CHARLES UNIVERSITY
FACULTY OF SOCIAL SCIENCES
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Connectedness between Stocks of Cryptocurrency-linked US companies and the Cryptocurrency market.

Bachelor's thesis

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Declaration of Authorship

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Prague, August 1, 2023

Tomáš Šamaj

Abstract

This Bachelor's thesis studies connectedness effects between returns of US-listed cryptocurrency-linked stocks (CLS), the traditional US stock market, and major cryptocurrencies. We present results of connectedness measures obtained by utilizing the Dynamic Networks framework. Our dataset contains daily returns of 20 CLS, the stock market index S&P 500 and five major cryptocurrencies, with a time span ranging from September 2021 to July 2023. The connectedness measures indicate a significant total connectedness among variables within the system, across the whole time span. We also present directional connectedness measures for individual variables and decompose the total connectedness into time horizons. We report the short-term horizon of connectedness effects between 1-5 days to be the most significant. Finally, we build Ordinary Least Squares (OLS) regressions for CLS returns and find connectedness measures to influence returns of CLS with high exposure to the cryptocurrency market most significantly.

Keywords Connectedness effects of returns, Cryptocurrencies, Bitcoin, Dynamic Networks, Cryptocurrency-linked stocks, Stock market

Title Connectedness between Stocks of Cryptocurrency-linked US companies and the Cryptocurrency market.

Abstrakt

Tato bakalářská práce zkoumá efekty propojenosti mezi výnosy akcií s vazbou na kryptoměny obchodovaných v USA (CLS), americkým akciovým trhem a největšími kryptoměnami. Prezentujeme výsledky míry propojenosti získané pomocí metodologie Dynamic Networks. Náš soubor dat obsahuje denní výnosy 20 CLS, indexu akciového trhu S&P 500 a pěti největších kryptoměn, s časovým rozpětím od září 2021 do července 2023. Míry propojenosti naznačují významnou celkovou propojenost mezi proměnnými v rámci systému po celou dobu sledování. Dále předkládáme směrově závislé míry propojenosti pro jednotlivé proměnné a rozklad celkové propojenosti na časové horizonty. Uvádíme, že nejsignifikantnější je krátkodobý horizont efektů propojenosti mezi 1-5 dny. Nakonec budujeme Ordinary Least Squares (OLS) regrese pro výnosy CLS a zjišťujeme, že míry propojenosti mají nejsignifikantnější vliv na výnosy CLS s vysokou expozicí na trh s kryptoměnami.

Klíčová slova Účinky propojenosti výnosů, Kryptoměny, Bitcoin, Síťová struktura, Akcie s vazbou na kryptoměny, Akciový trh

Název práce Propojenost mezi akciemi společností s vazbou na kryptoměny v USA a kryptoměnovým trhem.

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Acronyms

CLS Cryptocurrency-linked Stocks (Stocks of companies with a significant exposure towards the cryptocurrency market)

VAR Vector Autoregression

TVP-VAR Time-varying Parameter Vector Autoregression

VMA Vector Moving Average

QBLL Quasi-Bayesian Local-Likelihood methods for estimation of TVP-VAR models

US United States of America

FVED Forecast Error Variance Decomposition

OLS Ordinary Least Squares

BTC Bitcoin

ETH Ethereum

BNB Binance Coin

XRP Ripple XRP

ADA Cardano

USDT Tether

USDC USD Coin

SPY S&P 500 Stock Market Index

ARBK Argo Blockchain plc

BITF Bitfarms Ltd.

BTBT Bit Digital Inc.

CAN Canaan Inc.

CIFR Cipher Mining Inc.

CLSK CleanSpark Inc.

EBON Ebang International Holdings Inc.

GREE Greenidge Generation Holdings Inc.

HIVE HIVE Blockchain Technologies Ltd.

HUT Hut 8 Mining Corp.

MARA Marathon Digital Holdings Inc.

NCTY The9 Limited

RIOT Riot Platforms Inc.

BKKT Bakkt Holdings Inc.

COIN Coinbase Global Inc.

MSTR MicroStrategy Inc.

SQ Block Inc.

FTFT Future FinTech Group Inc.

OSTK Overstock.com Inc.

PYPL PayPal Holdings Inc.

Bachelor’s Thesis Proposal

Author	Tomáš Šamaj
Supervisor	Mgr. Jan Šíla MSc.
Proposed topic	Connectedness between Stocks of Cryptocurrency-linked US companies and the Cryptocurrency market.

Research question and motivation The main research question that I would like to study is the connectedness between stocks of companies with high exposure to the cryptocurrency market and the cryptocurrency market itself.

The popularity of cryptocurrencies is growing rapidly, still following the trend of the last few years. Thus, it is not surprising that the biggest cryptocurrencies (especially Bitcoin), as well as the underlying technology of blockchain, attracted many companies that in some way started to participate in the crypto market. As a result, a few companies with high exposure to the cryptocurrency market went public in previous years, such as BITF and COIN (both had an IPO on Nasdaq in 2021). But there are also some companies with high crypto exposure that have been historically listed on stock exchanges (e.g. MSTR was listed on Nasdaq in 1998). These companies would provide valuable examples for studying desired effects in a longer timeframe.

Studying these effects might be interesting since the crypto sector is known for its volatility and unexplored methods of valuation [1]. Thus, the main motivation lies in contributing to research in the unexplored field of cryptocurrencies. My research could provide useful findings about the valuation and risk management of crypto-exposed companies.

In my thesis, I would like to study spillover effects of shocks in returns and volatility between cryptocurrency-linked stocks (CLS) and the crypto market. Previous research [2] studied these effects on publicly listed Australian companies but is missing in the context of crypto. My bachelor’s thesis would follow conceptually the previous research by examining the effects on US-listed companies and crypto, thus working with a potentially larger dataset, and describing findings about the biggest stock market worldwide. Recent research [12] examined jumps and co-jumps between Blockchain and crypto-exposed US companies and major cryptocurrencies, which further motivates my topic.

Contribution The main contribution of this thesis would be the examination of return and volatility spillover effects of the cryptocurrency market and US-listed CLS. I aim to model the dynamics between the volatile crypto market and traditional stocks and drivers of valuation of CLS. By doing so, my thesis would enlarge previous research, which is limited only to Australian companies. However, recent research examined jumps and co-jumps of CLS and cryptocurrencies also in the US. The thesis would also contribute by studying the relatively unexplored field of cryptocurrencies (especially the field of valuation of CLS and examination of volatility effects in the cryptocurrency market).

Methodology The work will examine the spillover effect using Dynamic Networks [10,11,13], a novel methodology expanding a widely used Diebold-Yilmaz framework [3,4,5]. The Diebold-Yilmaz framework is a vector autoregression system (VAR system), which is a statistical model used to capture relationships between multiple variables that change over time. Since I aim to study multiple variables, a VAR system is an appropriate choice. Based on published literature [10,11,13], I will build a Dynamic Network system, which models this dynamic and should indicate to us, whether these CLS are driven more by traditional stocks or by the cryptocurrency market. The results will have implications for the valuation and risk management of studied CLS. For my research I would like to use data about several US-listed CLS (e.g., COIN, MSTR, BITF), US stock indices (e.g., S&P 500, NASDAQ), biggest cryptocurrencies (BTC, ETH, BNB, ADA) and crypto-market indices.

Outline

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Author Supervisor

Chapter 1

Introduction

Since Nakamoto (2009) introduced Bitcoin, the first widely used cryptocurrency that was created as a reaction to the global financial crisis of 2008, numerous projects (e.g. Ethereum, Cardano, Litecoin, or Ripple) have tried to replicate its unprecedented success. These cryptocurrencies are built on the underlying technology of blockchain, which utilizes a transparent distributed ledger system to record and verify peer-to-peer transactions. Consequently, these digital currencies offer an alternative to the traditional, highly centralized financial system by allowing users to transfer money without the use of banking systems and financial institutions. Over the last fifteen years, Bitcoin, together with other major cryptocurrencies, has experienced a boom among users, which naturally caught the attraction of many businesses that ventured into the field of cryptocurrencies.

Nowadays, stocks of several publicly traded businesses with linkages to cryptocurrencies (cryptocurrency-linked stocks or CLS) can also be found on the US stock market. However, these assets represent a bridge between two financial markets with significant differences. In comparison to the cryptocurrency market, the traditional US stock market is highly regulated and overseen by government agencies such as the U.S. Securities and Exchange Commission. Moreover, the US stock market represents a very mature financial market with a centuries-long history, while cryptocurrency markets emerged less than fifteen years ago. Other main distinctions include the different trading hours of stocks, which are usually traded during regular business hours, whereas cryptocurrencies are traded continuously, including public holidays and weekends. These dissimilarities between the two markets pose severe challenges for the multifaceted analysis of CLS returns dynamics.

Therefore, this Bachelor's thesis aims to contribute to the unexplored area of valuing publicly traded companies with links to the cryptocurrency market by examining the return connectedness between CLS and major cryptocurrencies, as well as the traditional stock market. In other words, we examine the influences of the traditional US stock market and the cryptocurrency market on the returns of CLS.

The reciprocal influences across different financial markets and assets can be characterized by examining connectedness measures of their returns. These measures (sometimes referred to as return spillovers) quantify the interdependence and shock transmission across financial markets and assets. Several methods and frameworks for such connectedness measures have been introduced by researchers in the past. Baruník & Křehlík (2018) elaborate on a frequently used methodology for spillover effect measurement proposed by Diebold & Yilmaz (2012) by introducing horizon-specific measurements, which allow distinguishing between long-, medium- and short-term connectedness within the system. Barunik & Ellington (2020b) introduce a novel methodology Dynamic Networks, that employs time-varying parameter vector autoregression (TVP-VAR) to estimate dynamic measures of network connectedness at each point in time. The TVP-VAR model allows for changes in vector autoregression coefficients over time and thus captures dynamic relationships between variables and replaces Rolling window estimations. Additionally, the utilization of the Quasi-Bayesian local-likelihood approach (QBLL) following Petrova (2019) allows us to obtain confidence intervals for the dynamic connectedness measures.

Previous research by Frankovic *et al.* (2022) studied return and volatility spillover effects between Australian-listed CLS and the cryptocurrency market by following the methodology of Diebold & Yilmaz (2012). However, there has been no academic research addressing a similar analysis for US-listed CLS. The research of Xu *et al.* (2022) focused on US-listed CLS and examined the role of jump spillover effects between cryptocurrency markets and 16 US-listed companies with high exposure to blockchain technology or cryptocurrencies.

In this Bachelor's thesis, we aim to quantify and analyze the return connectedness of US-listed CLS, major cryptocurrencies, and the US stock market by utilizing the Dynamic Networks framework proposed by Barunik & Ellington (2020b). This methodology allows us to examine the dynamic time evolution of connectedness measures (along with confidence intervals) and obtain measures for specific time horizons. We also create several Ordinary Least Squares

(OLS) models for CLS returns to model the effect of obtained connectedness measures on CLS returns.

The thesis is structured in the following way: Chapter 2 provides a review of published literature regarding spillover effect measurement and cryptocurrency-linked stocks. Chapter 3 contains specifications about the methodology used in this thesis. Chapter 4 explains the process of obtaining data and describes the final dataset. In Chapter 5, obtained results are presented and discussed. Finally, Chapter 6 is devoted to the conclusion of our findings and the whole thesis.

Chapter 2

Literature Review

In this chapter, we present available literature that is relevant to our research topic. This review includes primarily literature regarding the methodology of return connectedness measurement (especially Dynamic Networks and Diebold-Yilmaz frameworks), literature on CLS, and academic publications about the cryptocurrency market in general. The following literature motivates the research question and the aim of this thesis, which is to enlarge previous research by studying a relatively unexplored field of CLS valuation, as well as the transmission of return spillover effects between CLS and the cryptocurrency market, and CLS and the traditional stock market.

2.1 Return Connectedness Measurement

To begin with, we will provide a brief review of available literature regarding the quantitative measures of return spillover effects (or return connectedness), which yield relevant information for entities operating on financial markets, since shocks in returns of a certain asset often influence returns of other assets (Diebold & Yilmaz (2009)).

A widely-used framework for measuring volatility and return spillover effects of financial assets was introduced by Diebold & Yilmaz (2009) and further elaborated in the following papers: Diebold & Yilmaz (2012), Diebold & Yilmaz (2014). This framework provides an effective methodology, which is based on forecast error variance decomposition (FVED), to measure the interdependence of asset returns and volatilities both in non-crisis and crisis periods of time.

The framework created by Diebold & Yilmaz (2014) was further expanded by a novel methodology introduced in Barunik & Ellington (2020a) and Barunik

& Ellington (2020b). This framework measures connectedness in dynamic network structures and enlarges the frequency-dependent setting introduced by Baruník & Křehlík (2018), which allows distinguishing between multiple layers in the network structure (e.g., long- and short-term horizons of connectedness effects). Extensive subsequent literature simulates time dynamics within the system by using rolling windows (e.g., Demirer *et al.* (2018)). However, this approach suffers from dimensionality issues, and problems with inference and produces only point estimates. Barunik & Ellington (2020b) use a TVP-VAR instead of rolling windows to eliminate these problems and to estimate confidence intervals instead of point estimates. In contrast to Geraci & Gnabo (2018), who also use TVP-VAR models to estimate network structures, Barunik & Ellington (2020b) rely on establishing the network structure from a single TVP-VAR model that allows for the measurement of different properties.

Kumar *et al.* (2022) study the connectedness among 10 most capitalized cryptocurrencies in the period ranging from October 2017 to January 2021 (thus including the COVID-19 pandemic). They measure connectedness by analyzing spillover effects within the framework introduced by Diebold & Yilmaz (2012), as well as using the horizon-specific perspective of Baruník & Křehlík (2018). The authors found the total connectedness of cryptocurrencies to increase during the COVID-19 outbreak, which indicates the sensitivity of cryptocurrency return spillover effects to exogenous shocks. They also found spillover effects from Ethereum to other cryptocurrencies to be most dominant since Ethereum passed its shocks on to other cryptocurrencies but was less affected by shocks in other cryptocurrencies. Regarding time-specific horizons, the connectedness was most significant over short-time horizons of one day to one week.

Ji *et al.* (2021) use the Diebold & Yilmaz (2014) framework to study the connectedness in a system of Bitcoin exchanges. The authors base the measures of interconnectedness on the daily realized volatility of Bitcoin prices for each of the nine selected cryptocurrency exchanges, and they find Coinbase Global Inc. to be the market leader among exchanges.

2.2 Cryptocurrency-linked Stocks

Although the number of publicly listed companies with direct exposure toward the cryptocurrency market is growing, it remains an unexplored field in academia. Cryptocurrencies are typically considered an independent asset class. However, CLS are one of the bridges to the "conventional" financial market since these assets connect cryptocurrencies with the traditional stock market. This motivates us to examine linkages between the return dynamics because such research is essential for the valuation purposes of these assets and thus can be extremely useful for investors interested in CLS since we quantify the connectedness effects affecting the returns of these stocks.

Frankovic *et al.* (2022) study spillover effects between CLS listed in Australia and the cryptocurrency market by utilizing the framework created by Diebold & Yilmaz (2012). In the former paper, daily price data of 31 Australian-listed CLS, ranging from September 2017 to June 2018, are used. The authors distinguish between different categories of these companies based on their involvement in the cryptocurrency market. They find significant unidirectional spillover effects of returns and weak volatility spillover effects from the cryptocurrency market towards CLS. The strength of these effects varies across categories of CLS, being more significant for CLS with great exposure to the cryptocurrency market and for CLS with high involvement in blockchain technology. The authors' findings indicate that investors integrate the price dynamics of the cryptocurrency market in their investment decisions toward CLS.

Xu *et al.* (2022) examine the presence of jumps and co-jumps in returns of major cryptocurrencies and US-listed CLS. They use daily price data of 16 US-listed CLS and a sample period from January 2018 to October 2021. Xu *et al.* (2022) find jump behavior to be present in returns of both the cryptocurrency market and CLS. Furthermore, jumps in returns of major cryptocurrencies increase the probability of jumps in returns of US-listed CLS, which indicates the presence of spillover effects similar to the mentioned research by Frankovic *et al.* (2022).

2.3 Cryptocurrency Market

Since the introduction of Bitcoin, the largest peer-to-peer decentralized payment system created by Nakamoto (2009), cryptocurrencies have become a heavily discussed topic, which has motivated numerous researchers to study cryptocurrency markets. Bitcoin and the following adoption of its blockchain technology also inspired the emergence of many other cryptocurrencies (e.g. Ethereum, Litecoin, Solana, etc.) and the whole cryptocurrency market became attractive to investors. Therefore, academic literature studying these markets is nowadays highly relevant and desired.

Härdle *et al.* (2020) summarize an overview of the available literature on cryptocurrencies and present potentially interesting research topics in this field of study. The authors claim that the research of cryptocurrencies is only beginning, which creates an extraordinary opportunity for academic researchers, as detailed transaction and historical price data are easily and freely available. As examples of potentially interesting research avenues in cryptocurrencies, Härdle *et al.* (2020) mention the topics of bubbles, institutions, portfolio diversification, adoption, or valuation, which motivates the research question of this thesis.

Chapter 3

Methodology

3.1 Dynamic Networks Framework

The Dynamic Networks framework introduced by Barunik & Ellington (2020b) elaborates on Diebold & Yilmaz (2014) and Baruník & Křehlík (2018) by creating a TVP-VAR setting for connectedness estimation within dynamic network systems. This framework relies on the spectral decomposition of a time-varying variance decomposition matrix, which defines a dynamic adjacency matrix used for connectedness estimation within dynamic networks. This methodology allows users to distinguish between shocks with transitory effects (short-term spillovers) and persistent effects (long-term spillovers) while allowing users to retrieve adjacency matrices for different frequencies depending on their interests. Barunik & Ellington (2020b) assume the economy to follow a single locally stationary TVP-VAR model of lag order p in the following form

$$X_{t,T} = \Phi_1(t/T)X_{t-1,T} + \ldots + \Phi_p(t/T)X_{t-p,T} + \epsilon_{t,T} \tag{3.1}$$

where $X_{t,T} = (X^1_{t,T}, \ldots, X^N_{t,T})^T$ is a process that describes all variables in an economy and is approximated by a stationary process in the neighborhood of a fixed time point. $\Phi(t/T) = (\Phi_1(t/T), \ldots, \Phi_p(t/T))^T$ are time varying coefficients and $\epsilon_{t,T}$ is the residual term. The rescaled time index $u = t/T$ is a continuous time parameter, where T is the number of observations and t is the discrete time index. Moreover, the process $X_{t,T}$ can be represented as a time-varying VMA (∞) (Dahlhaus & Polonik (2009), Roueff & Sanchez-Perez (2016))

$$X_{t,T} = \sum_{h=-\infty}^{\infty} \Psi_{t,T}(h)\epsilon_{t-h} \tag{3.2}$$

where $\Psi_{t,T}(h)$ is a stochastic process with an infinite number of lags. Therefore, the moving average coefficients are approximated at $h = 1, \ldots, H$ finite horizons, and transformations of $\Psi_{t,T}(h)$ (variance decompositions) allow the estimation of connectedness measures that quantify contributions of shocks to the network.

However, shocks do not automatically emerge alone in the system, and thus an identification scheme is essential. In this case, Barunik & Ellington (2020b) modify the identification scheme introduced by Pesaran & Shin (1998) for locally stationary TVP-VAR. The horizon specification (i.e., long-run and short-run connections) of networks proposed by Baruník & Křehlík (2018) is applied by using a time-varying local frequency response function $\Psi_{t/T}e^{-i\omega} = \sum_h e^{-i\omega h}\Psi_{t,T}(h)$ that is retrieved by Fourier transformation of the coefficients, where $i = \sqrt{-1}$. The time-frequency variance decompositions of variable j at a given rescaled time $u = t_0/T$ with regards to shocks in variable k on a given frequency band $d = (a, b); a, b \in (-\pi, \pi), ; a < b$ shape the dynamic adjacency matrix, which is characterized by the following equation

$$[\Theta(u, d)]_{j,k} = \frac{\sigma_{kk}^{-1} \int_a^b |[\Psi(u)e^{-i\omega} \sum(u)]_{j,k}|^2 d\omega}{\int_{-\pi}^{\pi} [\{\Psi(u)e^{-i\omega}\} \sum(u) \{\Psi(u)e^{+i\omega}\}^T]_{jj} d\omega} \tag{3.3}$$

where $\Psi(u)e^{-i\omega} = \sum_h e^{-i\omega h}\Psi(u, h)$ is a local impulse transfer (or frequency response) function obtained by Fourier transformation of $\Psi(u, h)$.

The dynamic adjacency matrix can be aggregated across any horizon of interest d_s as

$$[\Theta(u, d)]_{j,k} = \sum_{d_s \in D} [\Theta(u, d_s)]_{j,k} \tag{3.4}$$

where D is a set of intervals that create a partition of $(-\pi, \pi)$ in such manner that $\cap_{d_s \in D} d_s = \varnothing$ and $\cup_{d_s \in D} d_s = (-\pi, \pi)$. Since the sum of each row in the aggregated Dynamic Adjacency Matrix is not always equal to one, every element is normalized by the sum of the corresponding row

$$[\tilde{\Theta}(u, d)]_{j,k} = [\Theta(u, d)]_{j,k} / \sum_{k=1}^{N} [\Theta(u)]_{j,k} \tag{3.5}$$

Local variance decompositions at a frequency band $\tilde{\Theta}(u, d)$ are sufficient estimates of the time-varying variance decompositions of $X_{t,T}$ (see Dahlhaus (1996)).

In previous network-related literature, adjacency matrices contained solely values of zero and one, which could only explain whether certain nodes (variables) are linked or not. However, in the setting of Barunik & Ellington (2020b), variance decompositions represent weighted links between nodes and thus show also the strength of the connection between nodes. Moreover, the links displayed in the adjacency matrix are directional, as the link from node j to node k is not necessarily the same as the link from k to j, which implies asymmetricity of the adjacency matrix.

Now, we can specify several connectedness measures obtained from the dynamic adjacency matrix. The local aggregated connectedness measure at a given frequency d and rescaled time u is defined as

$$C(u,d) = 100 \times \frac{\sum_{j,k=1;j\neq k}^{N}[\tilde{\Theta}(u,d)]_{j,k}}{\sum_{j,k=1}^{N}[\tilde{\Theta}(u,d)]_{j,k}} \tag{3.6}$$

This equation measures the Total connectedness within the network system, i.e., the contribution of all shocks within the system minus the contribution of own shocks.

Furthermore, directional connectedness measures can be defined within dynamic network systems. The local directional connectedness measure, which explains how much of the variance of variable j is caused by shocks in the other variables $k; k \neq j$, is the so-called FROM connectedness, which is characterized by the following equation

$$C_{j\leftarrow\bullet}(u,d) = 100 \times \frac{\sum_{k=1;k\neq j}^{N}[\tilde{\Theta}(u,d)]_{j,k}}{\sum_{j,k=1}^{N}[\tilde{\Theta}(u)]_{j,k}} \tag{3.7}$$

In the same way, the contribution of shocks in variable j to variances of other variables $k; k \neq j$ in the system is measured by the so-called TO connectedness as

$$C_{j\bullet\rightarrow}(u,d) = 100 \times \frac{\sum_{k=1;k\neq j}^{N}[\tilde{\Theta}(u,d)]_{k,j}}{\sum_{k,j=1}^{N}[\tilde{\Theta}(u)]_{k,j}} \tag{3.8}$$

It is clear that both of these directional connectedness measures are characterized respectively as the sum of directional links to variable j from the system (or from variable j to the system), weighted by the total sum of the adjacency matrix. By subtracting the FROM connectedness from the TO connectedness, it is possible to obtain the so-called NET connectedness

$$C_j^{NET}(u,d) = C_{j\bullet\rightarrow}(u,d) - C_{j\leftarrow\bullet}(u,d) \tag{3.9}$$

The NET connectedness indicates whether variable j is a net transmitter ($C_j^{NET}(u,d) > 0$) or a net receiver ($C_j^{NET}(u,d) < 0$) of shocks within a certain dynamic network system.

Lastly, local network connectedness measures aggregated over frequencies can be calculated from the mentioned total and directional connectedness measures, respectively, by summing over intervals d_s from the set of intervals D

$$C(u) = \sum_{d_s \in D} C(u, d_s) \tag{3.10}$$

3.2 Estimation of the TVP-VAR model

Barunik & Ellington (2020b) assume the system of returns to follow a locally stationary TVP-VAR model presented in equation 3.1. Moreover, they follow the approach of Petrova (2019) in using the Quasi-Bayesian Local-Likelihood methods to obtain estimates of the time-varying coefficients $\widehat{\Phi}_1(u), \dots, \widehat{\Phi}_p(u)$ and time-varying covariance matrices $\widehat{\sum}(u)$ at a certain time u. This method utilizes a kernel weighting function, which prioritizes observations in the neighborhood of periods of interest by assigning higher valued weights to these observations. Barunik & Ellington (2020b) further mention that using QBLL for estimation provides a distribution of parameters used to build connectedness measures that produce confidence intervals instead of point estimates. They also provide efficient frameworks in `JULIA` and `MATLAB` that allow users to obtain dynamic network connectedness measures. In this Bachelor's thesis, we will utilize the code provided in `JULIA` programming language to estimate network connectedness of returns within our system of variables.

To begin with, we need to abbreviate the VMA (∞) representation of process $X_{t,T}$ by a finite approximation factor H, which according to Barunik & Ellington (2020b) should be sufficiently high. They record quantitatively similar results of frequency-dependent connectedness measures for $H \in \{50, 100, 200\}$ and chose to set $H = 100$. The next step involves choosing a bandwidth of the kernel depending on the characteristics of the data. Shorter bandwidths are feasible for time series that are volatile and contain frequent jumps. On the contrary, choosing a longer bandwidth results in a smoother time evolution of connectedness measures. The short- and long-term horizons also need to be specified, and here we follow Barunik & Ellington (2020b) to define short-term horizons as 1-5 business days and long-term horizons as periods greater than 5 business days. For TVP-VAR models, it is required to choose a lag of a certain order p. Barunik & Ellington (2020b) experimented with different values of the lag $p \in \{2, 3, 4, 5\}$, but experienced similar results for all options. Thus, we choose to set p=2 in order to reduce the computation time of our measures.

Considering all above mentioned characteristics, our proposed TVP-VAR model for estimation can be described by the following equation

$$X_{t,T} = \Phi_0(t/T) + \Phi_1(t/T)X_{t-1,T} + \Phi_2(t/T)X_{t-2,T} + \epsilon_{t,T} \tag{3.11}$$

where $\Phi_0(t/T)$ is the intercept, $\Phi_1(t/T)$ and $\Phi_2(t/T)$ are the parameters, $\epsilon_{t,T}$ is the error term and $X_{t,T}$ is a vector of all variables in our dynamic network system.

Before estimating the proposed TVP-VAR model, several parameters need to be specified. The number of lags L is set to be equal to two since experiments with higher numbers of lags produce similar results of connectedness measures. As a next step, the number of horizons H is set to be equal to 100, following Barunik & Ellington (2020b), who test that results are similar for $H \in \{50, 100, 200\}$ and set $H = 100$. The kernel bandwidth W is assigned the value of 8 since we aim to analyze short-term fluctuations of connectedness measures and higher values of the kernel bandwidth have a smoothing effect on dynamic network measures. Finally, we choose to generate 100 simulations (parameter $Nsim$) for connectedness measures.

Chapter 4

Data

In this thesis, we examine the return connectedness of 20 US-listed CLS, five major cryptocurrencies[1] and the US stock market (represented by a stock market index). Daily prices of all stocks, cryptocurrencies, and indices are obtained using the `Yfinance`[2] library in `Python` programming language, which utilizes the publicly available API of `Yahoo Finance`. Price data for the assets span from September 23rd, 2021, to July 16th, 2023, resulting in a total period of 662 days. For the five major cryptocurrencies and 20 US-listed CLS, equal-weighted portfolios are calculated to increase the clarity of connectedness effects of returns between asset classes within the system.

4.1 Cryptocurrency-linked Stocks

The main asset class that is examined in this thesis includes stocks of US-listed companies with links to the cryptocurrency market. Recently, such companies more commonly entered the US stock market. However, the number of publicly traded CLS in the US is still small. We choose a set of 20 US-listed CLS for the connectedness analysis of daily returns. These companies can be divided into the following four groups according to the nature of their link to the cryptocurrency market. Yet, some companies have several linkages to cryptocurrencies and thus can be included in multiple categories.

[1]Five major cryptocurrencies are chosen based on market capitalization, information available on `www.coinmarketcap.com`. Cryptocurrencies pegged to the US dollar, namely USDT, and USDC, are neglected because of the irrelevance of their daily returns.

[2]More information available on `www.pypi.org/project/yfinance`

Figure 4.1: CLS portfolio performance

Notes: (1) Figure 4.1 plots the daily performance of the equal-weight portfolio, which was calculated by taking the sum of "Adjusted Close" prices of individual CLS that are multiplied by an equal weight factor ($\frac{1}{20}$).

In Figure 4.1 we can see, that the plot of CLS portfolio performance exhibits relatively similar movements as prices of Bitcoin and Ethereum displayed in Figure 4.2. This fact might indicate significant connectedness effects between the performance of CLS and the price movements of major cryptocurrencies. CLS portfolio performance reached a top in November 2021 and a minimum in December 2022.

4.1.1 Mining Companies & Mining Hardware Producers

Cryptocurrency mining companies represent the largest category among US-listed CLS. These companies specialize in the mining industry of cryptocurrencies and usually own significant amounts of hardware used for mining purposes. Producers of such hardware are also an essential part of the whole industry. The cryptocurrency mining industry is heavily dependent on electricity costs and cryptocurrency prices, as energy consumption represents the major input for miners, and their profits depend on the price of mined cryptocurrencies.

4.1.2 Cryptocurrency Exchanges

In April 2021, a leading cryptocurrency exchange Coinbase Global Inc. (COIN) was listed on Nasdaq, which aroused a wave of public interest, as Coinbase represents the first publicly traded cryptocurrency exchange. Bakkt Holdings Inc. (BKKT) runs a platform for cryptocurrency trading and provides custody services and cryptocurrency payment solutions[3] for their clients. In the dataset of this thesis, we include both COIN and BKKT stocks as representatives of US-listed cryptocurrency exchanges.

4.1.3 Companies Investing in Cryptocurrencies

In this category, we include companies that invest in cryptocurrencies and hold them as part of their portfolios. MicroStrategy Inc.(MSTR) is arguably the biggest holder of Bitcoin (BTC) among public companies, with approximately 152 thousand BTC on their balance sheet as of July 2023. Another CLS heavily invested in cryptocurrencies that we include in the dataset of this thesis is Block Inc. (SQ).

4.1.4 Blockchain-linked Fintech Companies & Cryptocurrency-payment Companies

The last category of US-listed CLS is devoted to fintech companies that utilize blockchain technologies and to companies that provide cryptocurrency payments. As Block Inc. runs the product CashApp, which allows to transfer Bitcoin (as well as traditional currencies) among their users, the company can also be included in this category. PayPal Holdings Inc. (PYPL) mainly provides financial payment services but also allows users to buy and sell cryptocurrencies as well. Future FinTech Group Inc. (FTFT) provides financial services based on blockchain technologies. At last, Overstock.com Inc. (OSTK), an online furniture retailer that has accepted Bitcoin payments since 2014, is included in the dataset.

[3] Since Bakkt Holdings Inc. (BKKT) also offers cryptocurrency-payment services, it can be included in category 4.1.4 as well.

4.2 Cryptocurrencies

Five major cryptocurrencies, according to their market capitalization (available on `www.coinmarketcap.com`) are as of July 2023: Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple XRP (XRP) and Cardano (ADA). In the choice of most capitalized cryptocurrencies, the so-called stablecoins, namely Tether (USDT) and USD Coin (USDC), are neglected since their value is pegged to the value of the US dollar, and thus the daily returns of these cryptocurrencies are irrelevant.

Figure 4.2: Prices of Bitcoin and Ethereum

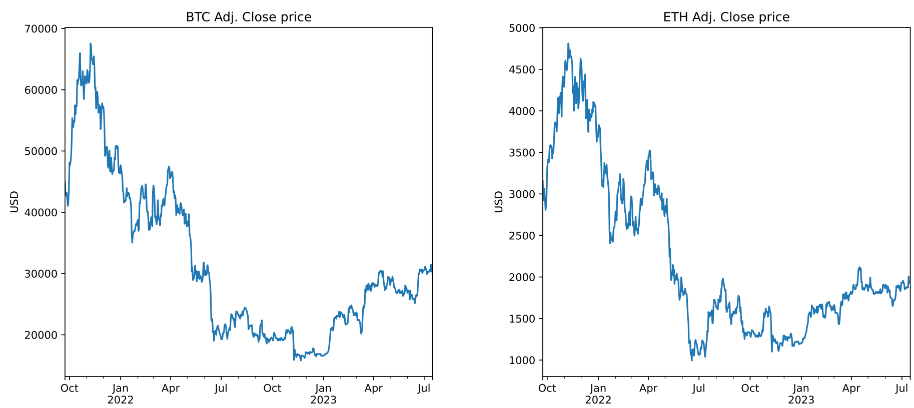
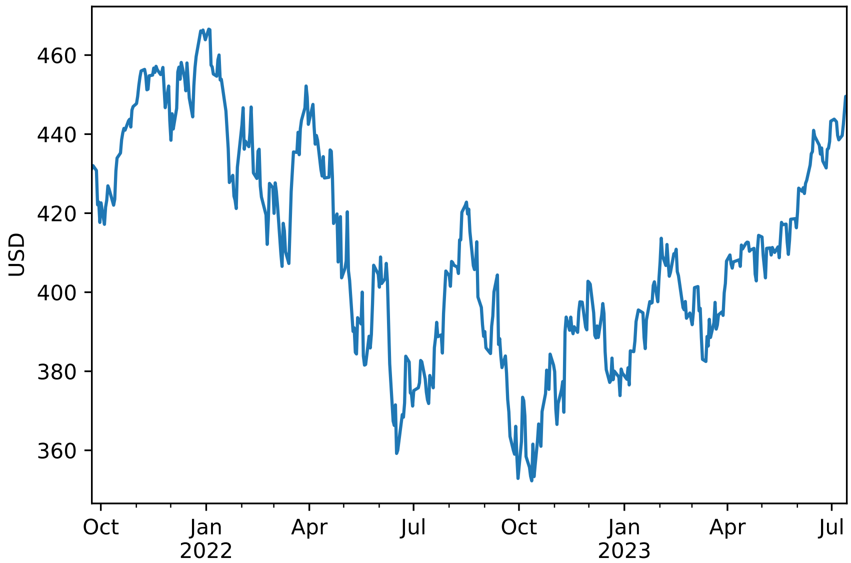


Figure 4.2 plots daily prices of the two largest cryptocurrencies by market capitalization: Bitcoin (BTC) and Ethereum (ETH), across the time span of the dataset used throughout this thesis. The curves of both plots are similar to each other, which potentially indicates a significant correlation between the two major cryptocurrencies. Both graphs peak in December 2021. Except for several pull-backs, prices of both cryptocurrencies followed a downward trend in 2022. The trend changed in January 2023, and since then, the prices of Bitcoin and Ethereum have been increasing until today.

4.3 Stock Market Index

As a proxy for the US stock market, the stock market index S&P 500 (SPY) is chosen in this thesis. This index represents a suitable performance measure of the whole US stock market, as it includes hundreds of stocks listed on the US stock market. Figure 4.3 shows Adjusted Close prices of the S&P 500 index.

Figure 4.3: Adjusted Close price of S&P 500



4.4 Non-business Days

Cryptocurrencies are traded on the market at any point in time, whereas stocks are usually traded only during normal business hours and days. The absence of trade on stock markets during weekends and public holidays poses a challenge for comparing the two asset classes. In this thesis, that difficulty is solved by applying a resample function on the dataset using the `Pandas` library for data analysis in `Python` programming language. The daily price data are resampled according to the US federal holiday calendar. Thus, weekends and public holidays are merged into a single day either with the previous (Friday for weekends) or the following business day (Monday for weekends). This creates two different versions of the dataset: "dataF" and "dataM", where non-business days are merged with the previous or following day accordingly.

4.5 Daily Returns

After resampling, the final datasets contain daily "Open", "Close", "High" and "Low" price data, as well as the daily "Volume" of trade for all assets. We measure the connectedness of returns of CLS, cryptocurrencies, and the stock market, and therefore, daily returns for all individual assets are calculated as

$$Daily\ return_{i,t} = \frac{Closing\ price_{i,t}}{Closing\ price_{i,t-1}} - 1 \tag{4.1}$$

where $Closing\ price_{i,t}$ represents the "Adjusted Close" price of asset i on day t.

Table 4.1: Descriptive statistics of daily returns for dataM

	Obs.	Mean (%)	Std. dev.	Min. (%)	Max. (%)
Cryptocurrency - linked stocks					
a) Mining companies & mining hardware producers					
ARBK	453	−0.100	8.490	−43.655	36.539
BITF	453	0.030	6.986	−19.926	44.286
BTBT	453	0.044	6.958	−18.235	41.791
CAN	453	−0.003	6.456	−28.790	37.572
CIFR	453	0.178	8.573	−46.749	−44.928
CLSK	453	0.082	6.410	−16.667	27.778
EBON	453	−0.149	7.446	−26.973	41.479
GREE	453	−0.371	9.290	−39.024	60.606
HIVE	453	−0.003	6.314	−22.689	37.662
HUT	453	0.061	6.797	−17.935	22.222
MARA	453	0.136	7.808	−27.028	32.172
NCTY	453	−0.251	6.895	−21.127	37.180
RIOT	453	0.118	6.572	−19.178	17.925
b) Cryptocurrency exchanges					
BKKT[(1)]	453	0.262	14.510	−34.012	234.426
COIN	453	0.028	6.454	−26.401	24.491
c) Companies investing in cryptocurrencies					
MSTR	453	0.119	6.016	−25.554	20.648
SQ[(2)]	453	−0.169	4.707	−15.606	26.140
d) Blockchain-linked Fintech & Cryptocurrency-payment companies					
FTFT	453	0.495	17.500	−18.367	352.273
OSTK	453	−0.093	4.752	−11.748	22.826
PYPL	453	−0.247	3.175	−24.590	12.176
Cryptocurrencies					
BTC	453	−0.013	3.810	−22.681	19.866

ETH	453	0.009	4.795	−27.655	28.025
XRP	453	0.085	5.973	−19.518	73.075
BNB	453	−0.007	4.171	−22.214	13.950
ADA	453	−0.291	5.341	−22.119	37.266
Stock market index					
SPY	453	0.017	1.285	−4.348	5.495

Notes: (1) BKKT (Bakkt Holdings Inc.) operates a platform for cryptocurrency trading and provides cryptocurrency payment solutions for their clients, and thus might be included in category d) of CLS as well. (2) SQ (Block Inc.) can also be included in CLS categories c) and d), as the company invests in cryptocurrencies, but also offers cryptocurrency-payment solutions. (3) Descriptive statistics for the dataset dataF can be found in Appendix A.

Since differences between both versions of the dataset dataM and dataF are rather negligible, we present here only descriptive statistics of daily returns for the version dataM and choose this version as the primary dataset also for calculations of results included in the following chapter. Descriptive statistics and detailed results for version dataF can be found in Appendix A.

4.6 Crypto and CLS Portfolios

Finally, we create two equal-weighted portfolios: “CLS” for the 20 US-listed CLS and “Crypto” for the five major cryptocurrencies. These portfolios contain daily returns for the asset classes, which are calculated by taking arithmetic means of daily returns of individual assets (stocks or cryptocurrencies). Thus, the final system contains daily return data of three variables: “CLS”, “Crypto” and “SPY”.

Table 4.2: Descriptive statistics of daily returns (portfolios)

Number of obs. = 453	dataF			dataM		
	SPY	Crypto	CLS	SPY	Crypto	CLS
Mean (%)	0.017	−0.043	0.008	0.017	−0.046	0.008
Std. dev.	1.285	4.208	5.094	1.285	4.194	5.094
Min. (%)	−4.348	−22.095	−13.491	−4.348	−16.576	−13.491
Max. (%)	5.495	22.559	23.612	5.495	22.559	23.612

Notes: The table contains descriptive statistics for daily returns of the stock market index SPY and two equal-weighted portfolios: "Crypto" and "CLS". The statistics are provided for both versions dataF and dataM of the dataset. Note that descriptive statistics for CLS and SPY are identical for dataF and dataM, since stocks are not traded on weekends and holidays. Thus, these asset classes are not affected by differences in the resampling functions of dataF and dataM.

Chapter 5

Results and Discussion

This chapter is devoted to the presentation of the main results and the discussion about the possible implications of our findings. Firstly, individual results obtained from the analysis of network connectedness measures are presented. This analysis represents the core part of the thesis and includes the Total network connectedness and the directional TO, FROM, and NET connectedness measures. Furthermore, time horizon dynamics of connectedness effects within the system are presented and discussed. All connectedness measures are calculated for the datasets containing daily return data for three variables: “Crypto” (equal-weighted portfolio of five major cryptocurrencies), “CLS” (equal-weighted portfolio of 20 US-listed CLS), and “SPY” (S&P 500 stock market index). The dataset of daily returns contains 453 observations of daily returns, with the time span ranging from September 23rd, 2021, to July 16th, 2023. Connectedness measures are calculated for both versions of the dataset: dataM and dataF. Finally, we construct several versions of OLS regression models for daily returns of the whole “CLS” portfolio, as well as individual CLS in order to reveal the main drivers affecting returns of cryptocurrency-linked stocks within the system.

5.1 Network Connectedness Measures

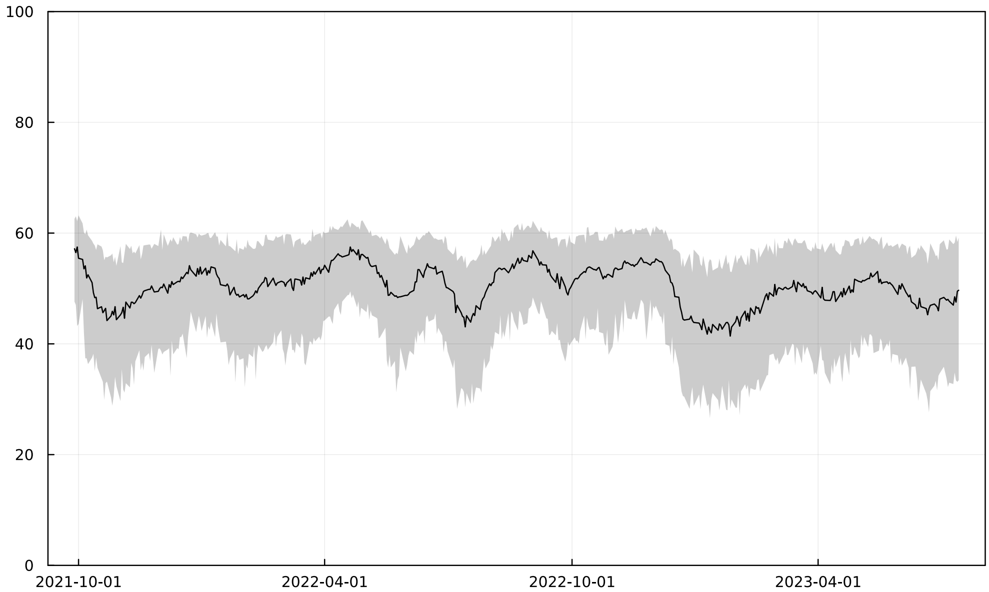
To obtain network connectedness measures of daily returns, we utilize the Dynamic Networks framework introduced in Barunik & Ellington (2020a) and Barunik & Ellington (2020b) and we use the `Julia` programming language code accompanying their papers[1].

[1]the code is available on `www.github.com/barunik/DynamicNets.jl`

5.1.1 Total Dynamic Network Connectedness

The Total network connectedness is a dynamic measure of the overall interconnectedness of the system, which in our case includes "Crypto" and "CLS" portfolios and the stock market index "SPY". Thus, higher levels of Total network connectedness indicate significant interrelations between the cryptocurrency and stock markets. We plot the Total connectedness for both versions dataM and dataF.

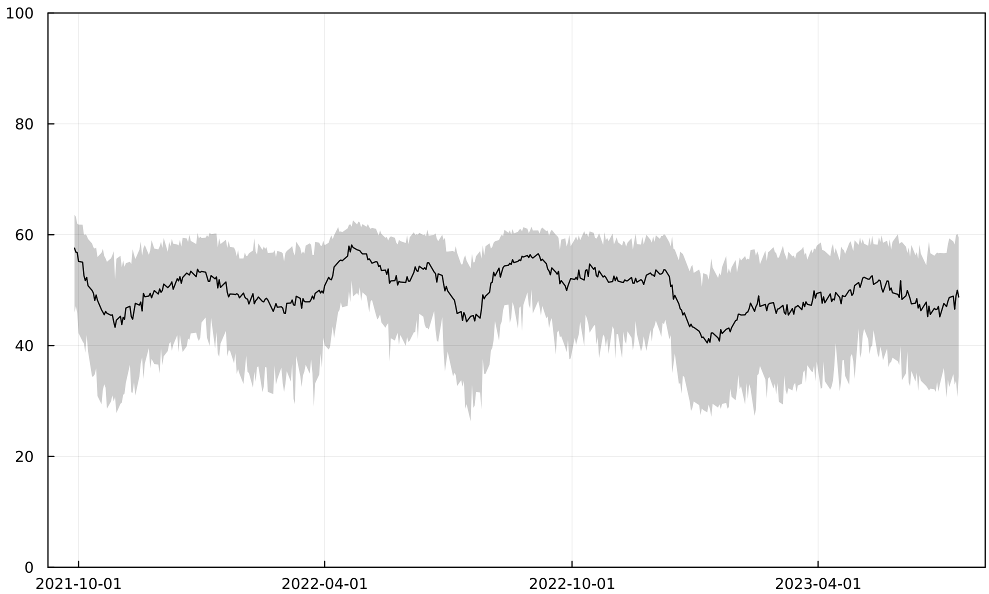
Figure 5.1: Total Dynamic Network Connectedness for dataM



Notes: (1) Figure 5.1 and Figure 5.2 plot Total Dynamic Network connectedness for the two versions of the dataset containing daily returns of "CLS", "Crypto", and "SPY". (2) These plots are the results of the Dynamic Networks setting with parameter Corr = FALSE. Results for Corr = TRUE can be found in Appendix B. (3) Total network connectedness is depicted by the black line and grey areas are bordered by 2.5% and 97.5% quantiles, and thus represent 95% confidence intervals of the measure.

As we can see on the graphs, in both cases the plot of Total connectedness follows a similar pattern and lies in the range from 40 to 60 for the entire time span. However, several peaks and troughs can be observed throughout the period, with a significant low in July 2022. In January 2023 Total connectedness dropped to a minimum level of 41.4. The system exhibited a maximum Total connectedness in September 2021, reaching a level of 57.5.

Figure 5.2: Total Dynamic Network Connectedness for dataF



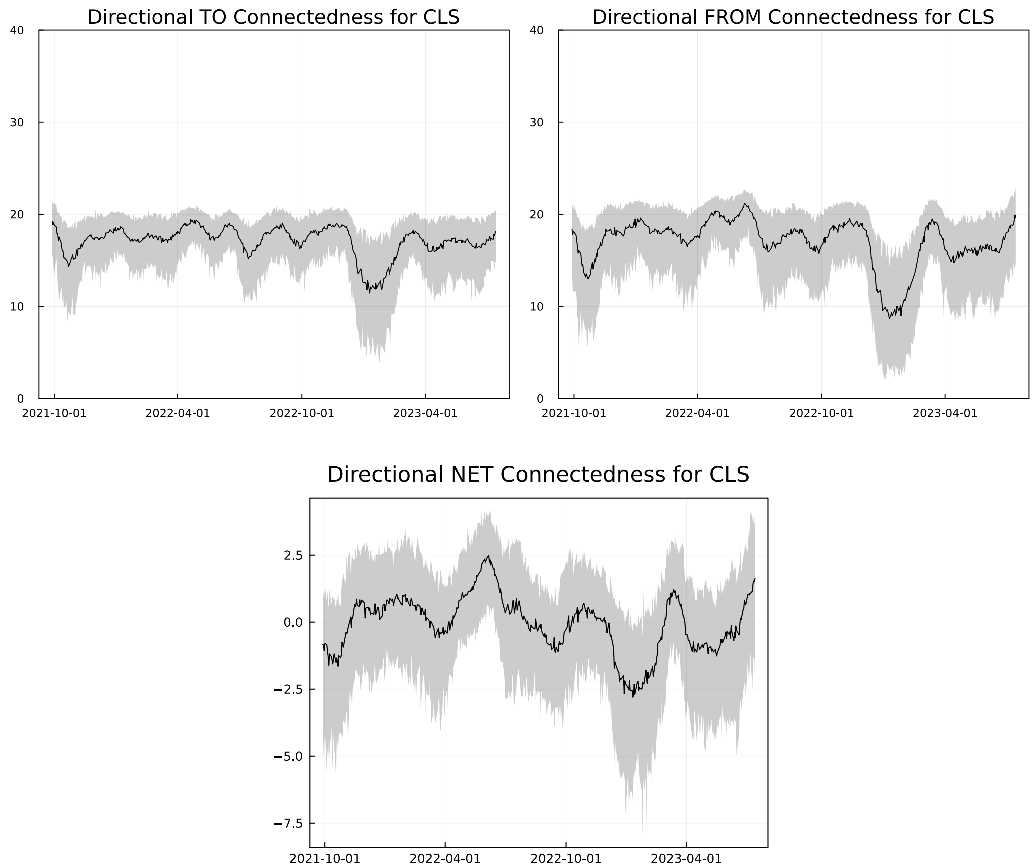
5.1.2 Directional Connectedness

To obtain a better understanding of connectedness effects among variables in the system, it is crucial to study directional connectedness measures. Barunik & Ellington (2020b) allow to study TO, FROM, and NET directional connectedness measures within the Dynamic Networks framework for each variable. We follow their methodology and plot these measures for the three variables "CLS", "Crypto" and "SPY". The so-called TO connectedness indicates, how much variable j contributes to variances of other variables in the system. On the other hand, FROM connectedness measures the contribution of shocks in other variables in the system to the variance of variable j. The directional NET connectedness is obtained by subtracting the FROM connectedness from the TO connectedness and indicates variable j's position in the system (net transmitter or receiver of shocks). The results of Directional connectedness measures below are obtained for the dataset version dataM and results for the version dataF are to be found in Appendix A.

CLS

The NET connectedness of "CLS" stayed in the range between -2.5 and 2.5 throughout the sample. The maximum of NET connectedness was reached in June 2022 and was equal to 2.5. "CLS" received shocks from other variables most significantly in January 2023, when NET connectedness hit a minimum of -2.8. Overall, we cannot easily claim, whether “CLS” is a net transmitter or receiver of shocks, since NET connectedness fluctuates significantly and both mean and median values of NET connectedness are close to zero.

Figure 5.3: Directional Connectedness for CLS

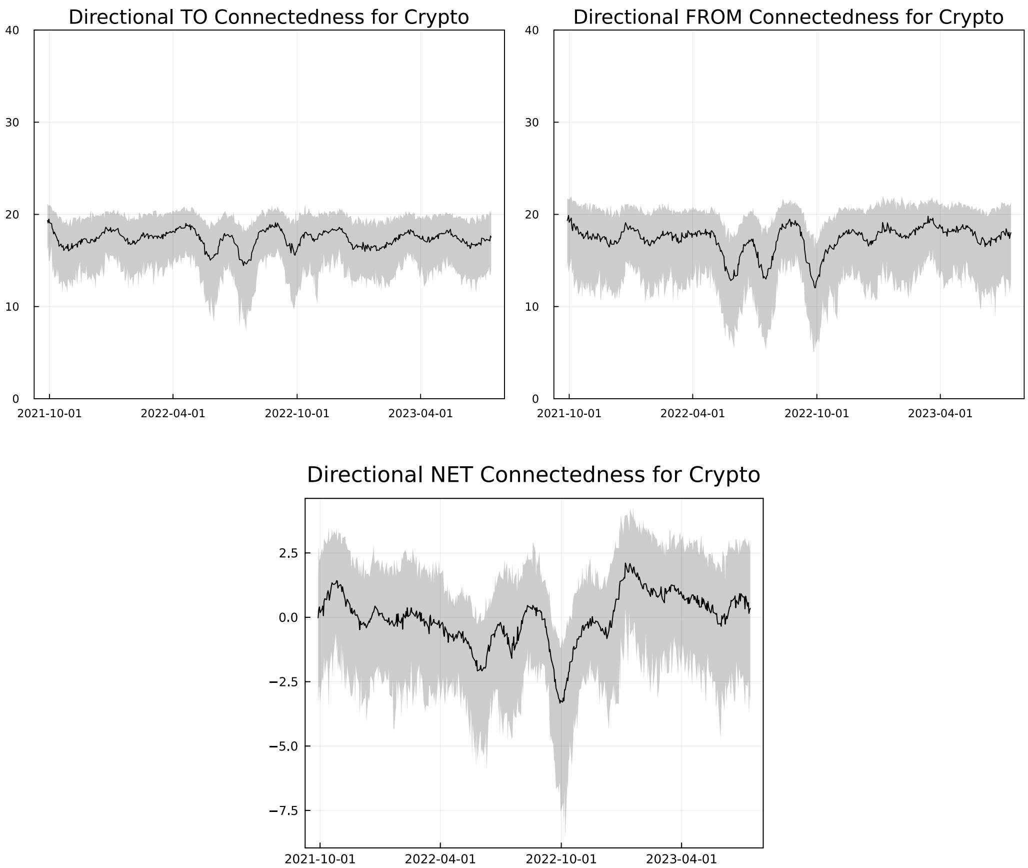


Notes: (1) Figure 5.3 plots Directional TO, FROM, and NET connectedness measures for variable “CLS” and dataset version dataM. Similar measures for version dataF can be found in Appendix A.

Cryptocurrencies

The "Crypto" portfolio cannot be easily categorized as a net receiver or transmitter of shocks, since both mean and median values of NET connectedness are very close to zero. However, NET connectedness fluctuates throughout the period, reaching a maximum of 2.1 in January 2023[2] and a minimum of -3.3 at the end of September 2022.

Figure 5.4: Directional Connectedness for Crypto



Notes: (1) Figure 5.4 plots Directional TO, FROM, and NET connectedness measures for variable "Crypto" and dataset version dataM. Similar measures for version dataF can be found in Appendix A.

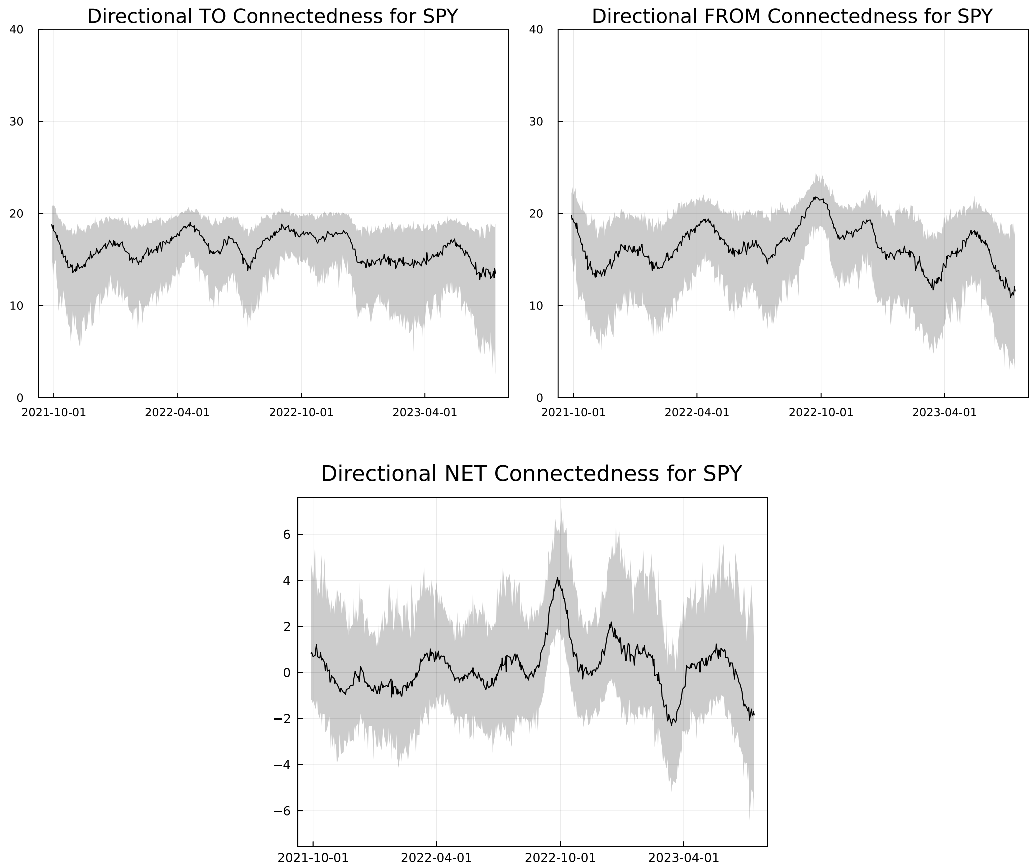
S&P 500 stock market index

NET connectedness of "SPY" was predominantly positive, implying that "SPY" transmits its shocks to the system more often than receives shocks from other variables. This effect was most significant in September 2022, when NET con-

[2]Note that NET connectedness of "CLS" reached a minimum around this period.

nectedness culminated at 4.1[3]. Contrarily, "SPY" hit a minimum NET connectedness of -2.3 in March 2022.

Figure 5.5: Directional Connectedness for SPY



Notes: (1) Figure 5.5 plots Directional TO, FROM, and NET connectedness measures for variable "SPY" and dataset version dataM. Similar measures for version dataF can be found in Appendix A.

5.1.3 Time Horizon Dynamics

The horizon decomposition of Total connectedness provides useful information about the characteristics of connectedness effects, which can be divided into three groups by time horizons. Connectedness effects are labeled as short-term for a time horizon of 1-5 days (corresponds to a week), medium-term for 5-20 days, and long-term for horizons greater than 20 days (greater than one month). We provide results of time horizon dynamic measures of connectedness for both versions of the dataset dataM and dataF. Note that black lines in Figure 5.6

[3] Note that NET connectedness of "Crypto" reached a minimum around this period.

and Figure 5.7 correspond to the Total connectedness measures presented in Figure 5.1 and Figure 5.2.

Figure 5.6: Time Horizon dynamics of Connectedness for dataM

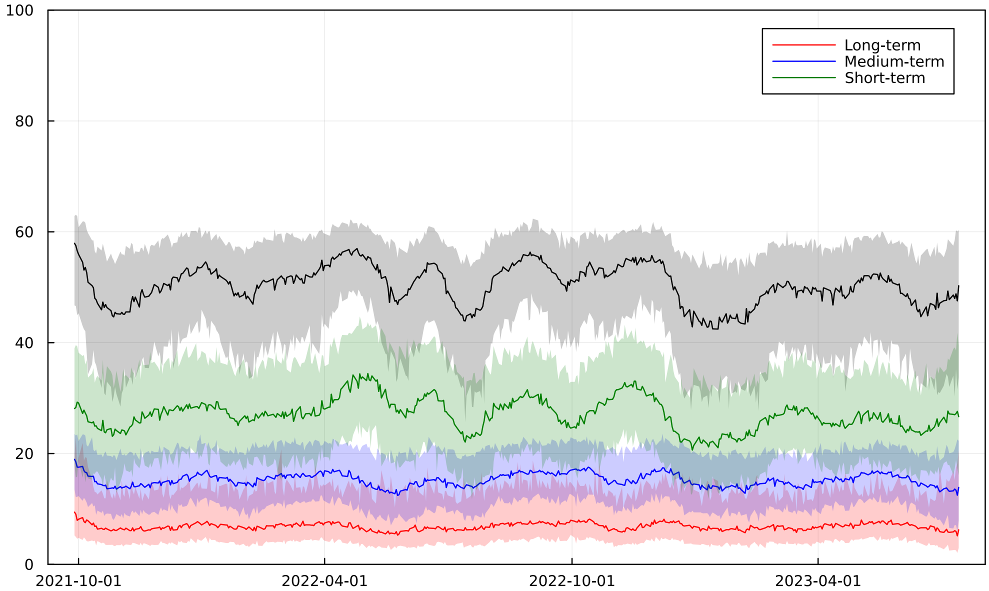
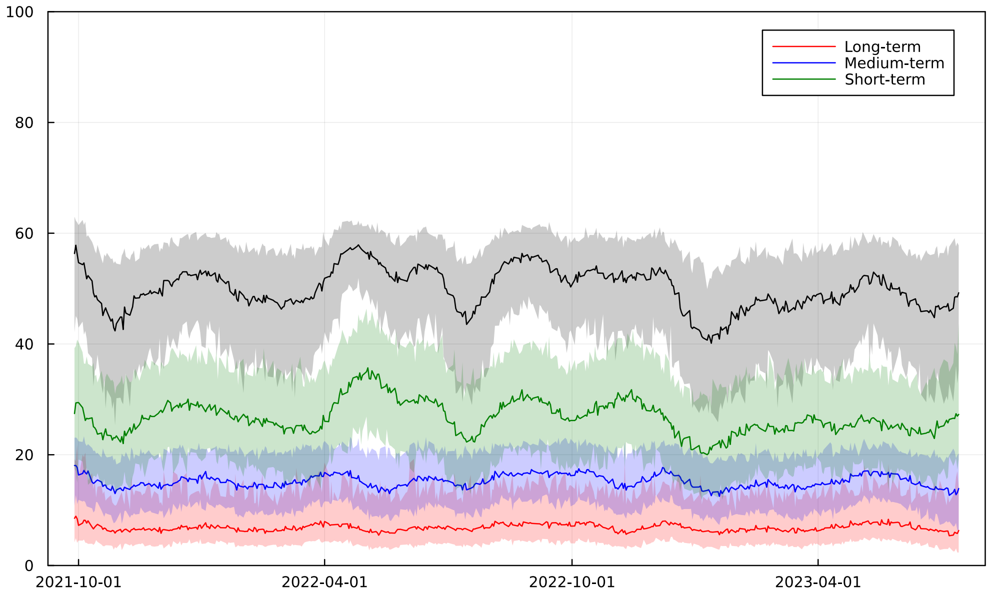


Figure 5.7: Time Horizon dynamics of Connectedness for dataF



Notes: (1) Figure 5.6 and Figure 5.7 plot horizon dynamics of network connectedness for the two versions of the dataset containing daily returns of “CLS”, “Crypto”, and “SPY”. (2) These plots are results of the Dynamic Networks setting with parameter Corr = FALSE. Results for Corr = TRUE can be found in Appendix B. (3) Total network connectedness is depicted by the black line. Lighter-colored areas are bordered by 2.5% and 97.5% quantiles and thus represent 95% confidence intervals of respective measures.

In both Figure 5.6 and Figure 5.7 short-term connectedness is the strongest among time horizons and lies in the range between 20 and 35 throughout the time span. Fluctuations in the short-term horizon mimic the shape of Total connectedness plots. Connectedness in the medium-term horizon is less volatile and ranges between 15 and 20. Long-term connectedness effects are the least significant and are represented by a relatively flat curve, which lies constantly below the level of 10.

5.2 OLS Regression of CLS Returns

In this subsection, we analyze the main drivers of daily returns of CLS, by building OLS regressions and estimating various models. We also try to demonstrate, how connectedness measures within the system influence and explain CLS returns. To be able to use connectedness measures as explanatory variables of CLS returns, we first have to modify the function `normker` in the Dynamic Networks `Julia` code by stopping the iteration at the present observation. This prevents the framework from looking at future observations when calculating network connectedness measures. After doing so, we can recalculate connectedness measures as shown in Section 5.1, and begin to build OLS regressions. Our baseline model for daily CLS returns is described by the following equation.

$$rCLS_t = \beta_0 + \beta_1 rSPY_t + \beta_2 TO\_diff_t + u_t \tag{5.1}$$

where $rCLS_t$ and $rSPY_t$ are daily returns of the "CLS" portfolio and S&P 500 index respectively, $TO\_diff_t = TO_{Crypto,t} - TO_{SPY,t}$ is the difference between the TO connectedness for variable "Crypto" and the TO connectedness for variable "SPY" and thus presents an interaction term between the cryptocurrency and stock markets. The error term is represented by u_t. Note that we use version dataM of the dataset for all OLS regressions within Section 5.2

Firstly, we estimate the regression for the whole "CLS" portfolio and secondly, for the 20 individual cryptocurrency-linked stocks as dependent variables. We present results of OLS estimations, as well as 95% confidence intervals for estimated coefficients. Following Wooldridge (2012) we apply the nonparametric bootstrapping method as a robustness test for OLS estimates, which allows us to generate confidence intervals from standard errors of the coefficient estimates. The method consists of drawing n random observations from the original dataset (of size n) with replacement, which produces a new dataset of the same size n. Then, OLS estimations are run on the new sample b, and new coefficient estimates $\hat{\theta}^{(b)}$ are saved. The resampling and estimation are repeated $m = 1000$ times and bootstrap standard errors of parameter estimates $bse(\hat{\theta})$ are calculated as sample standard deviations of estimates from bootstrap samples.

$$bse(\hat{\theta}) = \left[(m-1)^{-1} \sum_{b=1}^{m} (\hat{\theta}^{(b)} - \bar{\hat{\theta}})^2 \right]^{\frac{1}{2}} \tag{5.2}$$

where $\bar{\hat{\theta}}$ is the average of the bootstrap estimates $\hat{\theta}^{(b)}$, for $b = 1, 2, ..., m$. The 95% confidence intervals for estimated coefficients are then calculated in the usual way from the 2.5% and 97.5% percentiles using the bootstrap standard errors.

Table 5.1: OLS regression estimates for returns of the“CLS” portfolio

	Dependent Variable:
	$rCLS_t$
$Constant$	1.413***
	(0.148)
$rSPY_t$	2.418***
	(0.148)
TO_diff_t	0.419**
	(0.211)
Observations	451
R-squared	0.378
Adjusted R-squared	0.375

Notes: (1) *** - significant at 1% level, ** - significant at 5% level, * -significant at 10% level. (2) Numbers in parentheses represent standard errors.

Table 5.1 shows OLS estimates of the model with daily returns of the "CLS" portfolio. Both independent variables $rSPY_t$ and TO_diff_t are significant at the 5% level ($rSPY_t$ significant even at 1% level) and the model's Adjusted R-squared is equal to 37.5%, which means that the model explains almost 40% of the variance in daily returns of the "CLS" portfolio. The estimated coefficient of $rSPY_t$ is equal to 2.418, which means that an increase by one percentage point in daily returns of S&P 500 will, ceteris paribus, increase daily returns of the "CLS" portfolio by 2.4 percentage points. TO_diff_t has a positive estimated coefficient of 0.419, which can be interpreted as follows. An increase in the difference between $TO_{Crypto,t}$ and $TO_{SPY,t}$ by one percentage point will increase daily returns of the "CLS" portfolio by 0.4 percentage points, ceteris paribus. In other words, an increase in the TO connectedness of "Crypto", while keeping TO connectedness of S&P 500 constant, will have a positive effect on CLS returns. Such an effect is interesting since it suggests, that CLS returns are higher in periods of time when CLS are relatively more influenced by the cryptocurrency market than by traditional stocks.

Table 5.2: Confidence intervals for OLS regression estimates

	Estimated coefficient	95% CI
$Constant$	1.413	(1.165 , 1.676)
$rSPY_t$	2.418	(2.169 , 2.679)
TO_diff_t	0.419	(-0.051 , 0.905)

Notes: Table 5.2 shows estimated OLS coefficients of independent variables from Table 5.1 and respective 95% confidence intervals for these estimates. The confidence intervals were calculated by following the nonparametric bootstrapping method in Wooldridge (2012).

To examine in more detail the mentioned effect of connectedness measures on CLS returns, we run the OLS regression described in Equation 5.1 also for daily returns of each individual CLS as dependent variables and study changes in the estimated coefficients for TO_diff_t. Results of the 20 OLS regressions are presented in Table 5.3.

Table 5.3: OLS regression estimates for returns of individual CLS

Dep. variable	R^2	Adj. R^2	TO_diff_t	95% CI
a) Mining companies & mining hardware producers				
$rARBK_t$	0.089	0.085	0.303	(-0.544 , 1.074)
$rBITF_t$	0.270	0.267	0.405	(-0.166 , 1.056)
$rBTBT_t$	0.237	0.234	0.491	(-0.137 , 1.130)
$rCAN_t$	0.184	0.180	0.090	(-0.452 , 0.610)
$rCIFR_t$	0.093	0.089	1.158***	(0.241 , 2.131)
$rCLSK_t$	0.311	0.308	0.456*	(-0.067 , 0.995)
$rEBON_t$	0.098	0.094	0.678*	(-0.044 , 1.581)
$rGREE_t$	0.099	0.095	0.822*	(-0.103 , 1.760)
$rHIVE_t$	0.325	0.322	0.365	(-0.205 , 0.993)
$rHUT_t$	0.319	0.316	0.434	(-0.184 , 1.020)
$rMARA_t$	0.283	0.280	0.595*	(-0.128 , 1.381)
$rNCTY_t$	0.192	0.188	0.350	(-0.272 , 1.005)
$rRIOT_t$	0.312	0.309	0.789***	(0.119 , 1.448)
Median a)	0.237	0.234	0.456	(-0.137 , 1.074)
b) Cryptocurrency exchanges				
$rBKKT_t$	0.051	0.047	0.905	(-0.243 , 2.343)
$rCOIN_t$	0.330	0.327	0.454*	(-0.151 , 1.123)
Median b)	0.191	0.187	0.680	(-0.197 , 1.733)
c) Companies investing in cryptocurrencies				
$rMSTR_t$	0.375	0.372	0.234	(-0.356 , 0.789)
rSQ_t	0.509	0.506	-0.157	(-0.514 , 0.236)
Median c)	0.442	0.439	0.039	(-0.435 , 0.513)
d) Blockchain-linked Fintech & Cryptocurrency-payment companies				
$rOSTK_t$	0.280	0.277	0.042	(-0.322 , 0.398)
$rPYPL_t$	0.399	0.396	-0.207	(-0.454 , 0.019)
Median d)	0.340	0.337	-0.083	(-0.388 , 0.209)

Notes: (1) Table 5.3 presents 20 estimated OLS coefficients of TO_diff_t and 95% confidence intervals for these estimates. The confidence intervals were calculated by following the nonparametric bootstrapping method in Wooldridge (2012) for $m = 1000$.
(2) *** - significant at 1% level, ** - significant at 5% level, * - significant at 10% level.

Table 5.3 shows R-squared and Adjusted R-squared measures for all 20 individual OLS regressions, with a minimum Adj. R-squared equal to 5% for the model with $rBKKT_t$ as the dependent variable and a maximum Adjusted R-squared of 51% for dependent variable rSQ_t. Furthermore, estimated parameters of TO_diff_t and 95% confidence intervals of this measure are presented for each model[4]. Dependent variables are divided into four groups of CLS according to Section 4.1 and the nature of the company's linkage to the cryptocurrency market. We provide median values for all measures within each CLS category and study if the effects of connectedness measures on CLS returns vary significantly across individual categories.

The estimated effect of TO_diff_t on CLS returns is the largest for categories b) Cryptocurrency exchanges (median estimate equal to 0.680) and a) Mining companies & mining hardware producers (with a median estimate of 0.456). TO_diff_t is statistically significant at the 1% level for two models (those with $rCIFR_t$ and $rRIOT_t$ as dependent variables), and significant at 10% level for five models ($rCLSK_t$, $rEBON_t$, $rGREE_t$, $rMARA_t$ and $rCOIN_t$ as dependent variables) within these two categories. Furthermore, CLS within the first two categories have arguably a stronger linkage towards the cryptocurrency market in comparison to categories c) Companies investing in cryptocurrencies and d) Blockchain-linked Fintech & Cryptocurrency-payment companies, as for these companies cryptocurrency-linked activities often represent only a minor part of their business activities. This intuition is supported by median values of TO_diff_t estimates for groups c) and d), which are remarkably closer to zero. Moreover, the effect of TO_diff_t on CLS returns is insignificant for all models within categories c) and d). Within categories c) and d) the estimated effect of TO_diff_t on CLS returns is highest for the model with $rMSTR_t$ as the dependent variable and equal to 0.234.[5]

To sum up, the connectedness variable TO_diff_t might represent a useful measure for explaining CLS returns. The estimated effect and significance of connectedness measures on the returns of CLS vary across different categories of CLS, being more significant and higher for CLS with stronger linkages to cryptocurrencies. These findings are similar to those of Frankovic *et al.* (2022),

[4]Confidence intervals are results of the nonparametric bootstrapping method described in Wooldridge (2012).

[5]Note that MicroStrategy Inc. (MSTR) is arguably the biggest holder of Bitcoin among public companies. Thus, the linkage of MSTR to the cryptocurrency market might be significantly larger in comparison to other CLS in categories c) and d).

who find stronger connectedness effects of cryptocurrencies on CLS with relatively higher exposures towards the cryptocurrency market.

Chapter 6

Conclusion

This Bachelor's thesis studies the connectedness effects of returns between US-listed Cryptocurrency-linked stocks, five major cryptocurrencies, and the US stock market. By doing so, we contribute to the academically unexplored field of Cryptocurrency-linked stocks since a similar analysis for US-listed CLS has not been conducted before. We utilize the Dynamic Networks framework, a novel methodology proposed by Barunik & Ellington (2020b), for the measurement of connectedness effects within dynamic network systems.

In our findings, the network consisting of daily returns data of 20 US-listed CLS, five major cryptocurrencies, and the stock market index S&P 500 demonstrated significant levels of Total connectedness, which ranged from 41 to 57 throughout the sample.

Moreover, we present directional connectedness measures for individual variables, in order to analyze the main transmitters and receivers of shocks within the system. However, these measures fluctuate throughout the period of our sample, making the labeling of asset classes as "net transmitters" and "net receivers" of shocks rather difficult. Nevertheless, we identify several periods of increased or decreased NET directional connectedness for variables in the system and observe interesting interrelations of these measures. As an example, we point out the period of September 2022, when NET connectedness of cryptocurrencies reached a sample minimum, NET connectedness of S&P 500 hit a maximum and NET connectedness of CLS was close to zero.

We also decompose network connectedness into time horizons and report short-term horizons of one week to be most significant for connectedness effects. On the other hand, long-term connectedness effects within the horizon of 20+ days are the least significant.

Lastly, we study OLS regressions for CLS returns, to analyze significant explanatory variables among connectedness measures that explain returns of CLS. Firstly, we use the daily returns of the whole portfolio of 20 CLS as the dependent variable, and secondly, we substitute the whole portfolio with individual CLS returns as explained variables. We use TO_diff_t (the difference between the TO connectedness of the portfolio containing five major cryptocurrencies and the TO connectedness of S&P 500) as an interaction term between the cryptocurrency and stock market. This variable is statistically significant at the 5% level in the baseline model for CLS returns (see Table 5.1). The effect of TO_diff_t exhibits considerable variation across categories of CLS, being largest and most significant for categories with greater exposure to the cryptocurrency market. These findings corroborate Frankovic *et al.* (2022) who find stronger linkages between cryptocurrencies and CLS with high exposure to the cryptocurrency markets.

Our findings have implications for investors interested in the emerging and unexplored asset class of CLS, which represents a bridge between traditional stocks and the unconventional market of cryptocurrencies. Moreover, this thesis might also motivate other researchers to extend our research and contribute to this unexplored field of academia in the future.

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Appendix A

Results for Version dataF of the Dataset

Table A.1: Descriptive statistics of daily returns for dataF

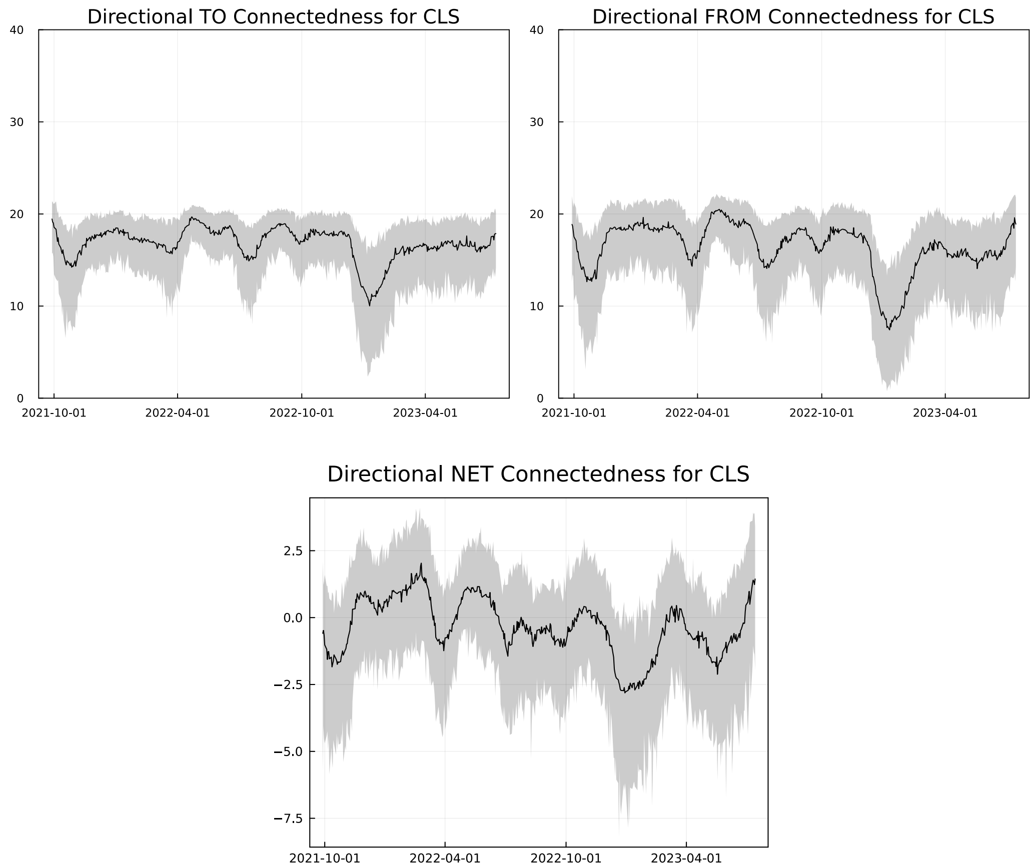
	Obs.	Mean (%)	Std. dev.	Min. (%)	Max. (%)
Cryptocurrency - linked stocks					
a) Mining companies & mining hardware producers					
ARBK	453	−0.1002	8.4900	−43.6548	36.5385
BITF	453	0.0302	6.9855	−19.9262	44.2857
BTBT	453	0.0444	6.9577	−18.2353	41.7910
CAN	453	−0.0032	6.4559	−28.7897	37.5723
CIFR	453	0.1781	8.5732	−46.7492	44.9275
CLSK	453	0.0822	6.4101	−16.6667	27.7778
EBON	453	−0.1494	7.4464	−26.9729	41.4791
GREE	453	−0.3712	9.2904	−39.0244	60.6061
HIVE	453	−0.0032	6.3135	−22.6891	37.6623
HUT	453	0.0607	6.7967	−17.9348	22.2222
MARA	453	0.1360	7.8080	−27.0284	32.1721
NCTY	453	−0.2511	6.8947	−21.1268	37.1795
RIOT	453	0.1185	6.5723	−19.1781	17.9245
b) Cryptocurrency exchanges					
BKKT[(1)]	453	0.2621	14.5098	−34.0116	234.4262
COIN	453	0.0278	6.4542	−26.4009	24.4910
c) Companies investing in cryptocurrencies					
MSTR	453	0.1190	6.0163	−25.5540	20.6482

SQ[2]	453	−0.1689	4.7067	−15.606	26.1396
d) Blockchain-linked Fintech & Cryptocurrency-payment companies					
FTFT	453	0.4951	17.4997	−18.3673	352.2727
OSTK	453	−0.0930	4.7519	−11.7479	22.8258
PYPL	453	−0.2468	3.1745	−24.5904	12.1755
Cryptocurrencies					
BTC	453	−0.0153	3.7869	−15.9747	14.5412
ETH	453	0.0033	4.7206	−19.2538	18.1149
XRP	453	0.0852	5.8218	−19.5181	73.0750
BNB	453	−0.0118	4.2135	−18.5654	16.2070
ADA	453	−0.2896	5.5212	−21.4970	29.2719
Stock market index					
SPY	453	0.0172	1.2849	−4.3483	5.4954

Notes: (1) BKKT (Bakkt Holdings Inc.) operates a platform for cryptocurrency trading and provides cryptocurrency payment solutions for their clients, and thus might be included in category d) of CLS as well. (2) SQ (Block Inc.) can also be included in CLS categories c) and d), as the company invests in cryptocurrencies, but also offers cryptocurrency-payment solutions.

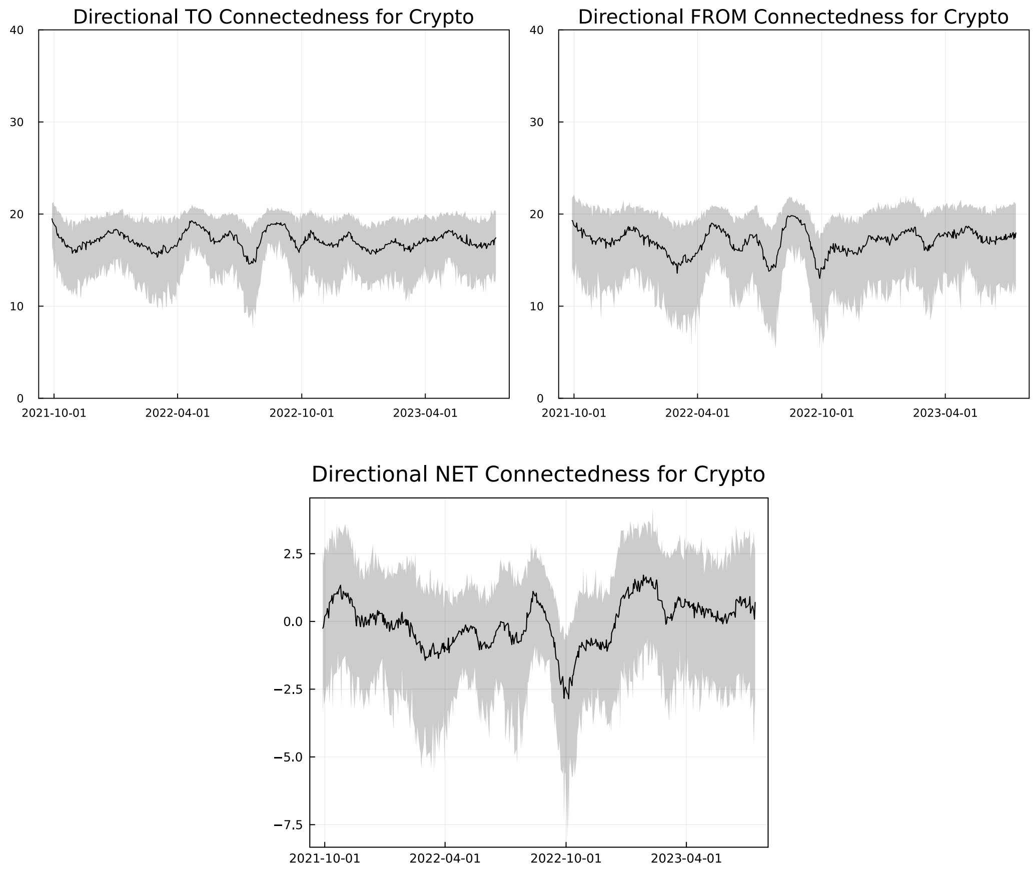
A.1 Directional Connectedness Measures for dataF

Figure A.1: Directional Connectedness for CLS (dataF)



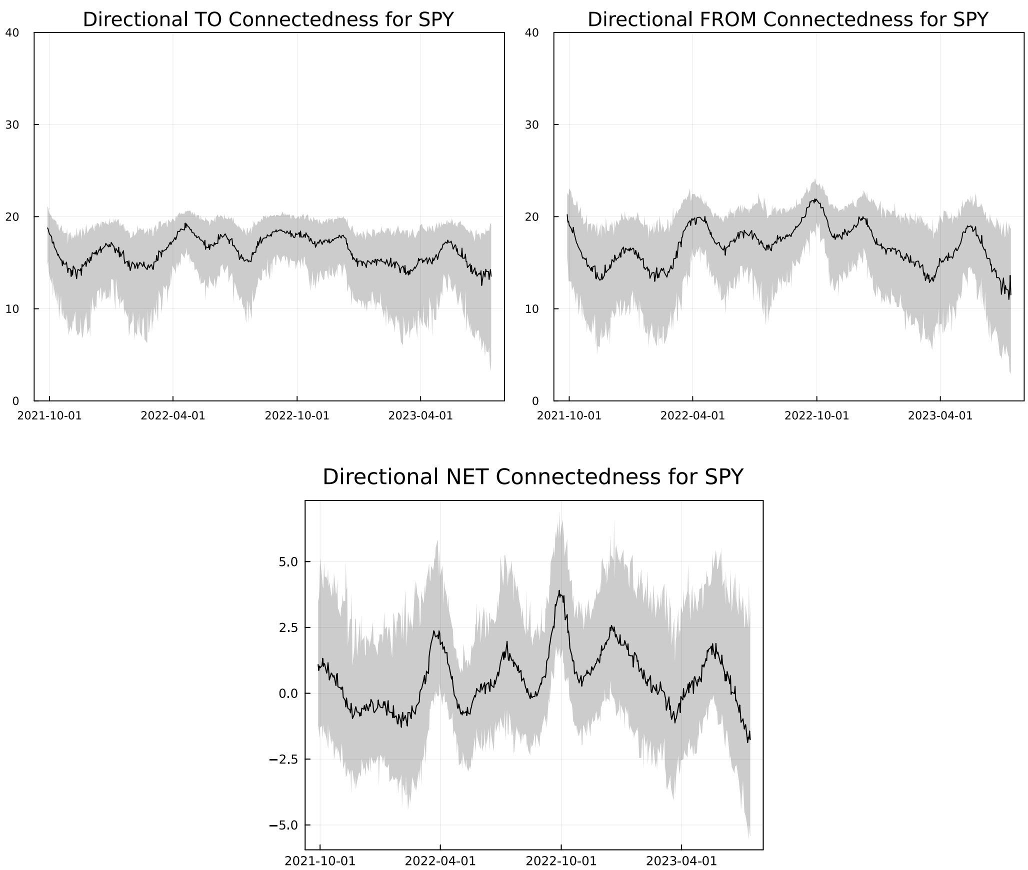
Notes: (1) Figure A.1 plots Directional TO, FROM, and NET Connectedness measures for variable "CLS" and dataset version dataF.

Figure A.2: Directional Connectedness for Crypto (dataF)



Notes: (1) Figure A.2 plots Directional TO, FROM, and NET Connectedness measures for variable "Crypto" and dataset version dataF.

Figure A.3: Directional Connectedness for SPY (dataF)



Notes: (1) Figure A.3 plots Directional TO, FROM, and NET Connectedness measures for variable "SPY" and dataset version dataF.

Appendix B

Connectedness Results for Parameter Corr=TRUE

Figure B.1: Total Dynamic Network Connectedness for dataM (Corr=TRUE)

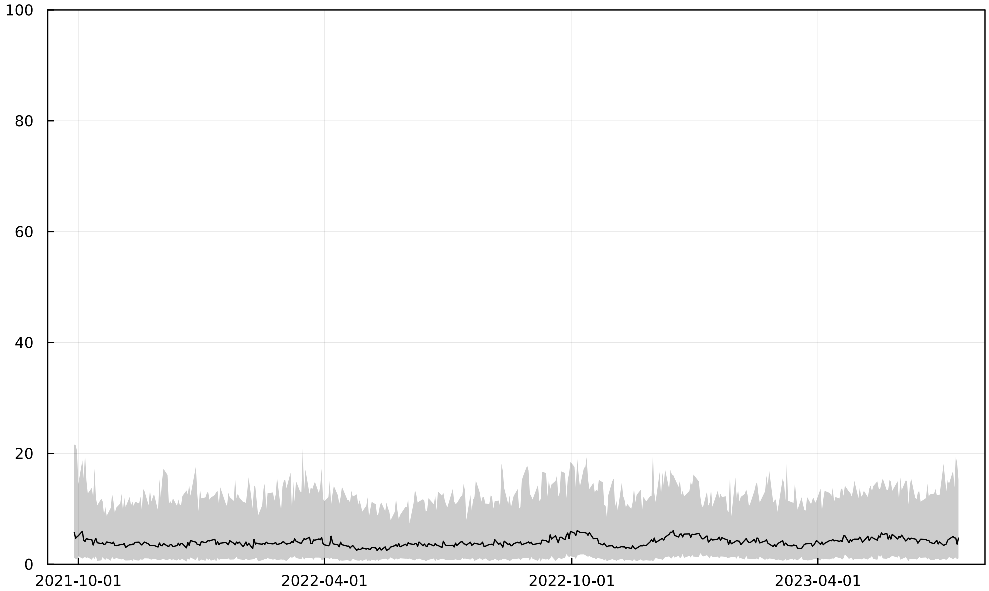
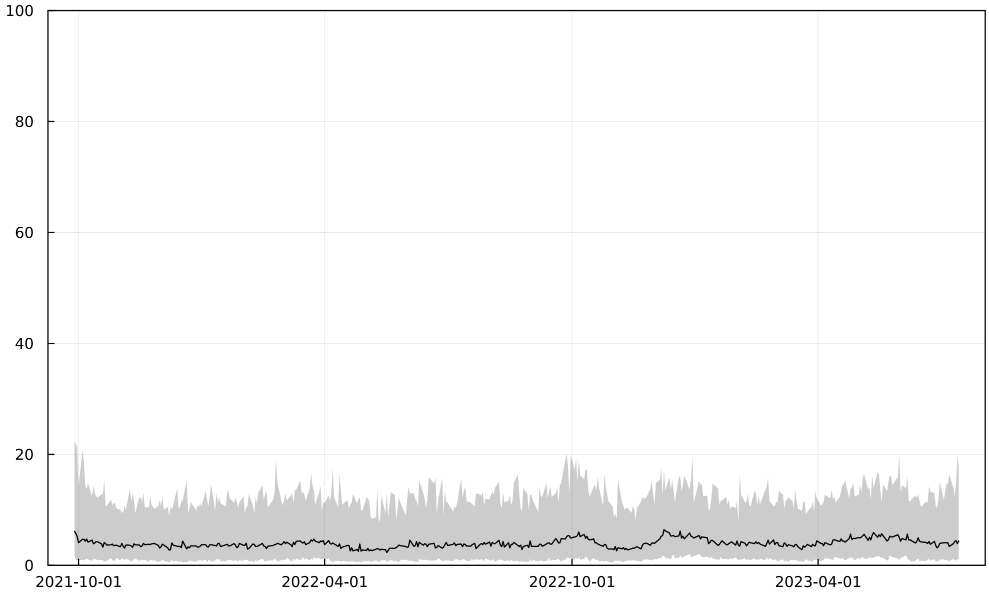


Figure B.2: Total Dynamic Network Connectedness for dataF (Corr=TRUE)



Notes: (1) Figure B.1 and Figure B.2 plot Total Dynamic Network Connectedness for the two versions of the dataset containing daily returns of “CLS”, “Crypto”, and “SPY”. (2) These plots are results of the Dynamic Networks setting with parameter Corr = TRUE. (3) Total Network Connectedness is depicted by the black line and grey areas are bordered by 2.5% and 97.5% quantiles, and thus represent 95% confidence intervals of the measure.

Figure B.3: Time Horizon dynamics of Connectedness for dataM (Corr=TRUE)

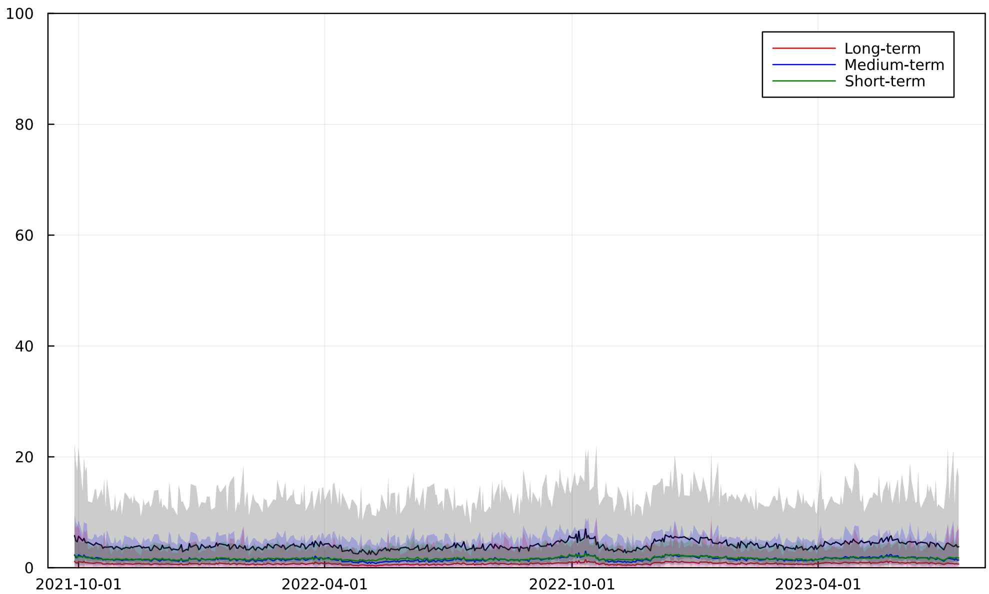
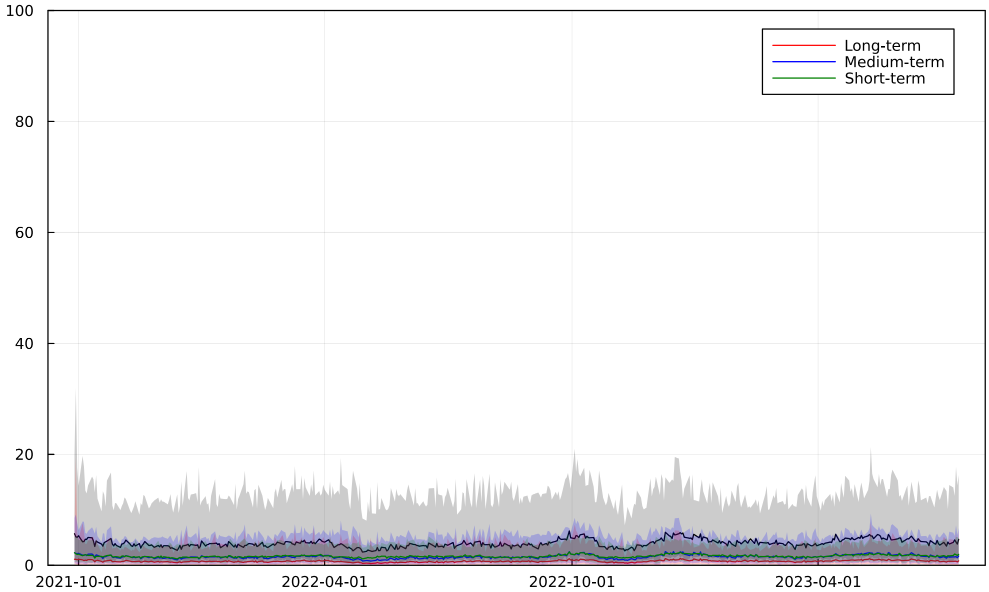


Figure B.4: Time Horizon dynamics of Connectedness for dataF (Corr=TRUE)



Notes: (1) Figure B.3 and Figure B.4 plot Horizon dynamics of Network Connectedness for the two versions of the dataset containing daily returns of "CLS", "Crypto", and "SPY". (2) These plots are results of the Dynamic Networks setting with parameter Corr = TRUE. (3) Total Network Connectedness is depicted by the black line. Lighter-colored areas are bordered by 2.5% and 97.5% quantiles and thus represent 95% confidence intervals of respective measures.