlation plot ----
corr_plot <- function(data = m_all){
  corrplot(data, tl.cex = 0.55, order = "original",
           tl.col = "Black",
           type = "lower",
           tl.srt = 360,
           tl.offset = 1,
           cl.ratio = 0.1
```

```r
            )
}

#==========================================================================#
# ----

# Function for rolling spillover plot ----
rolling_spillover_plot <- function(data = rolling_return,
                                   title = "Total return spillover index")
{

  # Create ggplot object
  rolling_plot <- ggplot(data, aes(x = as.Date(date))) +
    # Add line for sp_100
    geom_line(aes(y = sp_100, color = "sp_100")) +
    # Add line for sp_200
    geom_line(aes(y = sp_200, color = "sp_200")) +
    # Add line for sp_300
    geom_line(aes(y = sp_300, color = "sp_300")) +
    # Add legend for line colors
    scale_color_manual(values = c("sp_100" = "red",
                                  "sp_200" = "blue",
                                  "sp_300" = "green"),
                       ) +
    # Add axis labels and plot title
    xlab("") + ylab("Percentage") +
    ggtitle(title) +
    theme_classic() +
    theme(
       axis.title = element_text(size = 11),
       title = element_text(colour = "Black", size = 12, family = "sans"),
       plot.subtitle = element_text(size = 10, hjust = 0.5),
       plot.title = element_text(hjust = 0.5),
       panel.grid.major = element_blank(),
       panel.grid.minor = element_blank(),
       panel.background = element_blank(),
       panel.border =  element_rect(colour = "gray", fill=NA, size=0.5),
          ) +
    scale_x_date(date_labels =  "%Y", date_breaks = "1 year") +
    scale_y_continuous(breaks=(seq(0, 100, 5)), limits = c(85, 100))

}

#==========================================================================#
# ----

#==========================================================================#
# ================== VAR with HAC errors  ============================== #
#==========================================================================#

# Modification of VAR from the vars package to take HAC ----
"VAR_HAC" <- function (y,
                       p = 1,
                       type = c("const", "trend", "both", "none"),
```

```
                       season = NULL,
                       exogen = NULL,
                       lag.max = NULL,
                       ic = c("AIC", "HQ", "SC", "FPE"),
                       se_type = c("HC0", "HC1", "HC2", "HC3")
                       ) {

  y <- as.matrix(y)

  if (any(is.na(y)))
    stop("\nNAs in y.\n")

  if (ncol(y) < 2)
    stop("The matrix 'y' should contain at least two variables.
         For univariate analysis consider ar() and arima() in package stat
s.\n")

  if (is.null(colnames(y))) {
    colnames(y) <- paste("y", 1:ncol(y), sep = "")
    warning(paste("No column names supplied in y, using:",
                  paste(colnames(y), collapse = ", "), ", instead.\n"))
  }

  colnames(y) <- make.names(colnames(y))
  y.orig <- y
  type <- match.arg(type)
  obs <- dim(y)[1]
  K <- dim(y)[2]
  if(!is.null(lag.max)){
    lag.max <- abs(as.integer(lag.max))
    ic <- paste(match.arg(ic), "(n)", sep = "")
    p <- VARselect(y,
                   lag.max = lag.max,
                   type = type,
                   season = season,
                   exogen = exogen)$selection[ic]
  }
  sample <- obs - p
  ylags <- embed(y, dimension = p + 1)[, -(1:K)]
  temp1 <- NULL
  for (i in 1:p) {
    temp <- paste(colnames(y), ".l", i, sep = "")
    temp1 <- c(temp1, temp)
  }
  colnames(ylags) <- temp1
  yend <- y[-c(1:p), ]
  if (type == "const") {
    rhs <- cbind(ylags, rep(1, sample))
    colnames(rhs) <- c(colnames(ylags), "const")
  }
  else if (type == "trend") {
    rhs <- cbind(ylags, seq(p + 1, length = sample))
    colnames(rhs) <- c(colnames(ylags), "trend")
  }
```

```r
  else if (type == "both") {
    rhs <- cbind(ylags, rep(1, sample), seq(p + 1, length = sample))
    colnames(rhs) <- c(colnames(ylags), "const", "trend")
  }
  else if (type == "none") {
    rhs <- ylags
    colnames(rhs) <- colnames(ylags)
  }
  if (!(is.null(season))) {
    season <- abs(as.integer(season))
    dum <- (diag(season) - 1/season)[, -season]
    dums <- dum
    while (nrow(dums) < obs) {
      dums <- rbind(dums, dum)
    }
    dums <- dums[1:obs, ]
    colnames(dums) <- paste("sd", 1:ncol(dums), sep = "")
    rhs <- cbind(rhs, dums[-c(1:p), ])
  }
  if (!(is.null(exogen))) {
    exogen <- as.matrix(exogen)
    if (!identical(nrow(exogen), nrow(y))) {
      stop("\nDifferent row size of y and exogen.\n")
    }
    if (is.null(colnames(exogen))) {
      colnames(exogen) <- paste("exo", 1:ncol(exogen),
                                sep = "")
      warning(paste("No column names supplied in exogen, using:",
                    paste(colnames(exogen), collapse = ", "), ", instead.\
n"))
    }
    colnames(exogen) <- make.names(colnames(exogen))
    tmp <- colnames(rhs)
    rhs <- cbind(rhs, exogen[-c(1:p), ])
    colnames(rhs) <- c(tmp, colnames(exogen))
  }


  datamat <- as.data.frame(rhs)
  colnames(datamat) <- colnames(rhs)
  equation <- list()
  library(estimatr)
  for (i in 1:K) {
    y <- yend[, i]
    equation[[colnames(yend)[i]]] <- lm_robust(y ~ -1 + .,
                                               data = datamat,
                                               se_type = se_type,
                                               return_vcov = T)

    if(any(c("const", "both") %in% type)){
      attr(equation[[colnames(yend)[i]]]$terms, "intercept") <- 1
    }
  }
  call <- match.call()
```

```
  if("season" %in% names(call)) call$season <- eval(season)
  result <- list(varresult = equation, datamat = data.frame(cbind(yend,
                                                                   rhs)),
                 y = y.orig,
                 type = type,
                 p = p,
                 K = K,
                 obs = sample,
                 totobs = sample + p,
                 restrictions = NULL,
                 call = call)
  class(result) <- "varest"
  return(result)
}
#==========================================================================#
# ----

#==========================================================================#
# ==================== Extended spillover table ======================== #
#==========================================================================#

# Better function for decomposition of the VAR model ----
spillover_table <- function(VAR_data = "", n.ahead = 10, no.corr = F)
  {
  spillover12 <- spilloverDY12(VAR_data, n.ahead = n.ahead, no.corr = no.c
orr)
  # Splitting the data
  split_data <- as_tibble(unlist(spillover12[1])) %>%
    group_split(gl(n()/dim(VAR_data$y)[2], dim(VAR_data$y)[2]))
  # converting the new data, to column
  new_data <- bind_cols(split_data) %>% select(starts_with("value"))
  # Renaming the columns
  colnames(new_data) <- colnames(VAR_data$y)
  # Creating spillover table
  spillover_table = new_data[] %>%
    add_column(tickers = colnames(VAR_data$y), .before = 1) %>%
    mutate_if(is.numeric,funs(.* 100)) %>%
    mutate_if(is.numeric,funs(round(.,2)))
  # Adding Contribution to others, including to it self and others
  spillover_table_2 <- rbind(rbind(spillover_table,
                                   c("Contribution to self and others",
                                     colSums(spillover_table[,-1]))),
                             c("Contribution to others",
                               colSums(spillover_table[,-1] %>%
                                         replace(., col(.) == row(.), 0)))
)

  # List of contribution to others ----
  c_to = pivot_longer(spillover_table_2[nrow(spillover_table_2),],
                      cols = everything(),
                      names_to = "tickers",
                      values_to = "contribution to others") %>%
    slice(-1) %>%
    mutate(
```

```r
    `contribution to others` = as.numeric(`contribution to others`)
  )
  # list of contrebution from others ----
  c_from = tibble(
    tickers = names(VAR_data$varresult),
    `contribution from others` = rowSums(spillover_table[,-1] %>%
                                           replace(., col(.) == row(.), 0)
)
    )
  # Complete table
  complete_spillover_table = tibble(
    spillover_table_2,
    c_from = unlist(list(c(c_from$`contribution from others`, NA, NA)))
  )
  return(complete_spillover_table)
}
#==========================================================================#
# ----

#==========================================================================#
# ========= ARMA-GARCH information criterion loop ====================== #
#==========================================================================#

# Findig optimal orders for GARCH-type model ----
opt_orders <- function(data = data, max_order = 3, type = "eGARCH"){

  data = r_all

  # Defining the range of possible orders for arma and garch
  arma_order = c(max_order,max_order)
  garch_order = c(max_order,max_order)

  # Creating a list of all the possible combinations
  orderList <- tibble(
    expand.grid(0:arma_order[1], 0:arma_order[2], 0:garch_order[1], 1:garc
h_order[2])
  ) %>%
    unite("armaOrder",
          Var1,
          Var2,
          sep = ",") %>%
    unite("garchOrder", Var3, Var4,sep = ",") %>%
    mutate(
      armaOrder = paste("c(", armaOrder, ")", sep= ""),
      garchOrder = paste("c(", garchOrder, ")", sep= ""),
    )

  # data frame to store results for all time series
  all_results <- data.frame()

  # loop through each return series
  for (i in 1:ncol(data)) {

    # data frame to store results for current time series
```

```
    results <- data.frame()

    # loop through all combinations of garch and arma order
    for (j in 1:nrow(orderList)) {

      # get garch and arma order for current combination
      go <- as.character(orderList$garchOrder[j])
      ao <- as.character(orderList$armaOrder[j])

      # create ugarchspec model for current combination
      fit.spec <- ugarchspec(variance.model = list(model = type,
                                                   garchOrder = eval(parse
(text=go))),
                             mean.model = list(armaOrder = eval(parse(text
=ao)),
                                               include.mean = TRUE),
                             distribution.model = "std"
                             )

      # fit the model to current time series
      garchfit <- ugarchfit(data = data[,i], spec = fit.spec, solver = "hy
brid")

      # retrieve the information criteria
      info <- infocriteria(garchfit)[1]

      # store results for current combination in results data frame
      results <- rbind(results,
                       data.frame(ticker = colnames(data)[i],
                                  go = go,
                                  ao = ao,
                                  info = info))
    }

    # find the order that produces the lowest information criterion
    min_results <- results %>%
      filter(info == min(results$info))

    # append the minimum results to all_results data frame
    all_results <- rbind(all_results, min_results)
  }
  return(all_results)
}

#==========================================================================#
# ----

#==========================================================================#
# ==================== Multi ARCH test ================================ #
#==========================================================================#

# ARCH-test for multiple variabels ----
multi_ARCH <- function(VAR_model = var_return_all, max_order = 10){
```

```
  arch_results <- data.frame(lags = numeric(),
                             test_stat = numeric(),
                             p_value = numeric())

  # for loop to test for ARCH effects up to 10 lags
  for (i in 1:max_order) {
    # run arch test
    arch_test <- arch.test(VAR_model, lags.multi = i, multivariate.only =
TRUE)

    # extract relevant information from arch test result
    lags <- i
    test_stat <- arch_test$arch.mul$statistic
    p_value <- arch_test$arch.mul$p.value

    # add results to data frame
    arch_results <- rbind(arch_results, data.frame(lags = lags,
                                                   test_stat = test_stat,
                                                   p_value = p_value))
  }
  return(arch_results)
}
#=========================================================================#
# ----

#==========================================================================#
# =================== Multi serial test ================================ #
#==========================================================================#

# Brush-Godfrey test for mulitple variables ----
multi_BG <- function(VAR_model = var_return_all, max_order = 10){

  BG_results <- data.frame(lags = numeric(),
                           test_stat = numeric(),
                           p_value = numeric())

  # for loop to test for ARCH effects up to 10 lags
  for (i in 1:max_order) {
    # run arch test
    serial_test <- serial.test(VAR_model, lags.bg = i, type = "BG")

    # extract relevant information from arch test result
    lags <- i
    test_stat <- serial_test$serial$statistic
    p_value <- serial_test$serial$p.value

    # add results to data frame
    BG_results <- rbind(BG_results, data.frame(lags = lags,
                                               test_stat = test_stat,
                                               p_value = p_value))
  }
  return(BG_results)
}
```

```r
#==============================================================================#
# ----

#==============================================================================#
# ===================== Multi ADF test ================================ #
#==============================================================================#

# ADF for multiple variables ----
multi_ADF <-function(series = r_all, IC = c("AIC", "HQ")){

  # Creating a list outside loop that will contain optimal lags
  results_list <- list()

  if (IC == "AIC") {
    for (i in 1:ncol(series)) {
    ts <- series[,i]
    optimal_lag_AIC  <- VARselect(ts)$selection[[1]]
    optimal_lag_HQ  <- VARselect(ts)$selection[[2]]
    adf_test <- adf.test(ts, k=opt_lag_all)

     results_list[[i]] <- data.frame(
          asset_name = colnames(series)[i],
          AIC_lag = optimal_lag_AIC,
          p_value = adf_test$p.value,
          test_statistic = adf_test$statistic
          )
  }
  results_tibble <- bind_rows(results_list)
  # results_tibble

  return(results_tibble)
  } else{

    for (i in 1:ncol(series)) {
    ts <- series[,i]
    optimal_lag_AIC  <- VARselect(ts)$selection[[1]]
    optimal_lag_HQ  <- VARselect(ts)$selection[[2]]
    adf_test <- adf.test(ts, k=opt_lag_all)

     results_list[[i]] <- data.frame(
          asset_name = colnames(series)[i],
          HQ_lag = optimal_lag_HQ,
          p_value = adf_test$p.value,
          test_statistic = adf_test$statistic
          )
  }
  results_tibble <- bind_rows(results_list)
  # results_tibble

  return(results_tibble)

  }
  # Augmented Dicky-Fuller: Unit root test with optmal lag order ----
```

```
}
#========================================================================#
# ----

#========================================================================#
# ====================== Criteria table ================================ #
#========================================================================#

# Displaying optimal lags given different types of information criterion -
---
criterion_table <- function(data = r_all, type = c("r", "v")){

  r_criterion <- data.frame(criterion = c("AIC", "HQ", "SC", "FPE"),
                   lag_all = integer(4),
                   lag_18 = integer(4),
                   lag_19 = integer(4),
                   lag_20 = integer(4),
                   lag_21 = integer(4),
                   lag_22 = integer(4))

  # iterate over criteria
  for (i in 1:4) {
    # get lag_all for criterion i
    lag_all <- vars::VARselect(data, lag.max = 10, type = "const")$selecti
on[[i]]
    # iterate over years
    for (year in c("18", "19", "20", "21", "22")) {
      # get lag for criterion i and year
      lag <- vars::VARselect(get(paste0(type, "_", year)),
                             lag.max = 10,
                             type = "const")$selection[[i]]
      # fill in data.frame
      r_criterion[i, paste0("lag_", year)] <- lag
    }

    # fill in lag_all column
    r_criterion[i, "lag_all"] <- lag_all

  }
  return(r_criterion)
}
#========================================================================#
# ----

#========================================================================#
# ============== Display significant values of VAR ===================== #
#========================================================================#

# Extracting p-values from the VAR model----
VAR_signif <- function(VAR_model = var_return_all){

  coef <- as_tibble(coef(VAR_model))

  p_values <- as_tibble(lapply(coef, "[", , "Pr(>|t|)"))
```

```
  p_values <- p_values %>%
    mutate(colnames(VAR_model$datamat)[49:(length(VAR_model$datamat))], .b
efore = 1)

  p_values <- p_values %>% rename("Regressor" = colnames(p_values[,1]))

  return(p_values)
}
# ==========================================================================#
# ----

#===========================================================================#
# ==================== Rolling Spillovers ============================== #
#===========================================================================#

# Function for making a tibble of rolling spillvoers ----
rolling_spillovers <- function(r_series = r_all){

  opt_lag_all = vars::VARselect(r_series, lag.max = 10, type = "const")$se
lection[2]

  # Generating rolling data ----
  time_all <- as.character(as.Date(data[-1,]$Date, "%Y,%M,%D", tz = "UTC")
)

  # Add the dates as an index to the return series
  rownames(r_series) <- time_all

  # set the estimate parameters for the rolling window
  params_est = list(p = opt_lag_all, type = "const")


  # Get the rolling window estimates
  sp_return_300 <- spilloverRollingDY12(r_series,
                                        n.ahead = 10,
                                        no.corr = F,
                                        "VAR",
                                        params_est = params_est,
                                        window = 300)

  sp_return_200 <- spilloverRollingDY12(r_series,
                                        n.ahead = 10,
                                        no.corr = F,
                                        "VAR",
                                        params_est = params_est,
                                        window = 200)

  sp_return_100 <- spilloverRollingDY12(r_series,
                                        n.ahead = 10,
                                        no.corr = F,
                                        "VAR",
                                        params_est = params_est,
                                        window = 100)
```

```r
  sp_100 <- data.frame(
    date = data$Date[(100+1):length(data$Date)],
    sp_100 = overall(sp_return_100)
  )
  names(sp_100)[2] <- "sp_100"

  sp_200 <- data.frame(
    date = data$Date[(200+1):length(data$Date)],
    sp_200 = overall(sp_return_200)
  )
  names(sp_200)[2] <- "sp_200"

  sp_300 <- data.frame(
    date = data$Date[(300+1):length(data$Date)],
    sp_300 = overall(sp_return_300)
  )
  names(sp_300)[2] <- "sp_300"

  # Combine the data frames using bind_rows()
  combined_data <- bind_rows(sp_100, sp_200, sp_300)

  # Group by date and calculate sum of numbers for each date
  result <- combined_data %>%
              group_by(date) %>%
              summarize(sp_100 = sum(sp_100, na.rm = TRUE),
                        sp_200 = sum(sp_200, na.rm = TRUE),
                        sp_300 = sum(sp_300, na.rm = TRUE)) %>%
              # Replace 0 values with NA
              mutate_all(~ replace(., . == 0, NA))
  return(result)
}
#==========================================================================#
# ----

#==========================================================================#
# ================== Similarity index ================================== #
#==========================================================================#

# Test similarity index ----
similarity_index <- function(A, B) {
  n <- length(A)
  ranks_A <- sapply(A, function(x) match(x, B))
  ranks_B <- 1:n
  distances <- abs(ranks_A - ranks_B)
  similarities <- 1 - distances / pmax(n - ranks_B, ranks_B - 1)
  mean(similarities)
}


# Function for repeated minimum return similarity index
similarity_index_min <- function(listA, listB, n_reps) {
  min_sim_index <- Inf
```

```
  for (i in 1:n_reps) {
    listB <- sample(listA)
    sim_index <- similarity_index(listA, listB)
    if (sim_index < min_sim_index) {
      min_sim_index <- sim_index
    }
  }
  return(min_sim_index)
}

#==========================================================================#
# ----

# ======================================================================== #
# ================ Descriptive statistics ============================== #
# ======================================================================== #

descriptives <- descriptive_table(r_all)


# Statistics quantile table for full period ----
quantile_full <- tibble(
  Quantile = c("25%", "50%", "75%"),
  Mean = round(quantile(descriptives$Mean, c(0.25,0.5,0.75)),2),
  StdDev = round(quantile(descriptives$StdDev, c(0.25,0.5,0.75)),2),
  Min = round(quantile(descriptives$Min, c(0.25,0.5,0.75)),2),
  Max = round(quantile(descriptives$Max, c(0.25,0.5,0.75)),2),
  Kurtosis = round(quantile(descriptives$Kurtosis, c(0.25,0.5,0.75)),2),
  Skewness = round(quantile(descriptives$Skewness, c(0.25,0.5,0.75)),2),
  Sharpe = round(quantile(descriptives$Sharpe, c(0.25,0.5,0.75)),2)
)

# Correlations ----
m_all = cor(r_all, method = "spearman")

# Print plot
corr_plot(m_all)



#  The equally weighted index ----

# Create a date object outside loop
EW_index <- data.frame(date = data[,1])

# Iterate and make Equally weighted index
for (i in 1:nrow(data[,-1])) {
  indx <- sum(data[i,-1])/ncol(data[,-1])
  EW_index[i,2] <- indx
}

# Get natural log returns
EW_index_return <- EW_index %>% mutate(across(2:ncol(.), ~ (log(.x / lag(.
x))))) %>% slice(-1)
```

```
# Combine date, returns, and index
data <- data.frame(
  Year = EW_index[,1][1:(length(EW_index$V2)-1)],
  Volatility = EW_index_return$V2,
  Index = EW_index$V2[1:(length(EW_index$V2)-1)]
)

# construct separate plots for each series
obj1 <- xyplot(Volatility ~ Year, data, type = "l" , lwd=1.5, col="#42D0E1
")
obj2 <- xyplot(Index ~ Year, data, type = "l", lwd=1.5, col="#343232")

# Make the plot with second y axis:
EW_plot <- doubleYScale(obj1, obj2, add.ylab2 = TRUE)

#==========================================================================#
# =================== VAR model Returns ================================ #
#==========================================================================#

# IC criteria for VAR models ----
p = 2 # AIC(n):1,   HQ(n):2,  SC(n):3,  FPE(n): 4

# Selecting optimal lag order for the VAR model, given "p" ----
opt_lag_all = vars::VARselect(r_all, lag.max = 10, type = "const")$selecti
on[p]
opt_lag_18 = vars::VARselect(r_18, lag.max = 10, type = "const")$selection
[p]
opt_lag_19 = vars::VARselect(r_19, lag.max = 10, type = "const")$selection
[p]
opt_lag_20 = vars::VARselect(r_20, lag.max = 10, type = "const")$selection
[p]
opt_lag_21 = vars::VARselect(r_21, lag.max = 10, type = "const")$selection
[p]
opt_lag_22 = vars::VARselect(r_22, lag.max = 10, type = "const")$selection
[p]

# Returning optimal lag orders for all samples ----
VAR_Return_lags <- criterion_table(data = r_all, type = "r")

# Estimation of VAR model fro return series ----
var_return_all = vars::VAR(r_all, p = opt_lag_all, type = "const")
var_return_18 = vars::VAR(r_18, p = opt_lag_18, type = "const")
var_return_19 = vars::VAR(r_19, p = opt_lag_19, type = "const")
var_return_20 = vars::VAR(r_20, p = opt_lag_20, type = "const")
var_return_21 = vars::VAR(r_21, p = opt_lag_21, type = "const")
var_return_22 = vars::VAR(r_22, p = opt_lag_22, type = "const")

# Estimation of VAR model Including HAC ----
var_return_all_HAC = VAR_HAC(r_all, p = opt_lag_all, type = "const", se_ty
pe = "HC2")
var_return_18_HAC = VAR_HAC(r_18, p = opt_lag_18, type = "const", se_type
= "HC2")
var_return_19_HAC = VAR_HAC(r_19, p = opt_lag_19, type = "const", se_type
```

```
= "HC2")
var_return_20_HAC = VAR_HAC(r_20, p = opt_lag_20, type = "const", se_type
= "HC2")
var_return_21_HAC = VAR_HAC(r_21, p = opt_lag_21, type = "const", se_type
= "HC2")
var_return_22_HAC = VAR_HAC(r_22, p = opt_lag_22, type = "const", se_type
= "HC2")

# Extracting p-values from the VAR model----
var_pvals <- VAR_signif(VAR_model = var_return_all_HAC)

# Show only significant values as % of total observations ----
signif_VAR_return <- VAR_signif(VAR_model = var_return_all_HAC) %>%
  mutate(across(-1, ~ ifelse(. <= 0.05, ., NA))) %>%
  summarize(across(everything(), ~ sum(!is.na(.))/n()*100, .names = "{.col
}")) %>%
  pivot_longer(everything(), names_to = "Regressors", values_to = "Percent
age") %>% slice(-1) %>%
  arrange(desc(Percentage))


# ==================================================================== #
# ================== Diagnostics for return ============================ #
# ==================================================================== #

# Augemted Dick Fuller test on the returns ----
adf_test <- multi_ADF(series = r_all, IC="AIC")

# Serial correlation ----
serial_test_all <- multi_BG(var_return_all, max_order = 10)

# Heteroskedasticity ----
arch_test <- multi_ARCH(var_return_all, max_order = 10)

# Normal distribution of the residuals ----
norm_test_all <- normality.test(var_return_all, multivariate.only = TRUE)

norm_test_tibble <- tibble(
  Values = c("test statistic", "p-value"),
  JB_Test = c(norm_test_all$jb.mul$JB$statistic, norm_test_all$jb.mul$JB$p
.value),
  kurtosis = c(norm_test_all$jb.mul$Kurtosis$statistic, norm_test_all$jb.m
ul$Kurtosis$p.value),
  skewness = c(norm_test_all$jb.mul$Skewness$statistic, norm_test_all$jb.m
ul$Skewness$p.value)
)


# Testing for structural breaks in the residuals of the VAR model ----
stability_test <- stability(var_return_all, type = "OLS-CUSUM")

# List outside loop
stability_plots <- list()
# OLS-based CUSUM test
```

```r
for (i in stability_test$names){
  stability_plots[[i]] <- plot(stability_test$stability[[i]], main = i)
}

#==========================================================================#
# ===================== Return Spillovers ============================== #
#==========================================================================#

# Creating spillover talbes for all periods ----
spillovertb_all = spilloverDY12(var_return_all, n.ahead = 10, no.corr = F)
spillovertb_18 = spilloverDY12(var_return_18, n.ahead = 10, no.corr = F)
spillovertb_19 = spilloverDY12(var_return_19, n.ahead = 10, no.corr = F)
spillovertb_20 = spilloverDY12(var_return_20, n.ahead = 10, no.corr = F)
spillovertb_21 = spilloverDY12(var_return_21, n.ahead = 10, no.corr = F)
spillovertb_22 = spilloverDY12(var_return_22, n.ahead = 10, no.corr = F)

# Making a spillover table object (returning tibble)
spillover_table_return <- spillover_table(VAR_data = var_return_all, n.ahe
ad = 10, no.corr = F)
spillover_index <- round(sum(spillover_table_return[1:48,50])/48,2)


#==========================================================================#
# ==================== Rolling Spillovers ============================== #
#==========================================================================#

# Getting rolling spillover data for 100, 200, and 300 rolling days ----
# rolling_return <- rolling_spillovers(r_series = r_all)

# Retrieving pre-saved rollover data
rolling_return <- read_excel("rolling_spillover_return.xlsx", sheet = "rol
ling_spillover")

# Plotting rolling spillover
rolling_spillover_graph <- rolling_spillover_plot(data = rolling_return, t
itle = "Total return spillover index")

# Printing graph
rolling_spillover_graph

#==========================================================================#
# ====================== Marginal model ================================ #
#==========================================================================#

# # Optimal orders for all GARCH-type models.
# gna_order <- opt_orders(data = r_all, max_order = 1, type = "eGARCH")

# Loading pre-estimated optimal orders ----
gna_order <- read_excel("InfoCriteria_results.xlsx", sheet = "AIC OR HQC")

# Initializing a list to store the GARCH model results (Outside loop)
garch_results <- list()

for (i in 1:nrow(gna_order)) {
```

```
  # Extract the garchOrder and armaOrder values and convert them to numeri
c vectors
  garchOrder_vec <- as.numeric(strsplit(gsub("c\\(|\\)", "", gna_order$gar
chOrder[i]), ",")[[1]])
  armaOrder_vec <- as.numeric(strsplit(gsub("c\\(|\\)", "", gna_order$arma
Order[i]), ",")[[1]])

  # Create a row_spec object for the current row of gna_order
  row_spec <- ugarchspec(variance.model = list(model = "eGARCH",
                                               garchOrder = garchOrder_vec
),
                         mean.model = list(armaOrder = armaOrder_vec,
                                           include.mean = TRUE),
                         distribution.model = "std")
  # Fit the GARCH model for the i-th column
  garch_results[[i]] <- ugarchfit(data = r_all[,i], spec = row_spec)
}

# Assign the results to garch_results_i
for (i in 1:ncol(r_all)) {
  assign(paste0("garch_results_", i), garch_results[[i]])
}

# Returning P-values or Estimates for GARCH model ----

# function to generate tibble for each garch result
generate_tibble <- function(result) {
  coef_names <- names(result@fit$coef)
  Estimats <- round(as.tibble(result@fit$robust.matcoef)[, 1],4)
  p_values <- round(as.tibble(result@fit$robust.matcoef)[, 4],4)
  tibble(coef_names, Estimats, p_values)
}

# generate a list of tibbles using the generate_tibble function
tibble_list <- map(garch_results, generate_tibble)

# Create a function that takes a tibble and returns it grouped by `coef_na
mes`
group_by_coef_names <- function(tib, select = "Estimate") {
  tib %>%
    group_by(coef_names) %>%
    summarise_at(vars(contains(select)), mean, na.rm = TRUE)
}

# Use purrr::reduce to apply the function to all tibbles in the list, comb
ining them into one tibble
combined_tibble <- purrr::reduce(tibble_list, full_join, by = "coef_names"
) %>%
  group_by_coef_names() %>%
  rename_with(~gsub(".USD", "", colnames(r_all)), -coef_names)

#==========================================================================#
# ================ Marginal model diagnostics ======================== #
```

```
#=========================================================================#

# Loop over the garch_results_i objects and extract the residuals
for (i in 1:48) {
  # Extract the ith garch_results_ object
  fit_opt <- get(paste0("garch_results_", i))

  # Extract the residuals from the ith ugarchfit object
  resid_opt <- residuals(fit_opt, standardize = TRUE)

  # Store the residuals in a separate object named resid_i
  assign(paste0("resid_opt_", i), resid_opt)
}

# Autocorrelation (Ljung-Box Tests) ----
# Create an empty data frame to store the p-values
Box_results <- data.frame(
  ticker = character(),
  statistic = numeric(),
  p.value = numeric(),
  stringsAsFactors = FALSE
)

# Loop over the residuals and run the Box test
for (i in 1:48) {
  # Extract the ith residual vector
  resid <- get(paste0("resid_opt_", i))

  # Run the Box test on the ith residual vector
  box_test <- Box.test(resid^2, lag = min(10,48/2), type = "Ljung-Box")

  # Append the p-value to the data frame
  Box_results <- rbind(Box_results,
                           data.frame(ticker = colnames(r_all)[i],
                                      statistic = box_test[[1]],
                                      p.value = box_test$p.value,
                                      stringsAsFactors = FALSE
                                      )
                           )
}

# Normality test ----

# Create an empty data frame to store the results
shapiro_results <- data.frame(ticker = character(), statistic = numeric(),
p.value = numeric())

for (i in 1:48) {  # replace `n` with the number of objects you have
  # Perform Shapiro-Wilk test on the i-th object
  shapiro <- shapiro.test(as.vector(get(paste0("resid_opt_", i))))

  # Store the results in the data frame
  shapiro_results <- rbind(shapiro_results, data.frame(ticker = colnames(r
_all)[i],
```

```
                                                              statistic = shapiro
$statistic,
                                                              p.value = shapiro$p
.value
                                                              )
                           )
}

#========================================================================
======#
# ================== Retrieving volatility component ===================
===== #
#========================================================================
======#

# Initialising empty matrix to store the results
volatilities = matrix(nrow = nrow(r_all), ncol = ncol(r_all))

# Extracting the volatility component of every garch model
for (i in 1:ncol(r_all)) {
  # Extract the conditional standard deviation from the i-th fitted GARCH
model
  volatilities[,i] <- garch_results[[i]]@fit$sigma
}

# Assign the matrix to the object volatilities
volatilities <- as.data.frame(volatilities)
names(volatilities) <- colnames(r_all)
volatilities <- cbind(date = data[,1], volatilities)

# Convert date column to a format that only shows the year
volatilities$year <- format(volatilities$date, "%Y")

# Create a list of data frames, one for each year
df_list <- split(volatilities, volatilities$year)

# Create separate data frames for each year
v_all <- as.data.frame(volatilities) %>% select(-c(date, year))
v_18 <- df_list$`2018` %>% select(-c(date, year))
v_19 <- df_list$`2019` %>% select(-c(date, year))
v_20 <- df_list$`2020` %>% select(-c(date, year))
v_21 <- df_list$`2021` %>% select(-c(date, year))
v_22 <- df_list$`2022` %>% select(-c(date, year))

# =====================================================================
# ----

#========================================================================
======#
# ======================= VAR model of volatilities ====================
===== #
#========================================================================
======#
```

```r
#  AIC(n):1,   HQ(n):2,  SC(n):3,  FPE(n): 4
p = 2

# Selecting lag length for VAR model ----
#' 1: AIC
opt_vol_lag_all = vars::VARselect(v_all, lag.max = 10, type = "const")$sel
ection[p]
opt_vol_lag_18 = vars::VARselect(v_18, lag.max = 10, type = "const")$selec
tion[p]
opt_vol_lag_19 = vars::VARselect(v_19, lag.max = 10, type = "const")$selec
tion[p]
opt_vol_lag_20 = vars::VARselect(v_20, lag.max = 10, type = "const")$selec
tion[p]
opt_vol_lag_21 = vars::VARselect(v_21, lag.max = 10, type = "const")$selec
tion[p]
opt_vol_lag_22 = vars::VARselect(v_22, lag.max = 10, type = "const")$selec
tion[p]


# Showcasing the criterion ----
VAR_Volatility_lags <- criterion_table(data = v_all, type = "v")

# ====================================
# Adding the volatilities to the VAR model ----
var_vol_all <- VAR(v_all, p = opt_vol_lag_all, type = "const")
var_vol_18 <- VAR(v_18, p = opt_vol_lag_18, type = "const")
var_vol_19 <- VAR(v_19, p = opt_vol_lag_19, type = "const")
var_vol_20 <- VAR(v_20, p = opt_vol_lag_20, type = "const")
var_vol_21 <- VAR(v_21, p = opt_vol_lag_21, type = "const")
var_vol_22 <- VAR(v_22, p = opt_vol_lag_22, type = "const")

# Estimation of VAR model Including HAC ----
var_vol_all_HAC = VAR_HAC(v_all, p = opt_vol_lag_all, type = "const", se_t
ype = "HC2")
var_vol_18_HAC = VAR_HAC(v_18, p = opt_vol_lag_18, type = "const", se_type
= "HC2")
var_vol_19_HAC = VAR_HAC(v_19, p = opt_vol_lag_19, type = "const", se_type
= "HC2")
var_vol_20_HAC = VAR_HAC(v_20, p = opt_vol_lag_20, type = "const", se_type
= "HC2")
var_vol_21_HAC = VAR_HAC(v_21, p = opt_vol_lag_21, type = "const", se_type
= "HC2")
var_vol_22_HAC = VAR_HAC(v_22, p = opt_vol_lag_22, type = "const", se_type
= "HC2")



# Extracting p-values from the VAR model----
var_v_pval <- VAR_signif(VAR_model = var_vol_all_HAC)

# Show only significant values as % of total observations ----
signif_VAR_Volatility <- VAR_signif(VAR_model = var_vol_all_HAC) %>%
  mutate(across(-1, ~ ifelse(. <= 0.05, ., NA))) %>%
```

```
  summarize(across(everything(), ~ sum(!is.na(.))/n()*100, .names = "{.col
}")) %>%
  pivot_longer(everything(), names_to = "Regressors", values_to = "Percent
age") %>% slice(-1) %>%
  arrange(desc(Percentage))

#=========================================================================
======#
# ==================== Diagnostics for volatility VAR ===================
===== #
#=========================================================================
======#

# Augemted Dick Fuller test on the returns ----
adf_test <- multi_ADF(series = v_all, IC="AIC")

# Serial correlation ----
serial_test_all <- multi_BG(var_vol_all, max_order = 10)

# Heteroskedasticity ----
arch_test_vol <- multi_ARCH(var_vol_all, max_order = 10)

# Normal distribution of the residuals ----
norm_test_vol <- normality.test(var_vol_all, multivariate.only = TRUE)

norm_test_tibble_vol <- tibble(
  Values = c("test statistic", "p-value"),
  JB_Test = c(norm_test_vol$jb.mul$JB$statistic, norm_test_vol$jb.mul$JB$p
.value),
  kurtosis = c(norm_test_vol$jb.mul$Kurtosis$statistic, norm_test_vol$jb.m
ul$Kurtosis$p.value),
  skewness = c(norm_test_vol$jb.mul$Skewness$statistic, norm_test_vol$jb.m
ul$Skewness$p.value)
)


# Structural breaks in the residuals of the VAR model ----
stability_vol_test <- stability(var_vol_all, type = "OLS-CUSUM")

# List outside loop
stability_plots_vol <- list()
# OLS-based CUSUM test
for (i in stability_vol_test$names){
  stability_plots[[i]] <- plot(stability_vol_test$stability[[i]], main = i
)
}

#=========================================================================#
# ================ Volatility Spillovers ============================== #
#=========================================================================#

# Creating spillover talbes for all periods ----
spillovertb_all = spilloverDY12(var_return_all, n.ahead = 10, no.corr = F)
spillovertb_18 = spilloverDY12(var_return_18, n.ahead = 10, no.corr = F)
```

```
spillovertb_19 = spilloverDY12(var_return_19, n.ahead = 10, no.corr = F)
spillovertb_20 = spilloverDY12(var_return_20, n.ahead = 10, no.corr = F)
spillovertb_21 = spilloverDY12(var_return_21, n.ahead = 10, no.corr = F)
spillovertb_22 = spilloverDY12(var_return_22, n.ahead = 10, no.corr = F)

# Making a spillover table object (returning tibble)
spillover_table_volatility <- spillover_table(VAR_data = var_vol_all, n.ah
ead = 10, no.corr = F)

#==========================================================================#
# ==================== Rolling Spillovers ============================== #
#==========================================================================#

# loading previously computed rolling computations  from Excel sheet
rolling_spillover_data_vol <- read_excel("rolling_spillover_volatility.xls
x", sheet = "rolling_spillover")

# Plotting rolling spillover
rolling_spillover_graph_vol <- rolling_spillover_plot(data = rolling_spill
over_data_vol,
                                                      title = "Total retur
n spillover index")

# Printing graph
rolling_spillover_graph_vol

#==========================================================================#
# ================== Exploratory analysis ============================== #
#==========================================================================#

# Displaying largest contributors of spillover shocks ----

spillover_table__all <- spillover_table(VAR_data = var_vol_all, n.ahead =
10, no.corr = F)
spillover_table__18 <- spillover_table(VAR_data = var_vol_18, n.ahead = 10
, no.corr = F)
spillover_table__19 <- spillover_table(VAR_data = var_vol_19, n.ahead = 10
, no.corr = F)
spillover_table__20 <- spillover_table(VAR_data = var_vol_20, n.ahead = 10
, no.corr = F)
spillover_table__21 <- spillover_table(VAR_data = var_vol_21, n.ahead = 10
, no.corr = F)
spillover_table__22 <- spillover_table(VAR_data = var_vol_22, n.ahead = 10
, no.corr = F)

c_all <- tibble(
  tickers = colnames(r_all),
  c_to = as.double(unlist(spillover_table__all[nrow(spillover_table__all),
][2:49]))
) %>% arrange(desc(c_to))

c_18 <- tibble(
  tickers = colnames(r_all),
  c_to = as.double(unlist(spillover_table__18[nrow(spillover_table__18),][
```

```
2:49]))
) %>% arrange(desc(c_to))

c_19 <- tibble(
  tickers = colnames(r_all),
  c_to = as.double(unlist(spillover_table__19[nrow(spillover_table__19),][
2:49]))
) %>% arrange(desc(c_to))

c_20 <- tibble(
  tickers = colnames(r_all),
  c_to = as.double(unlist(spillover_table__20[nrow(spillover_table__20),][
2:49]))
) %>% arrange(desc(c_to))

c_21 <- tibble(
  tickers = colnames(r_all),
  c_to = as.double(unlist(spillover_table__21[nrow(spillover_table__21),][
2:49]))
) %>% arrange(desc(c_to))

c_22 <- tibble(
  tickers = colnames(r_all),
  c_to = as.double(unlist(spillover_table__22[nrow(spillover_table__22),][
2:49]))
) %>% arrange(desc(c_to))


# Create a combined tibble with all the data
combined <- bind_rows(list(
  Static = c_all,
  `2018` = c_18,
  `2019` = c_19,
  `2020` = c_20,
  `2021` = c_21,
  `2022` = c_22
), .id = "id")

# Group by ticker and id, and filter to keep only the top 3 c_to values
top <- combined %>%
  group_by(id) %>%
  top_n(3, c_to)

# Removing -USD from tickers
top$tickers <- gsub("-USD", "", top$tickers)

# plot the data
ggplot(top, aes(x = id, y = c_to, label = tickers, color = tickers)) +
  geom_point(size = 3) +
  geom_text_repel(size = 2.5, nudge_y = 2, box.padding = 0.5, point.paddin
g = 0.5) +
  labs(x = "Period", y = "Percentage", title = "") +
  theme_classic() +
  guides(color = FALSE)
```

```r
#==========================================================================#
# ================== Exploring similarities ============================ #
#==========================================================================#


# Creating a list of all the lists
c_lists <- list(c_all$tickers, c_18$tickers, c_19$tickers, c_20$tickers, c
_21$tickers, c_22$tickers)

# Create an empty matrix to store the results
results_matrix <- matrix(nrow = length(c_lists), ncol = length(c_lists))

# set the column and row names to the names of the c_..$tickers lists
colnames(results_matrix) <- paste0("c_", 1:length(c_lists), ".tickers")
rownames(results_matrix) <- paste0("c_", 1:length(c_lists), ".tickers")
colnames(results_matrix) <- rownames(results_matrix) <- c("all", "18", "19
", "20", "21", "22")

# iterate through all the combinations and calculate the similarity index
for (i in 1:length(c_lists)) {
  for (j in 1:length(c_lists)) {
    results_matrix[i,j] <- similarity_index(c_lists[[i]], c_lists[[j]])
  }
}

# Only show lower triangle of the matrix
results_matrix[upper.tri(results_matrix)] <- 0

# Set diagonal elements to 0
diag(results_matrix) <- 0

# Preview matrix
results_matrix


#===========================================================================#
# ================== Random order simulation ============================ #
#===========================================================================#

# Simulating lowest possible similarity index ----

# Generate a list of 48 letters ----
listi <-c(LETTERS, paste0(rep(LETTERS, 26), LETTERS))[1:48]

# Sample list A be such that it is a permutation of A
listj <- sample(listi)

# Find the minimum value of the similarity index for n random permutations
similarity_index_min(listi, listj, n_reps = 100000)
```

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