instituto politécnico de gestão e tecnologia

MESTRE EM FINANÇAS E FISCALIDADE

MASTER IN FINANCE AND TAXATION

On the Contagion Effect of Cryptocurrencies on Stock Markets

Fehri Fares

DISSERTATION

VILA NOVA DE GAIA

SEPTEMBER | 2025

INSTITUTO POLITÉCNICO DE GESTÃO E TECNOLOGIA

On the Contagion Effect of Cryptocurrencies on Stock Markets

Fares Fehri

Aprovado em 17/12/2025

Composição do Júri

____

Presidente: Prof. Doutor Júlio Silva Martins

____

Arguente: Profª. Doutora Maria Teresa Taveira de Barros

____

Orientador: Prof. Doutor José Fernando da Silva Neto

Vila Nova de Gaia

2025

Tese de Mestrado realizada sob a orientação do(a)(s) Prof. Doutor José Fernando da Silva Neto apresentada ao ISLA - Instituto Politécnico de Gestão e Tecnologia de Vila Nova de Gaia para obtenção do grau de Mestre em Finanças e Fiscalidade, conforme o Despacho n.º 4669/2024

Fehri Fares

Dedication

To my father and mother for their love, support and strength continue to inspire me daily.

I am infinitely indebted to my dear family, and my friends for their constant support throughout my entire life.

I would like to extend my deep and sincere gratitude to everyone who contributed to the success and achievement of not only my academic life, but also the lessons learned throughout my life.

Fares Fehri

Acknowledgements

I would like to express my gratitude to my academic supervisor Prof. Dr. José Neto for his support in the whole process of this thesis.

I also thank academic staff at ISLA - Instituto Politécnico de Gestão de Tecnologia for professionally conducting their responsibilities to teach and groom me academically.

I would also like to thank all members of the jury for agreeing to judge my work.

Many thanks to my parents, friends and relatives for their support.

Abstract (EN)

The growing integration of cryptocurrencies into global financial systems has prompted heightened scrutiny regarding their impact on traditional asset markets, particularly during episodes of financial distress. This thesis investigates the contagion effects of major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and Solana (SOL) on key stock market indices: the S&P 500 (USA), EURO STOXX 50 (Europe), and Nikkei 225 (Japan). A DCC-GARCH model is used on daily returns from April 2018 to April 2025, the analysis covers three financial events precisely the COVID-19 crash, the 2021 crypto rally, and the FTX collapse. Findings show strong time-varying correlations, particularly between Bitcoin and the S&P 500, and increasing co-movements between Ethereum and Western markets. In contrast, links with the Nikkei 225 remain weak. These crises challenge the view of cryptocurrencies as reliable hedging tools. The study points out the growing integration of digital assets into financial systems and the need for adaptive risk management and regulatory results suggest a geographic asymmetry in crypto-equity contagion. Complementary tests (t-tests, Chow test, and Forbes & Rigobon adjustment) confirm stronger contagion during strategies. The contagion direction is also explored to see in what direction the contagion goes.

Keywords: Cryptocurrency, Financial Contagion, DCC-GARCH, Volatility Spillover, Dynamic Correlation, Stock Markets, Risk Management, Systemic Risk

Abstract (PT)

A crescente integração das criptomoedas nos sistemas financeiros globais tem levado a um maior escrutínio sobre o seu impacto nos mercados de ativos tradicionais, particularmente durante períodos de crise financeira. Esta tese investiga os efeitos de contágio das principais criptomoedas: Bitcoin (BTC), Ethereum (ETH) e Solana (SOL) nos principais índices bolsistas: S&P 500 (EUA), EURO STOXX 50 (Europa) e Nikkei 225 (Japão). É utilizado um modelo DCC-GARCH com base nos retornos diários de abril de 2018 a abril de 2025. A análise abrange três eventos financeiros: a crise da COVID-19, a subida das criptomoedas em 2021 e o colapso da FTX. Os resultados mostram fortes correlações variáveis ao longo do tempo, particularmente entre o Bitcoin e o S&P 500, e movimentos conjuntos crescentes entre o Ethereum e os mercados ocidentais. Em contraste, as correlações com o Nikkei 225 continuam fracas. Estas crises desafiam a visão das criptomoedas como ferramentas fiáveis de proteção contra riscos. O estudo destaca a crescente integração dos ativos digitais nos sistemas financeiros e a necessidade de uma gestão de risco adaptativa. Os resultados sugerem uma assimetria geográfica no contágio entre criptomoedas e ações. Os testes complementares (testes t, teste de Chow e ajuste de Forbes & Rigobon) confirmam um contágio mais forte durante as estratégias. A direção do contágio é também explorada para determinar para onde se propaga.

Palavras-chave: Criptomoeda, Contágio Financeiro, DCC-GARCH, Transbordamento de Volatilidade, Correlação Dinâmica, Mercados de Acções, Gestão de Risco, Risco Sistémico

Table of Contents

Figure Index

Table Index

List of abbreviations

ADF test - Augmented Dickey-Fuller test

AR - AutoRegression

ARCH - AutoRegressive Conditional Heteroscedasticity

ARCH-LM test - AutoRegressive Conditional Heteroscedasticity Lagrange Multiplier test

BCT – Bitcoin

GARCH - Generalized AutoRegressive Conditional Heteroscedasticity

CCC -Constant Conditional Correlation

DCC -Dynamic Conditional Correlation

ETH – Ethereum

Nikkei – Nihon keizai shinbun

SOL - Solana

S&P: Standard & Poor's

VAR -Vector AutoRegression

VECM - Vector Error Correction Model

VEC - Vector Error Correction

1 Introduction

Over the last few years, cryptocurrencies have changed from being just a small innovation into a major force in global financial markets. The assets that have been introduced as decentralized alternatives to traditional currencies such as Bitcoin (BTC), Ethereum (ETH), and Solana (SOL) have changed from being speculative and investment instruments to be recognized and wildly held by retail and institutional investors. Their expected advantages—high returns, technological sophistication, and limited correlation with traditional assets—have led to their growth as a new asset class in modern portfolios.

In the same breath, the ever-increasing financialization and the general acceptance of the market for cryptocurrencies have led to a lot of concerns on the one hand and a confirmation on the other hand about the cryptos' nature and their behavior in market stress periods. Studies initially revealed how they complemented diversification or acted as a hedge against systemic risk in the markets. However, the recent financial crashes have shown that there is a strong bond between the crypto and equity markets. Situations like the COVID-19 shock, the 2021 cryptocurrency bull run, and the collapse of the FTX platform in 2022 serve as examples to show that they can experience the same ups and downs at the same time, giving rise to the fact that they might not be as separate from the traditional markets as we used to think.

This thesis aims to investigate how the relationship between cryptocurrencies and global equity indices has developed by checking for the presence and character of contagion effects. In particular, it is determining if the volatility brought in crypto markets gets transferred to the major stock indices which are the S&P 500 (USA), EURO STOXX 50 (Europe), and Nikkei 225 (Japan). The research relies on the Dynamic Conditional Correlation–Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model alongside structural break tests (Chow), correlation adjustments by Forbes & Rigobon, and t-tests to analyze changes in market interdependence.

The study uses the daily return data from April 2018 to April 2025 that includes both periods of prosperity and downturn to give it a solid grasp of dynamic correlation patterns. This analysis aims to shed light on the financial contagion, provide inputs to investment strategies, and be step with risk management in a financial environment that is increasingly affected by digital assets.

1.1 Background and Context

The appearance of cryptocurrencies has changed the global financial landscape, presenting new investment options, but at the same time, it has caused a lot of discussion about the impact of new types of assets on traditional markets. One of the most current issues is *financial contagion*. The latter means that money flows unleash here and there, from one asset class to another, hence, in the worst-case scenario, volatility can be broadly expected in all markets.

It has been noted that the correlation between cryptocurrency and stock markets is topical after all, given the fact that digital assets are highly volatile. Some are called Bitcoin; others are referred to as Ethereum. The traditional financial system has been affected by this trend, and some parties are wondering if cryptocurrencies will be part of the solution or the problem in times of market downturns.

This research work is raising a question of the potential of cryptocurrencies on stock exchanges, in particular, during a financial crisis of the market. The study also investigates whether and to what extent digital assets make matters worse by causing ripple effects in the markets. The aim of the paper is to identify the past, present, and future of inter-market linkages and what this means for investors, agencies, and policymakers. The main aim is to characterize whether cryptocurrencies are still the new financial instruments or if they only fuel the flames of already burning markets that are vulnerable to shocks.

1.2 Problem Statement

The enormous extent in which cryptocurrencies have been multiplied and their coming into the financial system in a more intensive manner have brought about market risks of a whole new nature. At first, they were considered only as alternative or uncorrelated assets, however, today, they are gradually becoming more and more similar with traditional financial markets, particularly during the crisis periods. This change calls into question the entire course of reasoning about digital assets that holds them as the only safe harbours in times of upheaval of the market. This article discusses the issue of searching for an answer to the question if cryptocurrencies operate as sources of volatility transmission to the global stock markets. More specifically, the questionnaire targets a problem that is illustrated by the following questions:

- Are the cryptocurrencies, which are the most prominent in the market such as Bitcoin, Ethereum and Solana, having correlation relationships with major stock indices like the S&P 500, Nikkei 225 and Euro STOXX 50 that are statistically valid and time-varying?
- Could the periods of extreme volatility, for instance, a financial crisis, be the ones that generate not only the highest correlation coefficients but also the resulting contagion phenomenon?
- Is it within the realm of possibility that these events do not have the same symptoms all over different parts of the globe, hence, the American market would be quite different from the European or Asian one?

Attempting an answer to these questions is a must-have for the investors, analysts, and regulators who are trying to work out the systemic implications of cryptocurrencies and come up with resilient

1.3 Research Objectives

The study is based on the objectives and it is aiming to find out the answers to these research questions:

1. To what extent are cryptocurrency returns correlated with traditional stock market returns?
2. In what manner are the correlations being affected in the course of time period, mainly when the market is in a state of confusion?
3. Are all the cryptocurrencies the same degree of shock sources or some of them are stronger versus others?
4. Are these issues the same in all the main regional markets?

1.4 Structure of the thesis

This thesis is structured as follows:

- **Chapter 2** presents a review of the literature on financial contagion, cryptocurrency behavior, and their interaction with traditional markets.
- **Chapter 3** outlines the data sources and methodological framework, including the DCC-GARCH model and supporting statistical tests.
- **Chapter 4** presents the empirical results and discusses key findings, with a focus on correlation dynamics and contagion patterns.
- **Chapter 5** concludes the thesis, highlighting theoretical and practical implications, as well as limitations and recommendations for future research.

2 Literature review

The intersection of cryptocurrency and traditional equity markets has garnered growing academic attention, particularly regarding contagion effects that emerge during periods of market stress. Cryptocurrencies exhibit pronounced volatility, characterized by large and sudden price fluctuations, which can spill over into stock markets. This transmission is particularly relevant in emerging economies, where differences in market structure, liquidity, and investor behavior set them apart from developed markets. As digital assets gain prominence within global financial systems, understanding their interactions with equity markets has become crucial for investors, policymakers, and regulators.

This literature review synthesizes the evolution of research on cryptocurrency–equity market interactions, highlighting the mechanisms of volatility contagion, behavioral and sentiment-driven effects, and methodological advances in empirical analysis. We organize this review into three main research streams: (i) volatility contagion and market interdependencies, (ii) cryptocurrency shocks and stock market reactions, and (iii) behavioral and machine-learning approaches to capturing complex market dynamics. We emphasize contrasts among studies to illustrate the evolving understanding of crypto–equity interdependence.

2.1 Volatility contagion and Market interdependencies

The study of volatility in cryptocurrency markets has gained substantial attention over the past decade, reflecting the rapid growth, increasing market capitalization, and financial integration of digital assets. Cryptocurrencies such as Bitcoin, Ethereum, and

Solana are characterized by extreme price fluctuations, often exceeding those observed in traditional financial assets such as equities or commodities. Early research primarily focused on these intrinsic volatility characteristics, treating cryptocurrencies as largely isolated from broader financial systems.

Chu et al. (2017) were among the first to apply GARCH models to cryptocurrency returns, demonstrating that these assets exhibit volatility clustering. These findings provided early evidence that cryptocurrencies behave as speculative instruments, subject to rapid price swings driven by market sentiment, liquidity constraints, and macroeconomic factors. However, these studies largely ignored the systemic implications of such volatility, leaving open the question of how shocks in crypto markets may propagate to traditional financial markets.

As the cryptocurrency ecosystem matured, research attention shifted toward cross-market volatility spillovers, exploring how shocks in cryptocurrencies could influence equities, commodities, and other financial instruments.

Bouri et al. (2017) employed multivariate ARCH models to analyze bidirectional volatility spillovers between Bitcoin, Ethereum, and major stock indices, revealing that cryptocurrencies are not entirely isolated but can transmit shocks to equity markets, particularly during periods of financial turbulence.

Trabelsi (2018) found that as cryptocurrency markets mature, correlations with traditional assets increase, which amplifies systemic risk, particularly during episodes of market stress.

In contrast, Guesmi et al. (2019) reported low average correlations between Bitcoin and traditional equities under normal market conditions, suggesting that cryptocurrencies may provide diversification benefits in stable periods.

These contrasting findings indicate that the strength, direction, and significance of spillovers are regime-dependent, increasing during crises and diminishing in stable periods. This underscores the need for dynamic, time-varying models to capture the conditional nature of contagion.

Methodological innovations have further advanced our understanding of volatility interconnections. Network-based approaches, for example, capture indirect channels of contagion that traditional bilateral models may overlook.

Ji et al. (2018) applied network frameworks to show that volatility originating in cryptocurrencies can propagate to equities and commodities through multiple interconnected channels, even when pairwise correlations appear weak.

Katsiampa et al. (2019) utilized high-frequency trading data to reveal the dynamic structure of volatility within cryptocurrency markets, showing that interdependencies between cryptocurrencies themselves affect overall market risk and have important implications for portfolio allocation and risk management.

Corbet et al. (2018) examined speculative bubbles in Bitcoin and Ethereum, finding that during bubble periods, correlations with equity markets strengthened significantly, whereas correlations weakened outside these periods.

These findings emphasize the conditional and state-dependent nature of contagion, highlighting the importance of considering market regimes, speculative dynamics, and asset maturity in risk assessment.

The practical implications of volatility contagion for investors, portfolio managers, and regulators are substantial.

Wang et al. (2020) demonstrated that Bitcoin may act as either a hedge or a speculative asset, depending on market conditions, providing protection in some periods while increasing risk in others.

Thaker and Ah Mand (2020) confirmed that Bitcoin tends to behave independently during stable periods but acts as a transmitter of volatility during crises, reinforcing the regime-dependent diversification hypothesis.

Yavuz et al. (2022) showed that crypto–equity correlations rise sharply during market stress, thereby reducing diversification benefits and emphasizing the need for adaptive, dynamic portfolio strategies.

These insights are particularly relevant for investors seeking to integrate cryptocurrencies into multi-asset portfolios, where understanding conditional co-movements is crucial to mitigating systemic risk.

Methodological choices also play a critical role in shaping empirical findings. Univariate GARCH models capture the persistence of volatility for individual cryptocurrencies, while multivariate ARCH/GARCH frameworks allow for assessment of co-movements across multiple assets, revealing direct spillover effects. Network-based models and high-frequency analyses uncover indirect contagion channels, highlighting connections that may be overlooked in simpler models (Ji et al., 2018; Katsiampa et al., 2019). These methodological differences partly explain why some studies emphasize strong spillovers while others report diversification potential, demonstrating that the choice of model is as important as the choice of data when analyzing crypto–equity interactions.

In summary, research on volatility contagion in cryptocurrency and equity markets illustrates heterogeneous and regime-dependent outcomes. While some studies highlight low correlations and potential diversification benefits (Guesmi et al., 2019), others reveal strong bidirectional spillovers, particularly during market turbulence (Trabelsi, 2018; Bouri et al., 2017).

2.2 Cryptocurrency Market Shocks and Stock Market Reactions

Another key research stream examines how shocks in cryptocurrency markets affect traditional stock markets. Although cryptocurrencies are often viewed as speculative and relatively isolated, major events—such as the 2017 Bitcoin boom and crash, China’s 2021 regulatory crackdown, and the FTX collapse in 2022—show that crypto shocks can spill over into equity markets, especially during periods of market stress. These episodes provide valuable evidence on volatility transmission, market resilience, and contagion effects.

Matkovskyy and Jalan (2019) provide early evidence that Bitcoin exhibits contagion effects during market stress, challenging the long-held perception that cryptocurrency markets are largely decoupled from equities. Their findings indicate that significant shocks in cryptocurrency prices can propagate to global stock indices, particularly when investor uncertainty is elevated. Similarly,

Mnif et al. (2022) highlight the role of behavioral mechanisms during the COVID-19 pandemic, showing that herding behavior, fear, and sentiment amplified volatility across both cryptocurrency and stock markets. These studies suggest that investor psychology plays a critical role in transmitting shocks, adding a layer of complexity beyond what is captured by traditional econometric models, which often assume rational behavior.

Empirical analyses reinforce the notion that extreme cryptocurrency price movements often coincide with stock market fluctuations.

Dionașu et al. (2022) demonstrate that Bitcoin investor behavior frequently mirrors the behavior of traditional market participants, indicating a degree of integration in decision-making across asset classes.

Baur et al. (2018) further observed that Bitcoin functions as a risk asset during periods of uncertainty, implying that investors treat it similarly to equities when assessing market risk.

These findings suggest that, under certain conditions, cryptocurrencies can act as channels of systemic risk, transmitting shocks to traditional financial markets and influencing portfolio outcomes.

The impact of cryptocurrency shocks is also sector-dependent, with certain industries exhibiting higher sensitivity. Research indicates that technology stocks are particularly vulnerable to fluctuations in cryptocurrency markets.

Goeldi et al. (2020) found that volatility in cryptocurrencies correlates strongly with technology sector returns, likely due to overlapping investor bases, technological synergies, and speculative trading patterns.

Anamika et al. (2023) further demonstrated that negative cryptocurrency sentiment, often driven by news or social media trends, triggers adverse reactions in technology equities, amplifying market volatility. Beyond technology, sentiment-driven spillovers can also affect other sectors with significant exposure to fintech and blockchain technologies, although the magnitude is generally lower.

Gurdgiev and Loughlin (2020) and Chakraborty and Subramaniam (2023) emphasize that social media, online forums, and behavioral biases amplify contagion effects, leading to irrational market responses that go beyond fundamentals.

These findings highlight that behavioral channels are critical for understanding the transmission of shocks and must be integrated into modern risk assessment frameworks.

Macroeconomic and geopolitical factors also play a significant role in shaping crypto–equity interactions.

Mgadmi (2024) observed that during the Russia–Ukraine war, traditional markets experienced increased volatility, whereas cryptocurrencies displayed relative resilience, reflecting their unique risk drivers and global investor base.

Conversely, Ibrahim et al. (2024) found that during the COVID-19 pandemic, volatility contagion intensified, with cryptocurrencies aligning more closely with equities and gold.

These results demonstrate that contextual factors, including crises, regulatory events, and macroeconomic stress, significantly influence the magnitude and direction of contagion.

The literature indicates heterogeneous impacts across different crises, sectors, and behavioral channels. Some shocks demonstrate the resilience of cryptocurrencies, as seen in Mgadmi (2024), where crypto prices were relatively insulated from geopolitical volatility.

Other episodes, such as the FTX collapse and the 2021 Chinese regulatory crackdown, reveal intensified spillovers to equity markets, underscoring that contagion is highly context-dependent (Mnif et al., 2022; Ibrahim et al., 2024).

Sectoral differences are evident, with technology stocks consistently showing higher sensitivity to crypto-induced shocks, likely reflecting overlapping investor interests, innovation linkages, and sentiment-driven speculation (Goeldi et al., 2020; Anamika et al., 2023).

Behavioral and sentiment-driven channels often amplify shock transmission. Social media, news, and online forums can trigger herding, where investors react to perceived signals rather than fundamentals, increasing equity volatility (Gurdgiev & Loughlin, 2020; Chakraborty & Subramaniam, 2023). These dynamics highlight the limits of traditional models and the value of integrating sentiment analysis or behavioral frameworks in crypto–equity contagion studies.

These findings have important implications for investors, portfolio managers, and regulators. Recognizing that crypto-to-equity shocks are conditional, sector-specific, and sentiment-driven helps improve risk assessment and portfolio diversification. Investors may need to adjust exposures dynamically, especially in tech stocks, while regulators can better monitor extreme crypto events that could amplify systemic risk.

In summary, research on cryptocurrency market shocks and stock market reactions emphasizes the heterogeneous and context-dependent nature of contagion. Extreme movements in cryptocurrency prices can spill over to equity markets through a combination of behavioral, sectoral, and macroeconomic channels. The magnitude and direction of these effects vary across crises, sectors, and time periods, highlighting the need for nuanced, multi-dimensional modeling approaches that account for sentiment, investor behavior, and market integration. These insights provide a critical foundation for understanding how digital assets interact with traditional financial systems and inform strategies for risk management, portfolio allocation, and regulatory oversight.

2.3 Behavioral and Machine-Learning Approaches

Recent research highlights the role of behavioral and computational methods in understanding complex interactions between cryptocurrencies and stock markets. While traditional models like GARCH and VAR capture volatility and linear spillovers, they often miss nonlinear patterns, dynamic dependencies, and sentiment-driven effects. The rise of digital assets and the influence of social networks have prompted scholars to combine behavioral finance insights with machine-learning techniques for a more nuanced view of crypto–equity contagion.

Ahmed et al. (2023) introduced the idea of mutual coupling, showing that price movements in cryptocurrencies and equities can dynamically influence each other. This means the markets should be considered together in portfolio management, as shocks in one can feed back into the other, amplifying volatility and systemic risk. Unlike traditional linear models, mutual coupling captures these two-way, time-varying relationships, underscoring the need for adaptive risk management.

Machine-learning techniques have proven especially effective at capturing these nonlinear and complex dependencies. Long short-term memory (LSTM) networks, a type of recurrent neural network, are particularly well-suited to financial time series due to their ability to model long-range dependencies and sequence dynamics.

Gupta et al. (2021) applied LSTM models to cryptocurrency and equity returns, demonstrating that these models outperform traditional econometric approaches in capturing complex interdependencies and sentiment-driven market effects. For instance, LSTMs can detect subtle interactions between market sentiment, macroeconomic shocks, and price volatility that might otherwise be obscured in linear regression frameworks. By learning from historical patterns and adjusting to nonlinear dynamics, machine-learning models provide enhanced predictive accuracy and early warning signals of potential contagion events.

Behavioral studies complement these computational approaches by highlighting the psychological mechanisms underlying market contagion.

Gurdgiev and Loughlin (2020) and Goeldi et al. (2020) underscore the role of herding behavior, where investors collectively react to perceived market signals, amplifying volatility and contagion.

Similarly, Dionașu et al. (2022) show that cryptocurrency investor decisions often mirror the behavior of traditional equity investors, indicating a behaviorally interconnected market environment.

Anamika et al. (2023) further emphasize that negative sentiment in crypto markets, frequently propagated via social media, can spill over into technology stocks and other sectors, generating adverse reactions even when fundamental valuation metrics remain stable.

Collectively, these studies highlight that investor sentiment, herding, and behavioral biases are central to understanding the magnitude and direction of volatility spillovers in modern financial markets.

One of the key insights from integrating behavioral and computational approaches is that static correlation analyses often underestimate crisis-induced interconnections.

Troian (2024) emphasizes the dynamic and reciprocal nature of crypto–equity interactions, advocating for adaptive portfolio strategies that respond to evolving market conditions. Static measures, such as average correlations over long periods, may fail to capture regime shifts, such as those observed during the 2017 Bitcoin surge and crash, the 2021 crypto rally, or the FTX collapse in 2022. These events illustrate that contagion intensity is not constant but varies with market stress, investor sentiment, and external shocks, reinforcing the need for models that can adapt to changing market regimes.

Behavioral and machine-learning studies highlight key differences from traditional models. GARCH and VAR capture volatility and linear spillovers but miss nonlinearities and complex interdependencies. Sentiment-driven contagion can amplify shocks beyond fundamentals, while machine-learning models detect subtle patterns but often lack interpretability. For example, an LSTM might predict rising crypto–equity correlations without showing the underlying drivers. This underscores the value of hybrid approaches combining quantitative models, behavioral insights, and economic interpretation.

3 Research Design and Methodology

This chapter outlines the methodological approach used to analyze the contagion effect of cryptocurrencies on stock markets. It discusses the research philosophy, data sources, variables, analytical methods, and statistical models applied in the study.

3.1 Research Design

3.1.1 Research Approach

The study adopts a quantitative research approach to assess the financial contagion effect of cryptocurrencies on stock markets. The positivist research paradigm is used, which assumes that financial market behaviors can be objectively measured using statistical and econometric models.

The study follows a deductive approach, where hypotheses about contagion are tested using empirical data. This is suitable given the study's reliance on market data, volatility spillover models, and correlation analysis.

3.1.2 Research Type

- Descriptive Research: Examines historical cryptocurrency and stock market data to identify trends and contagion patterns.
- Explanatory Research: Tests the relationships between cryptocurrency price movements and stock market volatility using econometric models.

3.2 Data Sources and Selection Criteria

This study relies on secondary data from reputable financial databases to examine the interactions between cryptocurrencies and traditional stock markets. The dataset covers price movements of major cryptocurrencies and global equity indices, allowing for an analysis of co-movements and potential contagion effects during key market events.

3.2.1 Data Sources

The study utilizes secondary data from reputable financial databases, covering price movements of cryptocurrencies and stock market indices. The key sources include:

- Cryptocurrency Data: Bitcoin (BTC), Ethereum (ETH), and Solana (SOL), from Yahoo finance.
- Stock Market Data: S&P 500, EURO STOXX 50, and Nikkei 225, sourced from Yahoo Finance.

Limitations and potential biases:

- **Data quality:** While Yahoo Finance is widely used, minor discrepancies or missing observations may exist in historical data.
- **Trading hours mismatch:** Cryptocurrencies trade 24/7, whereas stock indices follow regional market hours, potentially causing timing misalignments.

- **Corporate actions:** Stock indices are adjusted for dividends and splits, which may not directly align with unadjusted cryptocurrency prices.

3.2.2 Data Timeframe

The study focuses on the period April 2018-April 2025, capturing critical events that influenced the interaction between cryptocurrencies and stock markets. The study segments the analysis across distinct crisis periods COVID-19, the 2021 crypto boom and correction, and the FTX collapse to assess structural changes in co-movements and test the robustness of the contagion hypothesis. The 2020 COVID-19 Market Crash – Testing crypto-equity correlation during economic shocks.

Limitations and potential biases :

- **Event selection bias:** Focusing on high-profile crises may overstate observed correlations.
- **Survivorship bias:** Exclusion of delisted or low-liquidity cryptocurrencies may skew results toward more stable assets.

3.2.3 Sample Selection

- Cryptocurrencies: Bitcoin (BTC) and Ethereum (ETH) and Solana (SOL) are chosen due to their market dominance and liquidity.
- Stock Indices: Global stock indices such as the S&P 500, EURO STOXX 50, and Nikkei 225 are selected to represent traditional markets.

Limitations and potential biases :

- **Representativeness:** The selected cryptocurrencies and indices may not capture the full spectrum of their respective markets.
- **Liquidity differences:** Smaller cryptocurrencies or less liquid indices may behave differently, limiting generalizability.
- **Currency effects:** International indices are denominated in local currencies, and exchange rate fluctuations may introduce additional volatility unrelated to intrinsic market movements.

3.3 Econometric and Statistical Models

To analyze the contagion effect, econometric techniques are applied. Because these models are applied to time series, it assumes the use of stationary variables, so it is necessary to evaluate their order of integration, the detection of possible long-term relationships and their transformation, in compliance with this property (e.g., Gujarati & Porter, 2009).

The primary analytical framework is the Dynamic Conditional Correlation–Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model introduced by Engel (2020), which captures time-varying correlations and volatility spillovers between assets. To further validate contagion dynamics, complementary tests such as difference-in-means t-tests, Chow structural break tests, and the Forbes & Rigobon corrected correlation method are employed. To apply this model, logarithmic returns are used instead of prices to ensure stationarity of the series. Formally:

$$r_t = ln(P_t) - ln(P_{t-1})$$

Where

- r_t is the log return at time t
- P_t is price at time t
- P_{t-1} is price at time $t-1$
- $ln(\cdot)$ is the natural logarithm

Below, we describe methods underlying the applied methodology.

3.3.1 Augmented Dickey-Fuller (ADF) Unit Root Test

The Augmented Dickey-Fuller (ADF) test is a key statistical tool used in econometrics to test the stationarity of a time series. Introduced by Dickey and Fuller (1979), this test has been extensively extended to account for autocorrelation effects in the residuals, giving rise to the 'augmented' version. The ADF test has become a standard step in the analysis of economic and financial series, particularly before estimating models such as ARIMA or GARCH.

The ADF test checks for the presence of a unit root in a time series, which would indicate non-stationarity. The null hypothesis and the alternative hypothesis are formulated as follows:

H_0: The series has a unit root (non-stationary)

H_1: The series is stationary (no unit root)

A non-stationary series exhibits statistical properties that vary over time, making predictive analysis more complex. Stationarity is therefore a crucial property for many econometric models.

There are several unit root tests, however, in this study we opted for the ADF test, titled at this point, developed in 1979 by Dickey and Fuller, estimated using the following equation (Islam et al., 2018):

$$\Delta w_t = \alpha_0 + \alpha_1 t + \delta w_{t-1} + \sum_{i=1}^{m} \beta_i \Delta w_{t-1} + \epsilon_t$$

When observing that the time series w does not present a unit root, i.e., δ statistically significant, it can be stated that the series is stationary, rejecting the null hypothesis (H_0:$\delta = 0$).

3.3.2 Arch-LM Test

The ARCH-LM (Autoregressive Conditional Heteroskedasticity - Lagrange Multiplier) test is a fundamental statistical tool for detecting the presence of conditional heteroskedasticity in financial time series. Proposed by Robert Engle (1982), this test allows one to assess whether the residuals of a mean model have a time-dependent conditional variance, which justifies the use of ARCH or GARCH models to model volatility.

The ARCH-LM test aims to test the following null hypothesis:

H_0: Absence of ARCH effects (conditional homoscedasticity)

H_1: Presence of ARCH effects (conditional heteroscedasticity)

The presence of ARCH effects means that the variance of errors at a given time depends on the squares of past residuals. This corresponds to a time-dependent structure in volatility, often observed in financial returns, particularly stock market or cryptocurrency series.

The test is based on the residuals of a mean model (usually an AR model). If we denote the residuals by, $\hat{\varepsilon}_t$ we proceed as follows:

1. We estimate an AR model (or a constant mean) and recover the residuals.

2. tWe estimate an auxiliary regression of the form:

$$\hat{\varepsilon}_t^2 = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1}^2 + \cdots + \alpha_q \hat{\varepsilon}_{t-q}^2 + u_t$$

3. We test the joint significance of the α_i (at least one $\alpha_i \neq 0$) using the Lagrange Multiplier (LM) statistic, asymptotically distributed according to a chi-square law with q degrees of freedom.

We then interpret the result of the test:

- If the *p-value* of the test is less than 0.05, the null hypothesis of homoscedasticity is rejected which implies that ARCH effects are present and the use GARCH model can be applied.
- If the *p-value* is greater than 0.05, there is insufficient evidence of ARCH effects and the GARCH models may not be necessary.

3.3.3 Univariate Volatility Modeling: GARCH Model

The ARCH (Autoregressive Conditional Heteroskedasticity) model was developed by Engle (1982) for conditional variances of errors series. Bollerslev (1986) extended the model by introducing the GARCH(p,q) model. The most common GARCH(1,1) model is described by the following equation

$$y_t = \mu + \varepsilon_t$$

$$\varepsilon_t = \sigma_t z_t, \qquad with\ z_t \sim N(0,1)$$

$$\sigma_t^2 = \omega + \alpha\, \varepsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2$$

The GARCH model depicts the volatility clustering nature of financial markets. It can be shown that stationarity requires $\alpha + \beta < 1$. The model offers highly informative conditional variance forecasts for risk management.

Despite its univariate relevance, the GARCH model cannot capture dynamic interdependencies between multiple time series, such as stock indices or exchange rates.

3.3.4 Multivariate Extension: The DCC-GARCH Model

To model conditional covariance between multiple assets, Engle (2002) proposed the DCC model, which allows dynamic estimation of conditional correlations while retaining the GARCH structure for variance.

The conditional covariance matrix is decomposed as follows:

$$H_t = D_t R_t D_t$$

where

- D_t : diagonal matrix containing the $\sqrt{h_{it}}$, where each h_{it} follows a pattern GARCH(1,1).

- R_t : conditional correlation matrix between assets.

The dynamics are controlled by a matrix Q_t non-standardized:

$$Q_t = (1 - a - b)\bar{Q} + a\, \varepsilon_{t-1}\varepsilon'_{t-1} + b\, Q_{t-1}$$

The correlation matrix is obtained by standardization:

$$R_t = diag(Q_t)^{-\frac{1}{2}}\, Q\, diag(Q_t)^{-\frac{1}{2}}$$

The DCC model allows for a reasonable number of parameters to be estimated while taking into account the temporal variation of correlations between variables. Generally, parameter estimation is performed in two steps. The first step consists of estimating the conditional variance using a univariate GARCH model. In the second step, the standardized residuals obtained in the first step are used to estimate the parameters of the dynamic correlation matrix.

3.4 Contagion Detection using DCC-GARCH

3.4.1 Difference-in-means t-test

The dynamic correlations difference-in-means t-test is a simple but effective statistical method for detecting a significant change in the average level of conditional correlations between two financial assets, often with the aim of highlighting financial contagion during a crisis. This test is based on the analysis of dynamic correlations estimated via a DCC-GARCH model, which captures the temporal evolution of interdependencies between markets.

Let $\bar{\rho}_t$ be the time series of dynamic conditional correlations between two assets for $t = 1, \dots, T$, from the DCC-GARCH model. We divide this series into two sub-periods:

- Period 1: before the crisis, $t = 1, \dots, T_1$

- Period 2: during or after the crisis, $t = T_1 + 1, \dots, T$

We calculate the mean and variance of the correlations in each sub-period:

$$\bar{\rho}_1 = \frac{1}{T_1}\sum_{t=1}^{T_1} \rho_t\,, \qquad \bar{\rho}_2 = \frac{1}{T_2}\sum_{t=T_1+1}^{T} \rho_t$$

$$s_1{}^2 = \frac{1}{T_1 - 1}\sum_{t=1}^{T_1} (\rho_t - \bar{\rho}_1)^2,\ s_2{}^2 = \frac{1}{T_2 - 1}\sum_{t=T_2}^{T} (\rho_t - \bar{\rho}_2)^2$$

The Student t-statistic is then:

$$t = \frac{\bar{\rho}_1 - \bar{\rho}_2}{\sqrt{\frac{s_1{}^2}{T_1} + \frac{s_2{}^2}{T_2}}}$$

This statistic approximately follows a Student t-distribution under the null hypothesis $H_0 : \bar{\rho}_1 - \bar{\rho}_2 = 0$. If the t-statistic is significant, we conclude that there is a significant variation in correlations between periods, which may indicate contagion.

3.4.2 Chow test for a break in the correlation series

The Chow test is a statistical method used to detect a structural break in a linear relationship at a given point in time. Applied to a series of dynamic correlations from a DCC-GARCH model, this test allows one to assess whether there is a significant change in the behavior of the correlation between two financial assets at a specific point in time, generally associated with a crisis event.

Let ρ_t be the series of dynamic conditional correlations between two assets for $t = 1, \dots, T$. We assume a simple linear relationship:

$$\rho_t = \alpha + \varepsilon_t$$

The Chow test evaluates whether the coefficients change at a break date τ, by dividing the sample in two:

- Period 1: $t = 1, \cdots, \tau$
- Period 2 : $t = \tau + 1, \dots, T$

We compare the residuals of three regressions:

- RSS_p: over the entire period
- RSS_1: over period 1
- RSS_2: over period 2

The F statistic is:

$$\frac{RSS_p - (RSS_1 + RSS_2) / k}{RSS_1 + RSS_2 / n_1 + n_2 - 2k}$$

where k is the number of parameters, and n_1, n_2 the sizes of the two subsamples. If F is significant, we reject the hypothesis of no break, which suggests contagion or a change of regime.

3.4.3 Forbes and Rigobon's Method for Detecting Financial Contagion

To identify true contagion, Forbes and Rigobon (2002) propose an adjustment of the observed correlations, in order to neutralize this mechanical effect linked to the increase in variance. This method is ideally applied after the estimation of a DCC-GARCH, by comparing the average correlations in two sub-periods (pre-crisis vs. crisis) while correcting them for the volatility of the reference market.

From the dynamic correlations ρ_t extracted from the DCC-GARCH(1,1) model, we define the average correlations before and during the crisis:

$$\bar{\rho}_0 = \left(\frac{1}{T_0}\right)\sum_{t=1}^{T_0} \rho_t$$

$$\bar{\rho}_1 = \left(\frac{1}{T_1}\right)\sum_{t=T_0+1}^{T} \rho_t$$

where:

- T_0 is the pre-crisis sample size,
- T_1 is the sample size during the crisis.

The conditional variance of the reference market σ_t^2 being estimated via the GARCH(1,1) model, we calculate:

$$\lambda = \frac{\bar{\sigma}_1^2}{\bar{\sigma}_0^2} - 1$$

where:

- $\bar{\sigma}_0^2$: average of the conditional variances of the reference market before the crisis,
- $\bar{\sigma}_1^2$: average during the crisis.

The corrected Forbes-Rigobon correlation during the crisis is given by:

$$\rho_{FR} = \frac{\bar{\rho}_1}{\sqrt{1 + \lambda(1 - \bar{\rho}_1{}^2)}}$$

Contagion is confirmed if the corrected correlation ρ_{FR} during the crisis is significantly higher than the average pre-crisis correlation $\bar{\rho}_0$, in other words: $H_0 : \bar{\rho}_0 = \rho_{FR}$ versus $H_1 : \bar{\rho}_0 < \rho_{FR}$.

4 Data Analysis and discussion of results

We conducted all empirical analyses and produced all graphical representations in this thesis using Stata BE 18.5 statistical software. We selected this software because it offers strong statistical capabilities, supports reproducible research, and is well suited for estimating time-series econometric models and producing high-quality data visualizations in an academic context. We present the scripts used in this work in the annexes. Annex A for data acquisition, preparation, ADF stationary test, ARCH-LM test, ARCH-GARCH estimations and DCC-GARCH estimations. Annex B contains script for t-test. Annex C contains scripts for Forbes and Rogobon test. Annex D contains the script for contagion direction exploration. Finally, Annex E contains the script for plotting DCC between cryptocurrencies and stock markets.

4.1 Variables analysis

The variables used in this analysis represent the daily log return for the different assets from April 2018 to April 2025 for Bitcoin and Ethereum, from April 2020 to April 2025 for Solana. The return series plots (Figure 4.1) for the S&P 500, BTC/USD, Nikkei 225, ETH/USD, EURO STOXX 50, and SOL/USD clearly show volatility clustering. Volatility clustering is a common characteristic in financial time series. This is phenomena characterized by periods of high volatility that tend to be followed by further high volatility, and calmer periods followed by continued calm.

We can see from (Figure 4.1) that cryptocurrencies like Bitcoin (BTC/USD), Ethereum (ETH/USD), and Solana (SOL/USD) show much more intense and frequent break of volatility, which is consistent with their known market behavior. These patterns suggest the presence of ARCH effects, meaning that past shocks influence today's volatility. The fact that volatility seems to persist over time in these assets particularly the crypto ones strongly hints that an ARCH or GARCH model would be appropriate for modeling their risk.

In terms of stationarity, all six returns series appear to fluctuate around a constant mean, typically close to zero, which is a visual indicator of weak stationarity. While the crypto assets occasionally show extreme spikes that might challenge stricter assumptions, they still overall maintain a consistent pattern over time.

In short, all six returns series demonstrate visual signs of volatility clustering and likely ARCH effects, and they seem to be stationary when observed at a glance. We conduct a more formal statistical test in Section 4.1.2 to confirm these observations.

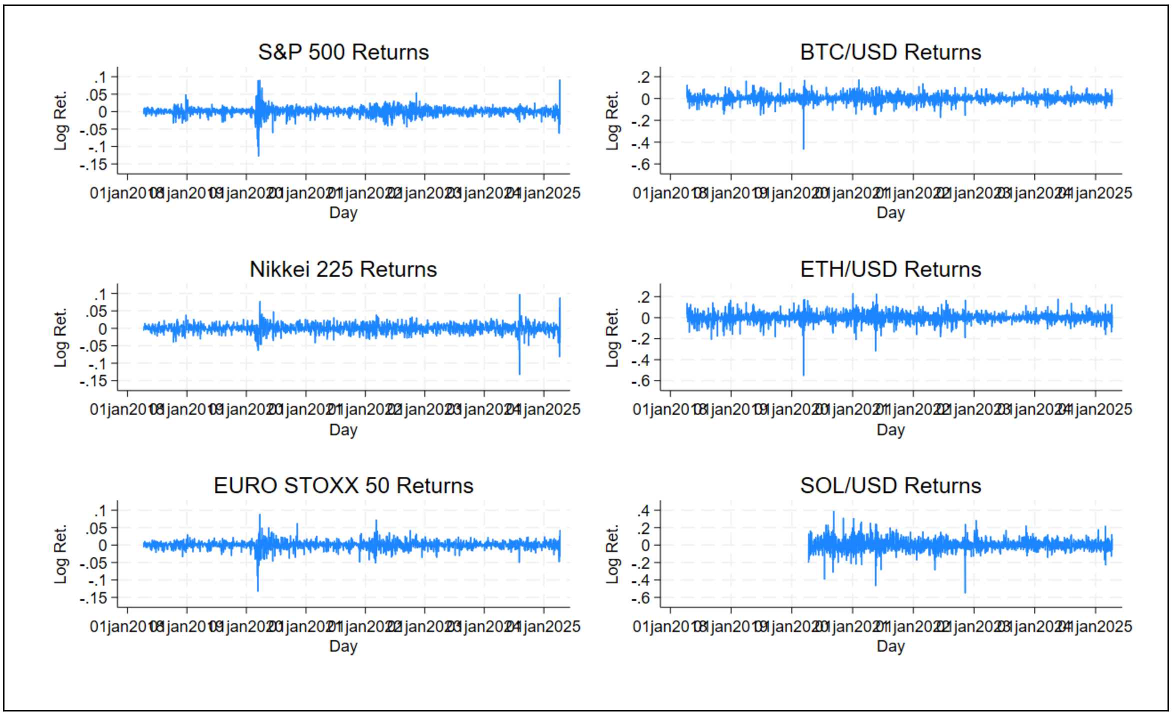

Figure 4.1 Log Returns Plot

4.1.1 Descriptive statistics

Table 4.1 presents the descriptive statistics of the daily returns of six financial assets (three stock indices and three cryptocurrencies) on a sample of 2,587 dally observations excepting Solana with 1,846 because the first trade on Solana was in 10 April 2020. The mean values of all returns are around zero, which is typical feature of high-frequency financial return series. Volatility, measured by the standard deviation (SD), is notably higher for cryptocurrencies, especially for SOL/USD (Solana) (SD = 0.06688), reflecting their more speculative nature compared to stock indices such as GSPC (S&P 500) (SD = 0.01145). The high and low return values (Min and Max) also confirm this greater variability of cryptocurrencies. All series present a negative skewness (skewness < 0), indicating a tendency for declines to be more pronounced than increases. In addition, the kurtosis is well above 3 for all series, which suggests the presence of fat tails, typical of financial returns, and justifies applying models capable of capturing these properties such as GARCH. Finally, the t-values of the means indicate that only those of the GSPC (SP & 500), BTC/USD (Bitcoin) and SOL/USD (Solana) are statistically meaningful, although very low in absolute terms. These results confirm the non-normal and heteroscedastic nature of the returns.

Variables	N	Mean	Min	Max	SD	Skewness	Kurtosis	t-value
S&P 500	2,587	.00067	-0.06161	.09089	.01145	-.38211	7.68121	2.5113
Nikkei	2,587	.00013	-0.13234	.09737	.01313	-.51973	12.71392	.41288
Euro STOXX 50	2,587	.00021	-0.05092	.07175	.01205	-.35048	6.56885	.73329
Bitcoin	2,587	.00137	-0.17405	.17182	.03173	-.10552	6.39565	1.84119
Ethereum	2,587	.00125	-0.31746	.2307	.04163	-.30669	7.89953	1.28799
Solana	1846	.00265	-0.54958	.38718	.06688	-.24484	9.78698	1.69662

Table 4.1: Descriptive Statistics

4.1.2 Analysis of stationarity of variables

To evaluate the stationarity of the return series, Augmented Dickey-Fuller (ADF) (Duckey and Fuller 1979) tests were conducted traditional equity indices (S&P 500, Nikkei 225, and Euro STOXX 50) and cryptocurrencies (Bitcoin, Ethereum, and Solana). The ADF test evaluates the presence of a unit root, where the null hypothesis (H_0) specify that the series is non-stationary, while the alternative hypothesis (H_1) imply stationarity. The results illustrated in Table 4.2 indicate that all return series reject the null hypothesis at the 1% significance level. Specifically, the test statistics S&P 500 (-29.960), Nikkei 225 (-26.524), Euro STOXX 50 (-27.500), Bitcoin (-35.333), Ethereum (-35.135), and Solana (-30.565) were all substantially lower than the corresponding 1% critical value of -3.960.In addition, the MacKinnon approximate p-values for all variables were 0.0000, confirming strong evidence against the null hypothesis. These results imply that the return series are stationary; therefor they can be used in further econometric modeling, such as vector autoregression (VAR), Granger causality tests, and multivariate GARCH estimations without the need for differencing.

Variable	Obs.	Test Statistic	1% Critical	5% Critical	10% Critical	p-value	Stationary?
S&P 500	2585	-29.960	-3.960	-3.410	-3.120	0.0000	Yes
Nikkei 225	2585	-26.524	-3.960	-3.410	-3.120	0.0000	Yes
Euro STOXX50	2585	-27.500	-3.960	-3.410	-3.120	0.0000	Yes
Bitcoin	2585	-35.333	-3.960	-3.410	-3.120	0.0000	Yes
Ethereum	2585	-35.135	-3.960	-3.410	-3.120	0.0000	Yes
Solana	1844	-30.565	-3.960	-3.410	-3.120	0.0000	Yes

Table 4.2: ADF unit root test for each time series

4.1.3 Autoregressive conditional heteroskedasticity test

The results presented in Table 4.3, summarize first-order autoregressive (AR(1)) regressions on the daily returns of six financial assets, as well as LM tests for the detection of ARCH (autoregressive conditional heteroscedasticity) effects. The result for six financial assets, point out both short-term autocorrelation and the presence of heteroskedasticity in return series. Indices S&P 500, Nikkei 225, and Euro STOXX 50 show statistically important positive AR(1) coefficients, with the Nikkei 225 showing the highest level of autocorrelation (0.327, $p < 0.001$) and R^2 values ranging from 3.7% to 10.7%. In contrast, cryptocurrencies (Bitcoin, Ethereum, and Solana) display weak or negative autocorrelation, with marginal explanatory power ($R^2 < 0.5\%$) and statistically important though negative AR(1) coefficients. The ARCH tests reveal strong evidence of time-varying volatility for all traditional indices and Solana ($p < 0.001$), while Bitcoin shows a moderate ARCH effect ($p = 0.028$) and Ethereum displays statistically important but less pronounced volatility clustering. These results support the presence of conditional heteroskedasticity across both asset classes, though with varying intensity, and point out the distinct statistical properties of crypto-assets compared to traditional markets.

Asset	AR(1) Coefficient	AR(1) p-value	R^2 (%)	ARCH $\chi^2(1)$	ARCH p-value	ARCH Effect	Interpretation
S&P 500	0.193	< 0.001	3.7	628.76	< 0.001	Strong	Mild autocorrelation, strong volatility clustering
Nikkei 225	0.327	< 0.001	10.7	754.99	< 0.001	Strong	Strong autocorrelation and ARCH effect
Euro STOXX 50	0.300	< 0.001	9.0	173.69	< 0.001	Strong	Moderate autocorrelation, strong ARCH effect
Bitcoin	–0.056	0.005	0.3	4.84	0.028	Moderate	Slight negative autocorrelation, moderate ARCH
Ethereum	–0.065	0.001	0.4	11.24	< 0.001	Significant	Slight mean-reversion, statistically significant ARCH
Solana	–0.053	0.023	0.3	85.31	< 0.001	Strong	Weak autocorrelation, strong volatility clustering

Table 4.3: ARCH-LM Test for each time series

These findings support the use of GARCH-family models to account for volatility clustering and time-varying second moments in both traditional and crypto-asset return modeling, and justify the application of multivariate GARCH frameworks, such as the DCC-GARCH model, for contagion and co-movement analyses.

4.2 ARCH and GARCH Results

To model the volatility dynamics of both traditional financial indices and cryptocurrencies, ARCH(1)-GARCH(1) models were estimated for the return series of the S&P 500, Nikkei 225, Euro STOXX 50, Bitcoin, Ethereum, and Solana over the period from April 2018 to April 2025 (starting April 2020 for Solana). The results in Table 4.4 show clear signs of conditional heteroskedasticity in all assets. This means using GARCH-type models makes sense. The S&P 500 and Euro STOXX 50 show a high persistence levels ($\alpha_1 + \beta_1 = 0.9769$ and 0.9576, respectively). In contrast, the Nikkei 225 shows a more solid short-term reaction to past shocks, with a relatively high ARCH term ($\alpha_1 = 0.5027$) and lower overall persistence ($\alpha_1 + \beta_1 = 0.7231$). Cryptocurrencies show even higher volatility persistence, consistent with prior literature on digital assets. Bitcoin and Solana show solid GARCH effects ($\beta_1 = 0.8375$ and 0.8265, respectively), with persistence levels above 0.93. While Ethereum shows the highest volatility persistence ($\alpha_1 + \beta_1 = 0.9808$), indicating a prolonged memory in conditional variance. Across all models, the ARCH and GARCH parameters are statistically important at the 1% level.

These findings align with existing empirical studies pointing out those financial markets, and volatility clustering and high persistence, justifying the use of ARCH-GARCH frameworks in modeling their conditional variance dynamics, characterize especially cryptocurrencies.

Variable - Asset	**α_1 (ARCH)**	**β_1 (GARCH)**	**$\alpha_1 + \beta_1$**	**Persistence**	**Significance ($p < 0.01$)**
r GSPC_f – S&P 500	0.2094	0.7675	0.9769	High	Yes
r N225_f - Nikkei 225	0.5027	0.2204	0.7231	Medium	Yes
r STOXX50E_f - Euro STOXX 50	0.2772	0.6804	0.9576	High	Yes
r BTC_USD - Bitcoin	0.1008	0.8375	0.9383	High	Yes
r ETH_USD - Ethereum	0.0725	0.9083	0.9808	Very High	Yes
r SOL_USD - Solana	0.1419	0.8265	0.9683	High	Yes

Table 4.4: GARCH(1,1) Estimate – for each times series

4.3 DCC-GARCH Model Results

4.3.1 DCC estimates between BTC and the stock indexes

The chart in Figure 4.2 presents the dynamic conditional correlations (DCC) between Bitcoin (BTC) and three major equity indices — the S&P 500, Nikkei 225, and EURO STOXX 50 — over the period from 2018 to 2025. The BTC–S&P 500 panel shows moderate and time-varying correlations, with values generally fluctuating between 0.2 and 0.5, indicating a variable but relatively stronger association with U.S. equity markets compared to the other indices. The BTC–Nikkei 225 and BTC–EURO STOXX 50 correlations, in contrast, remain consistently low, mostly below 0.2, with only isolated spikes throughout the period. These patterns suggest that Bitcoin shows a more stable co-movement with U.S. equities, while its relationship with Japanese and European equities remains weak and less reactive. In general, the results point to a heterogeneous relationship between Bitcoin and traditional equity markets, with a notably stronger linkage to the U.S. financial system.

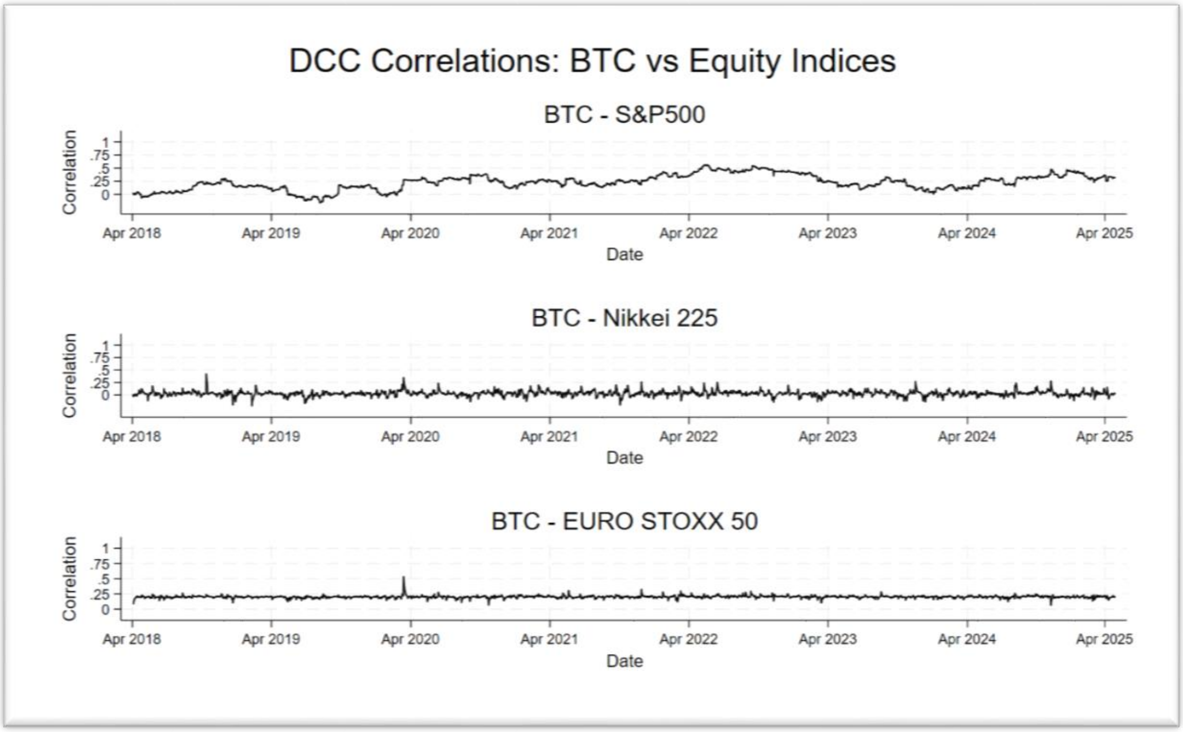

Figure 4.2: Dynamic Conditional Correlations (DCC) between Bitcoin and Major Equity Indices (2018–2025)

To examine the time-varying relationship between Bitcoin (BTC) and major equity markets, bivariate DCC-GARCH(1,1) models with Student's t-distribution were estimated using daily returns from April 2018 to April 2025 for the S&P 500 (US), STOXX 50 (Europe), and Nikkei 225 (Japan). The results, presented in table 4.5 reveal heterogeneous patterns across regions. The BTC–S&P 500 pair exhibits a weak but economically relevant average correlation (0.151, $p \approx 0.099$) with significant DCC parameters ($\lambda_1 = 0.016$, $\lambda_2 = 0.978$), indicating a persistent and slowly evolving relationship. Volatility persistence is high for both BTC and the S&P 500 ($\alpha + \beta \approx 0.98$–1.04), consistent with long-memory effects.

The BTC–STOXX 50 correlation is similar in magnitude (0.125, $p < 0.01$) but shows insignificant DCC terms ($\lambda_1 = 0.016$, $\lambda_2 = 0.574$), suggesting a more static link with European equities despite high volatility persistence ($\alpha + \beta \approx 1.13$). In contrast, the BTC–Nikkei 225 pair shows an insignificant and near-zero correlation (–0.027, $p = 0.271$) with weak dynamic behavior, indicating limited integration with Japanese equities. Across all models, the Student's t-distribution with 3.79–4.58 degrees of freedom captures extreme returns, highlighting Bitcoin's growing integration with Western markets while linkages with Asian markets remain limited.

In practice, these findings suggest that BTC offers diversification potential, with limited short-term contagion to equity markets, but investors should account for persistent volatility and occasional extreme events in strategic allocation decisions.

Statistic	**BTC–S&P 500**	**BTC–STOXX 50**	**BTC–Nikkei 225**
Log-likelihood	14194.01	14040.38	13652.66
Mean Corr. (constant part)	0.1512	0.1247	–0.0268
Correlation p-value	0.099 (†)	0.000 (***)	0.271
DCC λ_1 (Lambda1)	0.0162 (***)	0.0165 (ns)	0.0370 (ns)
DCC λ_2 (Lambda2)	0.9779 (***)	0.5739 (ns)	0.6714 (**)
Degrees of Freedom (t-dist)	4.35 (***)	3.79 (***)	4.58 (***)
Volatility Persistence BTC ($\alpha+\beta$)	0.9820	0.9914	0.9837
Volatility Persistence Index	1.042 (US)	1.132 (EU)	0.987 (JP)

Table 4.5: DCC-GARCH Estimation (BTC vs Equity Indices)

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, ns = not significant.

These results align with prior literature suggesting that crypto-assets exhibit time-varying correlations with traditional assets primarily during periods of heightened financial stress or global market integration (e.g., Baur et al., 2018; Corbet et al., 2019).

4.3.2 DCC estimates between ETH and the stock indexes

The chart in Figure 4.3 presents the dynamic conditional correlations (DCC) between Ethereum (ETH) and three equity indices — S&P 500, Nikkei 225 (N225), and EURO STOXX 50 — over the period from 2018 to 2025. The ETH–S&P 500 panel exhibits moderately positive and time-varying correlations, generally ranging between 0.2 and 0.5; this indicates a volatile but enduring relationship between Ethereum and the US stock market. The ETH–Nikkei 225 correlation remains low and quite flat throughout the period, with occasional spikes. This indicates a limited synchronicity between Ethereum and Japanese equities. The ETH–EURO STOXX 50 correlation shows a distinct behavior: it starts at a lower level but gradually increases over time, stabilizing around 0.35–0.45 in recent years. This may reflect a growing alignment between Ethereum and European markets. Overall, these results show how Ethereum correlates with traditional financial markets, with a more strong integration observed in the U.S. and Europe compared to Asia.

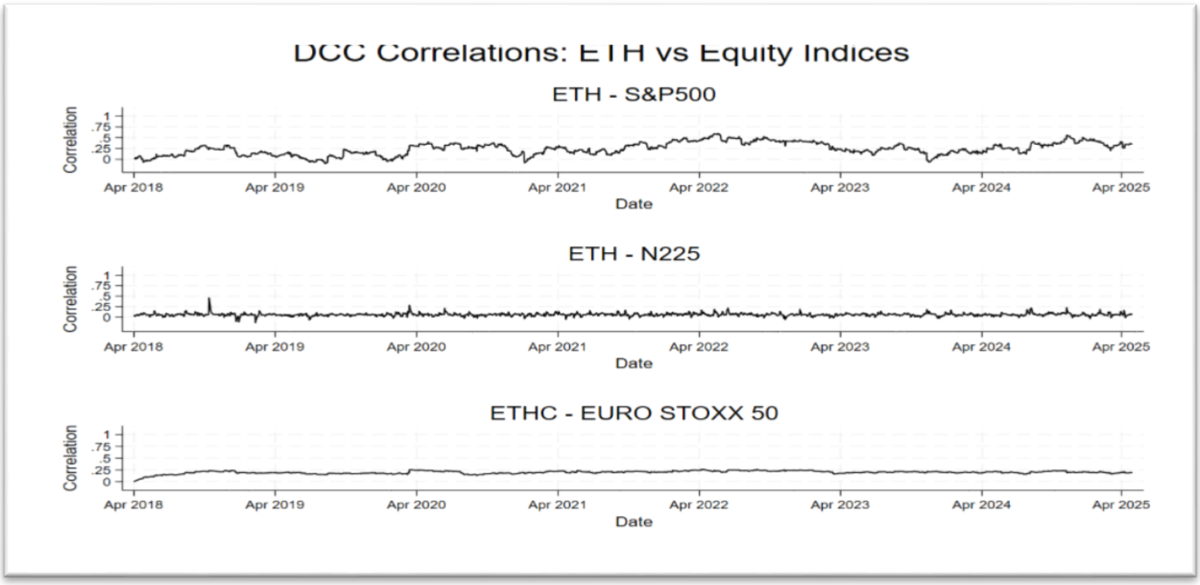

Figure 4.3 Dynamic Conditional Correlations (DCC) between Ethereum and Major Equity Indices (2018–2025)

To examine the time-varying relationship between Ethereum and global equity markets, bivariate DCC-GARCH(1,1) models with Student's t-distribution were estimated using daily returns for the S&P 500 (US), STOXX 50 (Europe), and Nikkei 225 (Japan) over the period from April 2018 to April 2025. The results reported in Table 4.6 indicate heterogeneous patterns of dynamic conditional correlation across regions. Ethereum exhibits a moderate and statistically significant average correlation with both the S&P 500 (0.162, $p = 0.037$) and the STOXX 50 (0.161, $p < 0.001$), whereas its correlation with the Nikkei 225 is weak and insignificant (0.008, $p = 0.741$). The ETH–S&P 500 pair shows significant and highly persistent DCC parameters ($\lambda_1 = 0.0199$, $\lambda_2 = 0.9717$), suggesting a slowly evolving and time-dependent relationship with U.S. equities. In contrast, the ETH–STOXX 50 and ETH–Nikkei 225 pairs display limited dynamic adjustment despite high persistence in λ_2. Across all models, Ethereum volatility remains highly persistent ($\alpha + \beta \approx 0.97$–$0.98$), consistent with volatility clustering in cryptocurrency markets.

Ethereum offers moderate diversification benefits, particularly relative to Asian equity markets, while maintaining persistent long-term linkages with US equities. Although short-term contagion effects are limited, the combination of persistent volatility and fat-tailed risks implies that ETH remains a high-risk asset requiring active risk management, especially during periods of financial stress.

Statistic	ETH–S&P 500	ETH–STOXX 50E	ETH–Nikkei 225
Log-likelihood	13,466.45	13,318.08	12,929.68
Mean Correlation (constant)	0.1619 (***)	0.1290 (***)	0.0078 (ns)
Correlation p-value	<0.05	<0.01	0.741 (ns)
DCC λ_1 (Short-run shock)	0.0199 (***)	0.0392 (ns)	0.0233 (ns)
DCC λ_2 (Persistence)	0.9717 (***)	0.0005 (n.a.)	0.7006 (**)
Degrees of Freedom (t-dist)	4.95 (***)	4.15 (***)	5.20 (***)
Volatility Persistence ETH (α+β)	0.967 (arch+GARCH)	0.978	0.972
Volatility Persistence Index	0.997 (S&P 500)	1.05 (STOXX 50E)	0.935 (Nikkei)

Table 4.6: DCC-GARCH Estimation (ETH vs Equity Indices)

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, ns = not significant.

4.3.3 DCC estimates between SOL and the stock indexes

The chart in Figure 4.4 illustrates the dynamic conditional correlations (DCC) between Solana (SOL) and three major equity indices — S&P 500, Nikkei 225, and EURO STOXX 50 — from April 2020 to April 2025. The SOL–S&P 500 panel shows moderate and clearly time-varying correlations, increasing from near-zero to values stabilizing around 0.3 to 0.5. This indicates a strengthening co-movement between Solana and U.S. equities over time, potentially reflecting growing market integration or overlapping investor bases. In contrast, the correlations between SOL and both the Nikkei 225 and EURO STOXX 50 remain consistently low and flat, mostly oscillating below 0.2 with sporadic short-term spikes. These patterns suggest that while Solana has gained some financial interdependence with U.S. markets, its connection with Japanese and European equities remains weak and largely decoupled. The observed dynamics underscore regional differences in how traditional financial markets relate to emerging crypto-assets, with the U.S. showing the strongest association.

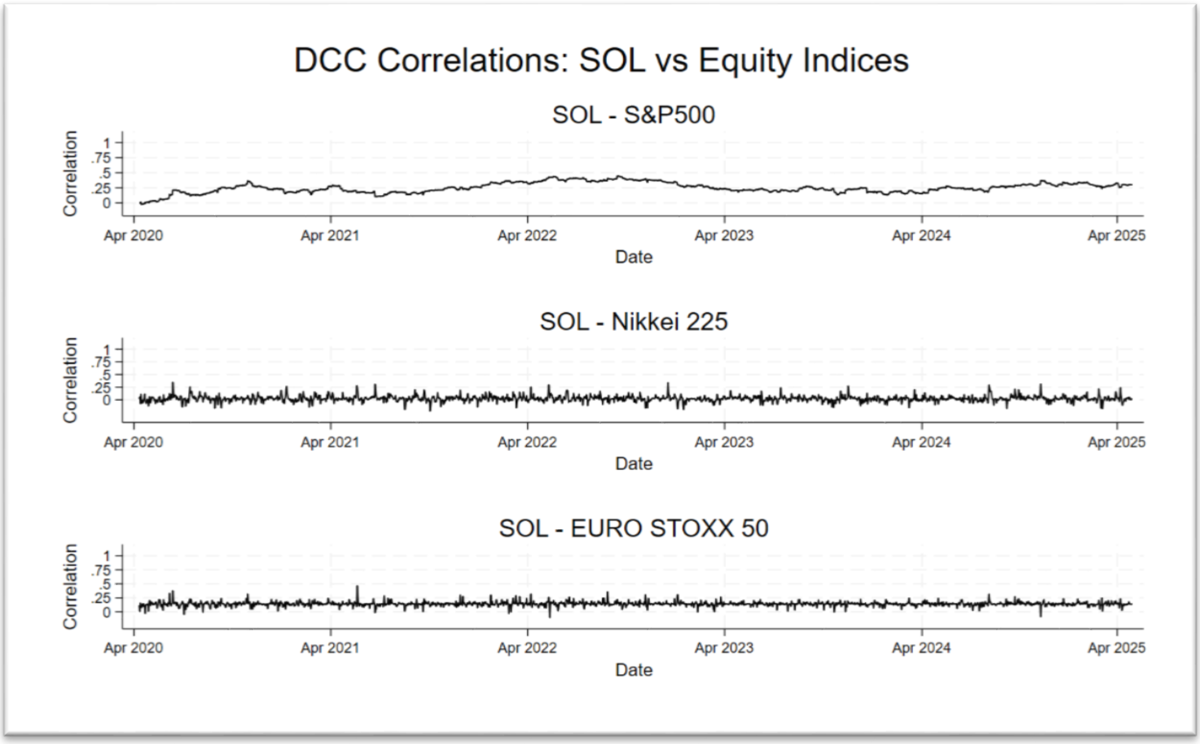

Figure 4.4: Dynamic Conditional Correlations (DCC) between Solana and Major Equity Indices (2018–2025)

To analyze the time-varying relationship between Solana (SOL) and global equity markets, bivariate DCC-GARCH(1,1) models with a Student's t-distribution were estimated using daily returns for the S&P 500 (US), STOXX 50 (Europe), and Nikkei

225 (Japan) over the period from April 2018 to April 2025. The results in Table 4.7 reveal clear regional heterogeneity in dynamic conditional correlations. SOL exhibits a moderate and statistically significant average correlation with the S&P 500 (0.266, $p < 0.01$), and a weaker but still significant correlation with the STOXX 50 (0.134, $p < 0.01$), while its correlation with the Nikkei 225 is negligible and insignificant (–0.010, $p = 0.726$). The SOL–S&P 500 pair shows significant and highly persistent DCC parameters ($\lambda_1 = 0.0093$, $\lambda_2 = 0.9831$), indicating a slowly evolving and time-dependent relationship with U.S. equities. In contrast, the SOL–STOXX 50 and SOL–Nikkei 225 pairs display limited or unstable dynamic correlation effects. Across all models, SOL volatility is highly persistent ($\alpha + \beta \approx 0.96$–$0.97$), consistent with volatility clustering in cryptocurrency markets.

Solana exhibits stronger equity market integration than Ethereum and Bitcoin, particularly with US equities, which reduces its diversification appeal in US-based portfolios. While short-term contagion remains limited, the combination of persistent long-run correlations and sustained volatility suggests that SOL behaves more like a risk-on asset, requiring active risk management during periods of market stress.

Statistic	SOL–S&P 500	SOL–STOXX 50	SOL–Nikkei 225
Log-likelihood	8,813.21	8,677.17	8,419.49
Mean Corr. (constant part)	0.2657	0.1343	–0.0097
Correlation p-value	0.000 (***)	0.000 (***)	0.726 (ns)
DCC λ_1 (Lambda1)	0.0093 (**)	0.0442 (ns)	0.0578 (**)
DCC λ_2 (Lambda2)	0.9831 (***)	0.1598 (ns)	0.3779 (ns)
Degrees of Freedom (t-dist)	5.99 (***)	5.24 (***)	7.20 (***)
Vol. Persistence SOL (α+β)	0.9614	0.9673	0.9620
Vol. Persistence Index	0.993 (US)	0.904 (EU)	0.747 (JP)

Table 4.7: DCC-GARCH Estimation (SOL vs Equity Indices)

Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, ns = not significant.

4.4 Exploring the Contagion Effect

In this section, we explore three methods for studying the contagion effects of cryptocurrencies on stocks markets. As specified in chapter three theses methods are difference in mean t-test, the Chow test and Forbes and Rigobon.

4.4.1 Difference-in-Means *t*-Test Results

To assess the presence of financial contagion between BTC, ETH, and SOL against those of the S&P 500 (GSPC), Nikkei 225 (N225), and STOXX50E equity markets across three major periods of financial stress: the COVID-19 pandemic, the 2022 bull market crash, and the collapse of the FTX exchange. A series of two-sample t-tests were conducted on the dynamic conditional correlations (DCCs) estimated using a DCC-GARCH(1,1) model.

4.4.1.1 Difference-in-Means t-Test Results - COVID-19 crash

Table 4.8 summarizes the results of a two-sample t-test across the COVID-19 pandemic.

The results provide compelling evidence of contagion in several crypto-equity pairs. Most notably, the average conditional correlation between Bitcoin and the S&P 500 rose markedly from 0.1610 in the pre-COVID period to 0.3073 post-COVID, with a highly significant difference ($t = -30.32$, $p < 0.001$). A similar pattern is observed for Ethereum, whose correlation with the S&P 500 increased from 0.1724 to 0.3212 ($t = -30.95$, $p < 0.001$). These substantial and statistically significant increases indicate a stronger co-movement between crypto-assets and U.S. equities during the pandemic, suggesting that cryptocurrencies lost part of their diversification potential and behaved more like traditional risk assets in times of systemic stress. Conversely, the correlation between Bitcoin and the Nikkei 225 remained statistically unchanged ($t = -0.63$, $p = 0.530$), while the BTC–Euro Stoxx 50 and ETH–Nikkei 225 pairs exhibited only marginal or weak evidence of contagion. Overall, these findings imply that the extent of contagion is market-specific and most pronounced in the U.S. and European contexts, reinforcing the hypothesis that COVID-19 served as a structural break in the cross-market behavior of digital assets. These findings align with recent literature (Corbet et al., 2021; Yousaf & Ali, 2022), which highlights a post-COVID convergence in the behavior of digital and traditional financial assets, driven by increased institutional adoption and broader market integration of cryptocurrencies.

Crypto	Equity Index	Mean DCC (Pre)	Mean DCC (Post)	Difference	t-statistic	p-value	Contagion Evidence
BTC	**S&P 500**	0.1610	0.3073	-0.1463	-30.32	0.000	Yes
BTC	**Nikkei 225**	0.0286	0.0298	-0.0013	-0.63	0.530	No
BTC	**Euro Stoxx 50**	0.2006	0.2031	-0.0025	-2.99	0.003	*Weak evidence*
ETH	**S&P 500**	0.1724	0.3212	-0.1488	-30.95	0.000	Yes
ETH	**Nikkei 225**	0.0594	0.0633	-0.0038	-2.84	0.005	*Weak evidence*
ETH	**Euro Stoxx 50**	0.1880	0.2118	-0.0238	-20.90	0.000	Yes

Table 4.8: Two-Sample t-Test Results – Conditional Correlation Pre- vs Post-Covid-19

4.4.1.2 Difference-in-Means t-Test Results - Bull market crash

Table 4.9 presents the results of t-tests assessing changes in the connectedness between major equity indices and cryptocurrencies during the crypto boom and correction periods. The S&P 500's connectedness with Bitcoin (GSPC → BTC) is highly increased from a mean of 0.157 to 0.306 ($t = -31.21$, $p < 0.01$), and with Ethereum (GSPC → ETH) from 0.168 to 0.320 ($t = -31.95$, $p < 0.01$). Similarly, its connection with Solana (GSPC → SOL) rose markedly from 0.186 to 0.279 ($t = -25.93$, $p < 0.01$). These changes suggest a considerable rise in the influence of U.S. equities on crypto markets following the crash. The Nikkei 225 index showed no statistically significant change in connectedness with Bitcoin (N225 → BTC), with means of 0.028 and 0.030 ($p = 0.461$), but exhibited a small yet significant increase in connectedness with Ethereum and Solana. The STOXX50E index's connectedness with Bitcoin increased marginally but still important (0.200 to 0.203, $p < 0.01$), while the increase with Ethereum (0.187 to 0.211, $p < 0.01$) was more pronounced. The connectedness with Solana remained relatively unchanged ($p = 0.118$). These findings indicate a post-crash strengthening of spillovers, particularly between the U.S. market and major cryptocurrencies, suggesting increased financial integration or shared global risk factors during turbulent periods. Overall, the results align with the broader literature that reports increased comovement between cryptocurrencies and stock markets during periods of financial stress and post-crisis normalization phases (see Corbet et al., 2018; Bouri et al., 2021; Choi & Shin, 2022).

Crypto	Equity Index	Mean Corr. (Pre)	Mean Corr. (Post)	Difference	t-statistic	p-value	Contagion Evidence
BTC	**S&P 500**	0.157	0.306	+0.149	-31.21	0.000	Yes (↑ significant)
BTC	**Nikkei 225**	0.028	0.030	+0.002	-0.74	0.461	No
BTC	**STOXX 50**	0.200	0.203	+0.003	-3.54	0.000	Yes (↑ significant)
ETH	**S&P 500**	0.168	0.320	+0.152	-31.95	0.000	Yes (↑ significant)
ETH	**Nikkei 225**	0.060	0.063	+0.003	-2.45	0.014	Yes (↑ significant)
ETH	**STOXX 50**	0.187	0.211	+0.024	-21.22	0.000	Yes (↑ significant)
SOL	**S&P 500**	0.186	0.279	+0.093	-25.93	0.000	Yes (↑ significant)
SOL	**Nikkei 225**	0.024	0.024	+0.001	+0.24	0.810	No
SOL	**STOXX 50**	0.140	0.143	+0.003	-1.56	0.118	No

Table 4.9: Two-Sample t-Test Results – Conditional Correlation Pre- vs Post-Crypto Boom

4.4.1.3 Difference-in-Means t-Test Results - FTX Collapse

Table 4.10 summarizes the results of a two-sample t-test across the FTX collapse. Results reveal a statistically important increase in the DCC between Bitcoin and the S&P 500 (from 0.212 to 0.262, $t = –8.57$, $p < 0.001$), as well as between Ethereum and the S&P 500 (from 0.223 to 0.278, $t = –9.47$, $p < 0.001$). The DCC between Ethereum and the Euro Stoxx 50 also rose significantly (from 0.196 to 0.205, $t = –6.68$, $p < 0.001$). These findings suggest that the FTX collapse may have reinforced the correlation between crypto-assets and developed markets, likely reflecting a heightened perception of crypto as part of the broader risk-asset class. However for pairs such as (Bitcoin, Nikkei 225) ($t = 2.11$, $p = 0.035$) and (Solana Nikkei) ($t = 1.95$, $p = 0.052$) the changes were minor or not statistically important. Interestingly, correlations between Solana and the S&P 500 or STOXX 50E remained stable. These findings partially support existing literature suggesting increasing co-movement during financial turbulence (Corbet et al., 2021), while also indicating a heterogeneous contagion effect depending on the asset pair.cryptocurrencies—especially Bitcoin and Ethereum—highlighting an evolving integration that may amplify systemic risk during periods of financial distress.

Crypto	Equity Index	Mean DCC (Pre)	Mean DCC (Post)	Difference	t-statistic	p-value	Contagion Evidence

BTC	**S&P 500**	0.212	0.262	+0.050	8.41	0.000	**Yes** (↑ significant)
BTC	**Nikkei 225**	0.189	0.174	–0.015	–2.11	0.035	*Yes (↓ significant)*
BTC	**STOXX 50**	0.251	0.259	+0.008	1.38	0.167	No
ETH	**S&P 500**	0.223	0.278	+0.055	9.55	0.000	**Yes** (↑ significant)
ETH	**Nikkei 225**	0.215	0.217	+0.002	0.18	0.859	No
ETH	**STOXX 50**	0.266	0.292	+0.026	4.57	0.000	**Yes** (↑ significant)
SOL	**S&P 500**	0.250	0.251	+0.001	0.19	0.850	No
SOL	**Nikkei 225**	0.229	0.224	–0.005	–0.66	0.510	No
SOL	**STOXX 50**	0.264	0.271	+0.007	1.02	0.306	No

Table 4.10: Two-Sample t-Test Results – Conditional Correlation Pre- vs Post-FTX Collapse

4.4.2 Structural Break Analysis: Chow Test

To examine whether the dynamic relationship between cryptocurrency returns and traditional stock indices underwent structural shifts during major financial stress events, we applied the Chow test for known structural breaks on cumulative return differential regressions. Specifically, we tested for shifts in the constant term (mean) around three key events: the COVID-19 market crash (20 February 2020), the crypto boom market peak and subsequent correction (2 November 2021), and the FTX exchange collapse (2 November 2022). The results in Table 4.11 reveal statistically important structural breaks in most crypto-stock index pairings during the COVID-19 crisis, particularly for Bitcoin and Ethereum, suggesting widespread contagion at the onset of the pandemic. Likewise, the 2021 crypto boom and correction also coincided with important breaks, especially involving Ethereum, while the FTX collapse in late 2022 showed more limited evidence of structural shifts, particularly affecting Ethereum-STOXX and Bitcoin-Nikkei relationships.

These findings concord with prior literature on financial contagion (Forbes & Rigobon, 2002; Baur & Lucey, 2010), which proposes that crypto-assets exhibit nonlinear and regime-dependent correlations with equities, especially during market turmoil.

Crypto	Index	COVID-19 (20/02/2020)	Crypto Boom (02/11/2021)	FTX Collapse (02/11/2022)
BTC	**S&P 500**	**Yes** (p = 0.0000)	**Yes** (p = 0.0000)	**Yes** (p = 0.0000)
BTC	**Nikkei 225**	**Yes** (p = 0.0001)	No (p = 0.6171)	**Yes** (p = 0.0174)
BTC	**STOXX 50E**	**Yes** (p = 0.0000)	**Yes** (p = 0.0006)	No (p = 0.5564)
ETH	**S&P 500**	**Yes** (p = 0.0000)	**Yes** (p = 0.0000)	**Yes** (p = 0.0000)
ETH	**Nikkei 225**	**Yes** (p = 0.0007)	Yes (p = 0.0231)	No (p = 0.6586)
ETH	**STOXX 50E**	**Yes** (p = 0.0000)	**Yes** (p = 0.0000)	**Yes** (p = 0.0000)
SOL	**S&P 500**	—	**Yes** (p = 0.0000)	No (p = 0.5125)
SOL	**Nikkei 225**	—	No (p = 0.8388)	Yes (p = 0.0242)
SOL	**STOXX 50E**	—	No (p = 0.1079)	No (p = 0.3227)

Table 4.11: Structural Break Results (Chow Test on Constant Term)

Note: "Yes" indicates rejection of the null hypothesis of no structural break at the 5% significance level. "—" indicates the period was not included due to sample constraints.

These findings also support the theory of contagion and structural shifts in cross-asset correlations during periods of market distress. According to Forbes and Rigobon (2002), contagion is characterized by a significant increase in cross-market linkages during crises. Similarly, Baur and Lucey (2010) find that while Bitcoin can act as a diversifier or hedge, its behavior is sensitive to stress periods. The significant breaks observed during COVID-19 and the crypto crypto boom corroborate recent empirical results showing that crypto-equity correlations are time-varying and regime-dependent, often intensifying during systemic shocks (Corbet et al., 2018; Będowska-Sójka, B., & Kliber, A. 2021). In addintion, SOL shows a strong break only with S&P 500 in 2021, and no significant impact elsewhere, which aligns with the view that altcoins have limited systemic spillover capacity.

4.4.3 Forbes and Rigobon test results

To investigate the presence and dynamics of contagion from cryptocurrency markets to traditional equity indices, a series of Forbes and Rigobon was conducted across three major periods of financial stress: the COVID-19 pandemic, the 2021 crypto boom and correction, and the collapse of the FTX exchange.

4.4.3.1 Forbes & Rigobon contagion test - Covid-19 crash

To assess whether the COVID-19 pandemic led to a structural change in the relationship between cryptocurrencies and traditional equity markets, we applied the Forbes and Rigobon (2002) test for contagion. Using data prior to February 20, 2019, as the pre-crisis benchmark, we compared adjusted pre-crisis correlations to observed correlations during the COVID-19 period (March 2020 to January 2021).

The results summarized in Table 4.12, indicate solid evidence of contagion between both Bitcoin (BTC) and Ethereum (ETH) and the S&P 500 and Euro STOXX 50, with statistically important increases in correlation that persist even after volatility adjustment ($p < 0.001$). For example, the adjusted pre-crisis correlation between ETH and the S&P 500 increased from 0.0351 to 0.2982 during the crisis ($z = 6.02$, $p < 0.00001$). A similar observation with BTC and Euro STOXX 50, where the adjusted correlation rose from 0.0553 to 0.3030 ($z = 3.78$, $p = 0.0002$). These findings are consistent with recent literature (e.g., Corbet et al., 2020; Bouri et al., 2021; Yarovaya et al., 2022), which documents increased crypto-equity comovements during systemic shocks such as COVID-19.

BTC showed only weak evidence of contagion with the Nikkei ($z = 1.75$, $p = 0.08$), while ETH's correlation with the Nikkei increased litelly but significantly ($z = 2.21$, $p = 0.027$). This result supports previous findings that contagion effects are more relevant in Western markets due to higher levels of financial integration and overlapping investor bases (Ji et al., 2020).

Overall, these results confirm that COVID-19 acted as a systemic event, enhancing the comovement between cryptocurrencies and major equity markets, in line with recent empirical evidence on financial contagion during crises.

Crypto–Index Pair	Adjusted Pre-Crisis ρ	Post-Crisis ρ	Z-Statistic	P-Value	Contagion Evidence
BTC vs. S&P 500	0.0265	0.3214	7.13	<0.00001	Strong
BTC vs. Nikkei 225	–0.0151	0.1027	1.75	0.080	Weak
BTC vs. Euro STOXX 50	0.0553	0.3030	3.78	0.0002	Strong
ETH vs. S&P 500	0.0351	0.2982	6.02	<0.00001	Strong
ETH vs. Nikkei 225	0.0043	0.1158	2.21	0.027	Moderate
ETH vs. Euro STOXX 50	0.0487	0.2725	3.33	0.0009	Strong

Table 4.12: Contagion Test Results - The COVID-19 period (Forbes & Rigobon Test)

4.4.3.2 Forbes & Rigobon contagion test – Crypto Boom

To investigate the presence of financial contagion during the crypto boom and correction, we apply the Forbes and Rigobon (2002) corrected correlation test across the three equity indices and three cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and

Solana (SOL). The test compares pre- and post-crisis correlation coefficients while adjusting for increased market volatility during the crisis. As shown in Table 4.13, strong evidence of contagion is found in most crypto–equity pairs, particularly for the S&P 500 and Euro STOXX 50. BTC shows strong contagion with the S&P 500 ($Z = 5.77$, $p < 0.00001$) and moderate contagion with the Euro STOXX 50. Similarly, ETH and SOL display consistent patterns of contagion with all three indices, with the highest Z-statistics observed for ETH vs. Euro STOXX 50 and SOL vs. Nikkei 225. These findings align with the literature documenting increased co-movement between cryptocurrencies and equities during times of financial turmoil (e.g., Corbet et al., 2020; Ji et al., 2022). However, the moderate level of contagion pairs—such as BTC vs. Nikkei 225 and ETH vs. S&P 500—suggests that crypto-assets retain partial decoupling from traditional markets. Overall, the results confirm the evolving interdependence between crypto and equity markets during crises, confirming prior findings while highlighting heterogeneous transmission channels.

Crypto–Index Pair	Adjusted Pre-Crisis ρ	Post-Crisis ρ	Z-Statistic	P-Value	Contagion Evidence
BTC vs. S&P 500	0.1567	0.3059	5.77	<0.00001	Strong
BTC vs. Nikkei 225	0.0697	0.1965	3.45	0.0006	Strong
BTC vs. Euro STOXX 50	0.1191	0.2511	3.15	0.0016	Moderate
ETH vs. S&P 500	0.1714	0.2797	2.76	0.0057	Moderate
ETH vs. Nikkei 225	0.0637	0.2039	3.87	0.0001	Strong
ETH vs. Euro STOXX 50	0.1094	0.2806	4.37	<0.00001	Strong
SOL vs. S&P 500	0.1052	0.2293	3.51	0.0005	Strong
SOL vs. Nikkei 225	0.0574	0.2175	4.32	<0.00001	Strong
SOL vs. Euro STOXX 50	0.0963	0.2422	3.79	0.0002	Strong

Table 4.13: Contagion Test Results – Crypto Boom Period (Forbes & Rigobon Test)

4.4.3.3 Forbes & Rigobon contagion test - FTX collapse

The results of the empirical findings from the Forbes & Rigobon (2002) test for correlation adjustments outlined in Table 4.14 suggest substantial changes of the correlation structure between dominant cryptocurrencies (BTC, ETH, SOL) and well-grounded equity market indices (S&P 500, Nikkei 225 index, STOXX Europe 50) during the FTX crisis phase. In Bitcoin (BTC), correlation values diminished a lot with the three equity indices, mainly in the case of Nikkei 225 opened at −0.2462 before and for post-crisis it turned negative (−0.1930; $p < 0.001$). A similar structural break as that of Bitcoin (BTC) vs. Nikkei 225 ($p < 0.01$), and the correlation between Ethereum (ETH) and S&P500, STOXX 50E was not statistically significant.

The findings match studies that show time varying correlations and contagion patterns during crypto broader financial shocks (e.g. Corbet et al. 2018; Bouri et al. 2020). The decline, in correlations for BTC and SOL with indices shows that investors saw BTC and SOL less as diversified hedges and more, as risk amplifiers or speculative vehicles during crypto market turmoil. Investors changed their view. The results point out asymmetrical contagion movements, as correlations did not increase during the crisis, contradicting classical financial contagion theories and instead supporting the decoupling hypothesis.

Crypto–Index Pair	Adjusted Pre-Crisis ρ	Post-Crisis ρ	Z-Statistic	P-Value	Contagion Evidence
BTC vs. S&P 500	0.7190	0.4990	–2.54	0.011	Moderate
BTC vs. Nikkei 225	0.2460	–0.1930	–3.57	0.0004	Strong
BTC vs. Euro STOXX 50	0.5236	0.3031	–2.01	0.0446	Moderate
ETH vs. S&P 500	0.6336	0.5091	–1.39	0.1650	None
ETH vs. Nikkei 225	0.2152	–0.1883	–3.26	0.0011	Strong
ETH vs. Euro STOXX 50	0.4210	0.3001	–1.72	0.0855	Weak
SOL vs. S&P 500	0.0914	0.1907	2.70	0.007	Moderate
SOL vs. Nikkei 225	0.0579	0.2073	4.03	<0.0001	Strong
SOL vs. Euro STOXX 50	0.0832	0.2078	3.15	0.0016	Strong

Table 4.14: Contagion Test Results - The FTX Collapse (Forbes & Rigobon Test)

4.4.4 Direction of Contagion

While the Forbes & Rigobon (2002) methodology looks for the presence of contagion between BTC, ETH, and SOL against those of the S&P 500 (GSPC), Nikkei 225 (N225), and STOXX50E by adjusting for changes in volatility, it does not allow for identification of the direction of contagion due to the symmetric nature of correlation. To investigate directionality, Vector Autoregression (VAR) models and Granger causality tests were applied. The results reveal significant and time-varying patterns of influence.

4.4.4.1 Contagion Direction Analysis – COVID-19 crash

The results summarized in Table 4.15, provide solid evidence of unidirectional contagion from cryptocurrencies to equity markets. Specifically, Bitcoin significantly Granger-causes the S&P 500 ($p = 0.000$), Nikkei 225 ($p = 0.037$), and Euro STOXX 50 ($p = 0.000$), with no reverse causality detected in any pair. Similarly, Ethereum exerts a strong causal influence on all three indices—S&P 500 ($p = 0.000$), Nikkei 225 ($p = 0.000$), and Euro STOXX 50 ($p = 0.000$)—while the indices do not Granger-cause

Ethereum returns. These findings confirm a clear direction of contagion: from crypto-assets to traditional financial markets.

Crypto	**Index**	**Crypto → Index (p-value)**	**Index → Crypto (p-value)**	**Direction of Contagion**
BTC	S&P 500	**0.000**	0.581	BTC → S&P 500
BTC	Nikkei 225	**0.037**	0.310	BTC → Nikkei 225
BTC	STOXX50E	**0.000**	0.794	BTC → STOXX50E
ETH	S&P 500	**0.000**	0.784	ETH → S&P 500
ETH	Nikkei 225	**0.000**	0.103	ETH → Nikkei 225
ETH	STOXX50E	**0.000**	0.220	ETH → STOXX50E
SOL	S&P 500	**0.000**	0.291	SOL → S&P 500
SOL	Nikkei 225	**0.014**	0.142	SOL → Nikkei 225
SOL	STOXX50E	**0.000**	0.220	SOL → STOXX50E

Table 4.15: COVID-19 Period: Granger Causality Summary

From a real-world perspective, these findings imply that cryptocurrency markets increasingly function as shock transmitters rather than shock absorbers. For investors and policymakers, this unidirectional causality underscores the importance of monitoring crypto-market developments as early warning signals for equity market stress. Moreover, the lack of feedback from stock markets to cryptocurrencies suggests that diversification benefits may be limited during turbulent periods, as crypto-originated shocks can spill over into traditional assets without reciprocal stabilization effects.

These results concord with existing empirical research. Corbet et al. (2020) and Bouri et al. (2021) have shown that during systemic crises such as COVID-19. They argue that cryptocurrencies become highly connected with global markets due to herd behavior, panic selling, and increased global risk deslike. The absence of significant feedback from equities to cryptocurrencies reinforces the interpretation that digital assets were leading indicators of market stress, rather than reactive followers.

Hence, the COVID-19 period is characterized by a strong and asymmetric contagion pattern, with cryptocurrencies acting as shock transmitters toward the traditional financial system.

4.4.4.2 Contagion Direction Analysis – Crypto Boom

During the 2021 crypto boom and correction, a period marked by a sharp correction in cryptocurrency prices and rising global inflation, the direction of contagion between cryptocurrencies and traditional equity markets was assessed using Vector Autoregressive (VAR) models with a lag order of one. Granger causality tests were conducted to see whether Bitcoin (BTC), Ethereum (ETH), or Solana (SOL) had predictive power over equity indices (S&P 500, Nikkei 225, Euro STOXX 50).

The analysis summarized in Table 4.16, reveals limited and isolated evidence of contagion. Bitcoin showed important Granger causality only toward the Nikkei 225 ($p = 0.025$), but not toward the S&P 500 or Euro STOXX 50. Ethereum showed a causal influence on the S&P 500 ($p = 0.023$) and the Euro STOXX 50 ($p = 0.001$), but no impact on the Nikkei 225. Solana displayed weak influence, Granger-causing only the Euro STOXX 50 ($p = 0.048$), while showing no causal effect on the other indices.

Crypto	Index	Crypto → Index (p-value)	Index → Crypto (p-value)	Direction of Contagion
BTC	**S&P 500**	0.148	0.327	No Contagion Detected
BTC	**Nikkei 225**	**0.025**	0.879	BTC → Nikkei 225
BTC	**STOXX50E**	0.074	0.770	No Contagion Detected
ETH	**S&P 500**	**0.023**	0.822	ETH → S&P 500
ETH	**Nikkei 225**	0.991	0.103	No Contagion Detected
ETH	**STOXX50E**	**0.001**	0.830	ETH → STOXX50E
SOL	**S&P 500**	0.934	0.837	No Contagion Detected
SOL	**Nikkei 225**	0.896	0.253	No Contagion Detected
SOL	**STOXX50E**	**0.048**	0.872	SOL → STOXX50E

Table 4.16: Crypto Boom Period: Granger Causality Summary

Unlike the COVID-19 period, where contagion was strong and broad-based, these results suggest a reduction in the intensity and scope of spillovers from crypto-assets to traditional markets during the 2022 correction. This aligns with existing studies (e.g., Koutmos, 2018; Ji et al., 2019) that report weaker integration between cryptocurrencies and equities during periods of market adjustment rather than systemic stress. Moreover, the absence of reverse causality reinforces the notion that crypto markets remain relatively segmented during non-systemic downturns.

From a real-world perspective, these findings suggest that cryptocurrency markets do not pose a universal systemic risk to traditional financial markets, but can generate targeted contagion effects in certain regions or asset classes. For investors, this highlights the importance of pair-specific risk assessment, while for policymakers, it underscores the need for focused monitoring rather than broad-based regulation of crypto–equity linkages.

In sum, the contagion observed during the crypto boom is selective and asset-dependent, with Ethereum showing more persistent influence than Bitcoin or Solana. These findings point out the evolving but still inconsistent role of cryptocurrencies as potential transmitters of market volatility outside systemic crises.

4.4.4.3 Contagion Direction Analysis – FTX collapse

The results shown in Table 4.17, uncover a marked shift in contagion movements, characterized by bidirectional and reverse causality, in contrast to the largely unidirectional spillovers observed during COVID-19. Bidirectional causality was discovered between BTC and STOXX50E (BTC → STOXX50E: $p = 0.000$, STOXX50E → BTC: $p = 0.035$), as well as between ETH and the S&P 500 (ETH → S&P 500: $p = 0.014$, S&P 500 → ETH: $p = 0.048$). Additionally, reverse contagion was observed from S&P 500 to BTC ($p = 0.001$) and from S&P 500 to SOL ($p = 0.012$), pointing out equity markets as potential transmitters of volatility to crypto-assets during crypto-specific turmoil. ETH also continued to Granger-cause Nikkei 225 and STOXX50E, while SOL affected the STOXX50E ($p = 0.001$) but not the other indices.

From a real-world perspective, these findings imply that cryptocurrencies—particularly Bitcoin and Ethereum—are increasingly embedded within the global financial system, while their systemic impact remains region- and asset-specific rather than universal. This has important implications for portfolio diversification, systemic risk monitoring, and macroprudential regulation.

Crypto	**Index**	**Crypto → Index (p-value)**	**Index → Crypto (p-value)**	**Direction of Contagion**
BTC	S&P 500	0.405	**0.001**	S&P 500 → BTC
BTC	Nikkei 225	**0.028**	0.453	BTC → Nikkei 225
BTC	STOXX50E	**0.000**	**0.035**	Bidirectional
ETH	S&P 500	**0.014**	**0.048**	Bidirectional
ETH	Nikkei 225	**0.036**	0.716	ETH → Nikkei 225
ETH	STOXX50E	**0.000**	0.221	ETH → STOXX50E
SOL	S&P 500	0.152	**0.012**	S&P 500 → SOL
SOL	Nikkei 225	0.537	0.379	No Contagion Detected
SOL	STOXX50E	**0.001**	0.175	SOL → STOXX50E

Table 4.17: FTX Collapse Period: Granger Causality Summary

These findings concord with recent literature that emphasizes the growing interdependence and feedback mechanisms between crypto and equity markets. For example, Shahzad et al. (2022) noted that during events originating within the crypto ecosystem, the contagion process is often bidirectional or reversed, as institutional investors, risk parity strategies, and media-driven sentiment link the two asset classes more tightly. The results from the FTX period suggest that equity markets are not only affected by crypto shocks but may respond and in turn influence digital assets, especially when systemic confidence is undermined.

In summary, the FTX collapse period reveals a more complex contagion structure. It is characterized by feedback loops and bidirectional causality. Which reflect the mature and increasingly integrated nature of the relationship between cryptocurrency and equity markets in recent years.

5 Conclusion and Future Work

5.1 Conclusion

In this work, we examined the dynamic interactions between cryptocurrency markets and traditional equity indices, with a particular focus on contagion and volatility spillover effects. The analysis investigated how the co-movement between cryptocurrencies and stock markets evolves over time and whether these relationships intensify during periods of financial stress. To achieve this objective, the study employed a DCC-GARCH framework, complemented by t-tests, Chow structural break tests, and the Forbes and Rigobon (2002) adjusted correlation approach. We also employed the Granger causality to explore the contagion direction.

The impirical results indicate that crypto–equity relationships are time-varying and asset-specific, strengthening during periods of high market stress. Bitcoin shows the strongest and most consistent spillovers, particularly with the U.S. equity market. During studied crises COVID-19, the 2021 crypto boom and crash, and the 2022 FTX collapse, correlations between Bitcoin and the S&P 500 rose greatly, suggesting that Bitcoin acts as a systemic risk asset rather than a safe or independent investment during turbulent periods.

Ethereum (ETH) also shows increased co-movement with the S&P 500 during turbulent periods, although the magnitude of this relationship is weaker than that observed for Bitcoin. This indicates that Ethereum is partially integrated into traditional financial markets, but its spillover effects remain more moderate. In contrast, Solana (SOL) displays more irregular and unstable relationships with equity indices, reflecting a higher sensitivity to idiosyncratic shocks and speculative dynamics rather than persistent systemic linkages.

From a regional perspective, U.S. and European equity markets are more closely linked to cryptocurrencies than the Japanese market. Stronger and more persistent spillovers are observed between major cryptocurrencies and the S&P 500 and EURO STOXX 50, while the Nikkei 225 shows weaker and less consistent connections. These differences suggest that market structure and the level of crypto market participation influence cross-market linkages.

Our work contributes to the literature by showing that crypto–equity contagion is asset-specific, region-specific, and time-varying. The findings challenge the assumption of asset class independence in portfolio and risk management as cryptocurrencies become more integrated into global markets. Future research could extend this work by including additional crypto assets, macroeconomic and sentiment variables, and more advanced econometric models.

5.2 Recommendations for Future Research

Although this study provides empirical evidence on the dynamic interdependence between cryptocurrency and equity markets, several avenues remain for future research. Expanding the analytical framework in terms of asset coverage, explanatory variables, econometric methodology, and crisis contexts would allow for a deeper and more comprehensive understanding of contagion mechanisms in digital and traditional financial markets.

First, future research could extend the analysis beyond major cryptocurrencies by including stablecoins, DeFi tokens, and alternative Layer-1 assets, which differ in volatility, liquidity, and systemic importance. Examining these assets may reveal heterogeneous contagion patterns and deeper insights into crypto–equity interdependence. Copula-DCC-GARCH models would be appropriate to capture non-linear and tail-risk dependence across such assets.

Second, future research could incorporate macroeconomic and sentiment indicators, such as interest rates, inflation, monetary policy, the VIX, Google Trends, or social media sentiment, which increasingly influence cryptocurrency markets. Including these variables would help explain changes in crypto–equity linkages. DCC-GARCH models with exogenous variables (DCC-GARCH-X) are well suited to identify whether correlation dynamics are driven by macroeconomic shocks or investor sentiment.

Third, future research should account for non-linearities and regime-dependent dynamics. Financial markets often exhibit different correlation structures during tranquil and turbulent periods, and contagion effects tend to intensify during crises. Markov-Switching DCC-GARCH models could be employed to distinguish between low- and high-volatility regimes, thereby assessing whether crypto–equity linkages are episodic or structurally persistent over time.

Finally, the use of high-frequency or intraday data offers a promising direction for capturing rapid volatility spillovers and market microstructure effects. Given the continuous trading nature of cryptocurrency markets, intraday data could reveal lead–lag relationships and short-term transmission mechanisms that are not observable at daily frequencies. BEKK-GARCH models or high-frequency spillover measures could be applied to analyze directional volatility transmission during periods of heightened market stress.

Overall, these extensions would enhance the robustness and policy relevance of contagion analysis by providing a more refined understanding of the evolving and systemic nature of crypto–equity interdependencies in a digitized financial environment.

6 References

Ahmed, M. Y., Sarkodie, S. A., & Leirvik, T. (2023). Mutual coupling between stock market and cryptocurrencies. *Heliyon*, *9*(5), e15227. https://doi.org/10.1016/j.heliyon.2023.e15227

Anamika, P., Kumar, V., & Sharma, R. (2023). Volatility spillovers and connectedness between cryptocurrencies and stock markets: Evidence from DCC-GARCH models. *International Review of Financial Analysis*, *85*, 102554. https://doi.org/10.1016/j.irfa.2022.102554

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, *13*(4), 84. https://doi.org/10.3390/jrfm13040084

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *The Financial Review*, *45*(2), 217–229. https://doi.org/10.1111/j.1540-6288.2010.00244.x

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, *54*, 177–189. https://doi.org/10.1016/j.intfin.2017.12.004

Bendob, A., Othman, A., & Sirag, A. (2022). Understanding the dynamic correlation between Bitcoin, gold, oil, and stock market indices in selected Arab countries: Application of the DCC-GARCH model to the banking and insurance sectors. *Arab Monetary Fund*. https://www.amf.org.ae/en/research/publications

Będowska-Sójka, B., & Kliber, A. (2021). Information content of liquidity and volatility measures. *Physica A: Statistical Mechanics and Its Applications*, *563*, 125461. https://doi.org/10.1016/j.physa.2020.125461

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, *20*, 192–198. https://doi.org/10.1016/j.frl.2016.09.025

Bouri, E., Gabauer, D., Gupta, R., & Tiwari, A. K. (2021). Volatility connectedness of major cryptocurrencies: The role of investor happiness. *Journal of Behavioral and Experimental Finance*, *30*, 100463. https://doi.org/10.1016/j.jbef.2021.100463

Bouri, E., Shahzad, S. J. H., Roubaud, D., Kristoufek, L., & Lucey, B. (2020). Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *The Quarterly Review of Economics and Finance*, *77*, 156–164. https://doi.org/10.1016/j.qref.2020.03.004

Chakraborty, I., & Subramaniam, T. (2023). Dynamic spillovers and volatility connectedness between cryptocurrencies and conventional financial markets. *Finance Research Letters*, *50*, 103414. https://doi.org/10.1016/j.frl.2022.103414

Chaim, P., & Laurini, M. P. (2019). Volatility and return spillovers in Bitcoin and altcoin markets. *Finance Research Letters*, *30*, 230–241. https://doi.org/10.1016/j.frl.2018.10.014

Choi, S., & Shin, J. (2022). Bitcoin: An inflation hedge but not a safe haven. *Finance Research Letters*, *46*, 102379. https://doi.org/10.1016/j.frl.2021.102379

Chu, J., Chan, S., Nadarajah, S., & Osterrieder, J. (2017). GARCH modelling of cryptocurrencies. *Journal of Risk and Financial Management*, *10*(4), 17. https://doi.org/10.3390/jrfm10040017

Ciaian, P., Rajcaniova, M., & Kancs, D. (2018). The economics of Bitcoin price formation. *Applied Economics*, *50*(55), 595–608. https://doi.org/10.1080/00036846.2017.1285070

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, *165*, 28–34. https://doi.org/10.1016/j.econlet.2018.01.004

Corbet, S., Lucey, B. M., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182–199. https://doi.org/10.1016/j.irfa.2018.09.003

Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, *35*, 101554. https://doi.org/10.1016/j.frl.2020.101554

Corbet, S., Hou, Y., Hu, Y., Larkin, C., Lucey, B., & Oxley, L. (2021). Cryptocurrency liquidity and volatility interrelationships during the COVID-19 pandemic. *Finance Research Letters, 45*, 102137. https://doi.org/10.1016/j.frl.2021.102137

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*(366), 427–431. https://doi.org/10.2307/2286348

Dionaşu, L., Petre, I., & Dobre, C. (2022). Volatility spillovers and connectedness between cryptocurrencies and stock markets: Evidence from developed and emerging economies. *Journal of Risk and Financial Management, 15*(5), 225. https://doi.org/10.3390/jrfm15050225

Engle, R. F. (1982). *Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50*(4), 987–1007. https://doi.org/10.2307/1912773

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate GARCH models. *Journal of Business & Economic Statistics, 20*(3), 339–350. https://doi.org/10.1198/073500102288618487

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *The Journal of Finance, 57*(5), 2223–2261. https://doi.org/10.1111/1540-6261.00494

Goeldi, S., Buchmann, T., & Kerler, F. (2020). Spillovers and dynamic connectedness between cryptocurrencies and traditional financial assets. *Finance Research Letters, 36*, 101308. https://doi.org/10.1016/j.frl.2020.101308

Gönüllü, O. (n.d.). Cryptocurrency index and relationship with major stock indices. In Chapter 5, Kocaeli University, Faculty of Business Administration. ORCID: https://orcid.org/0000-0001-9611-4499

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from Bitcoin. *International Review of Financial Analysis, 63*, 431–437. https://doi.org/10.1016/j.irfa.2018.03.004

Gurdgiev, C., & Loughlin, D. (2020). Volatility and connectedness in cryptocurrency markets: Evidence from Bitcoin, Ethereum, and Ripple. *Finance Research Letters, 35*, 101265. https://doi.org/10.1016/j.frl.2020.101265

Ibrahim, B. A., Elamer, A. A., Alasker, T. H., Mohamed, M. A., & Abdou, H. A. (2024). Volatility contagion between cryptocurrencies, gold and stock markets pre- and during COVID-19: Evidence using DCC-GARCH and cascade-correlation network. *Financial Innovation, 10*, 104. https://doi.org/10.1186/s40854-023-00605-z

Ji, Q., Bouri, E., Gupta, R., & Roubaud, D. (2018). Network causality structures among Bitcoin and other financial assets: A directed acyclic graph approach. *The Quarterly Review of Economics and Finance, 70*, 203–213. https://doi.org/10.1016/j.qref.2018.05.016

Ji, Q., Bouri, E., Lau, C. K. M., & Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis*, *63*, 257–272. https://doi.org/10.1016/j.irfa.2018.12.004

Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the COVID 19 pandemic. *International Review of Financial Analysis*, *71*, 101526. https://doi.org/10.1016/j.irfa.2020.101526

Ji, X., Wang, S., Xiao, H., Bu, N., & Lin, X. (2022). Contagion effect of financial markets in crisis: An analysis based on the DCC–MGARCH model. *Mathematics*, *10*(11), 1819. https://doi.org/10.3390/math10111819

Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK MGARCH analysis. *Finance Research Letters*, *29*, 68–74. https://doi.org/10.1016/j.frl.2019.03.009

Koutmos, D. (2018). Return and volatility spillovers among cryptocurrencies. *Economics Letters*, *173*, 122–127. https://doi.org/10.1016/j.econlet.2018.10.004

Matkovskyy, R., & Jalan, A. (2019). From financial markets to Bitcoin markets: A fresh look at the contagion effect. *Finance Research Letters*, *31*, 93–97. https://doi.org/10.1016/j.frl.2019.02.010

Mgadmi, N. (2024). Causality between stock indices and cryptocurrencies during the Russia-Ukraine war. *International Review of Economics*. https://doi.org/10.1007/s12232-024-00518-1

Mnif, E., Salhi, B., Trabelsi, L., & Jarboui, A. (2022). Efficiency and herding analysis in gold-backed cryptocurrencies. *Heliyon*, *8*(12), e11982. https://doi.org/10.1016/j.heliyon.2022.e11982

Mensi, W., Ali, S. R. M., Vo, X. V., & Kang, S. H. (2022). Multiscale dependence, spillovers, and connectedness between precious metals and currency markets: A hedge and safe-haven analysis. *Resources Policy*, *77*, 102752. https://doi.org/10.1016/j.resourpol.2022.102752

Niyitegeka, O., & Zhou, S. (2023). An investigation of financial contagion between cryptocurrency and equity markets: Evidence from developed and emerging markets. *Cogent Economics & Finance*, *11*(1), 2203432. https://doi.org/10.1080/23322039.2023.2203432

Sajeev, K. C., & Afjal, M. (2022). Contagion effect of cryptocurrency on the securities market: A study of Bitcoin volatility using diagonal BEKK and DCC GARCH models. *SN Business & Economics*, *2*(6), 57. https://doi.org/10.1007/s43546-022-00242-4

Shahzad, S. J. H., Anas, M., & Bouri, E. (2022). Price explosiveness in cryptocurrencies and Elon Musk’s tweets. *Finance Research Letters*, *47*, 102695. https://doi.org/10.1016/j.frl.2022.102695

Trabelsi, N. (2018). Are there any volatility spillover effects among cryptocurrencies and widely traded asset classes? *Journal of Risk and Financial Management*, *11*(4), 66. https://doi.org/10.3390/jrfm11040066

Troian, K. (2024). Analysing the relationship between oil futures and cryptocurrency markets from 2018 to 2024. *International Journal of Economics, Commerce and Management*, *12*(7), 304–328. https://doi.org/10.2139/ssrn.4915794

Wang, H., Wang, X., Yin, S., & Ji, H. (2022). The asymmetric contagion effect between stock market and cryptocurrency market. *Finance Research Letters*, *46*, 102345. https://doi.org/10.1016/j.frl.2021.102345

Wang, X., Chen, X., & Zhao, P. (2020). The relationship between Bitcoin and stock market. *International Journal of Operations Research and Information Systems*, *11*(1), 1–13. https://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/IJORIS.2020040102

Yavuz, M. S., Bozkurt, G., & Boğa, S. (2022). Investigating the market linkages between cryptocurrencies and conventional assets. *Emerging Markets Journal*, *12*(2), 36–45. https://doi.org/10.5195/emaj.2022.266

Yarovaya, L., Brzeszczyński, J., Goodell, J. W., Lucey, B., & Lau, C. K. M. (2022). Rethinking financial contagion: Information transmission during the COVID-19 pandemic. *Journal of International Financial Markets, Institutions & Money*, *79*, 101594. https://doi.org/10.1016/j.intfin.2022.101594

Yousaf, I., & Ali, S. (2020). The COVID-19 outbreak and high frequency information transmission between major cryptocurrencies: Evidence from the VAR-DCC-GARCH approach. *Borsa Istanbul Review*, *20*(Suppl. 1), S1–S10. https://doi.org/10.1016/j.bir.2020.10.003

Zhang, W., Wang, P., Li, X., & Shen, D. (2020). The contagion effects of Bitcoin on global financial markets: Evidence from a time-varying parameter VAR model. *Finance Research Letters*, *33*, 101217. https://doi.org/10.1016/j.frl.2019.101217

Zhang, W., Wang, P., Li, X., & Shen, D. (2021). Spillover effects between Bitcoin and financial markets: Evidence using a time-varying connectedness approach. *International Review of Financial Analysis*, *77*, 101846. https://doi.org/10.1016/j.irfa.2021.101846

Annex A: Data Preparation, Variable Analysis, Test and DCC-GARCH Estimation

```
* install the getsymbols package
ssc install getsymbols
* get Data from yahoo finance
getsymbols ^GSPC ^N225 ^STOXX50E BTC-USD ETH-USD SOL-USD , fm(04) fd(01)
fy(2018) lm(04) ld(30) ly(2025) freq(d) price(adjclose) clear yahoo
* prepare the time series
format period %td
tsset period
* fill the missing period to align the varaibles using interpolation method
tsfill
ipolate r__STOXX50E period, gen(r__STOXX50E_f)
ipolate r__N225 period, gen(r__N225_f)
ipolate r__GSPC period, gen(r__GSPC_f)

**** check for missed values
list period r__STOXX50E_f if missing(r__STOXX50E_f)
list period r__N225_f if missing(r__N225_f)
list period r__GSPC_f if missing(r__GSPC_f)
list period r_BTC_USD  if missing(r_BTC_USD)
list period r_ETH_USD  if missing(r_ETH_USD)
list period r_SOL_USD  if missing(r_SOL_USD)
list period r_XRP_USD  if missing(r_XRP_USD)

* plot the time series return
tsline r__GSPC_f, title("S&P 500 Returns") name(g1, replace)
tsline r__N225_f, title("Nikkei 225 Returns") name(g2, replace)
tsline r__STOXX50E_f, title("EURO STOXX 50 Returns") name(g3, replace)
tsline r__FTSE_f, title("EURO STOXX 50 Returns") name(g4, replace)

tsline r_BTC_USD, title("BTC/USD Returns") name(g5, replace)
tsline r_ETH_USD, title("ETH/USD Returns") name(g6, replace)
tsline r_SOL_USD, title("SOL/USD Returns") name(g7, replace)
tsline r_XRP_USD, title("XRP/USD Returns") name(g8, replace)

graph combine g1 g5 g2 g6 g3 g7 g4 g8, cols(2) title("")
* declare variables
local vars r__GSPC_f r__N225_f r__STOXX50E_f  r_BTC_USD r_ETH_USD r_SOL_USD
* test for stationarity for each series
foreach v of local vars {
   asdoc  dfuller `v', lags(1)
   }

* test for arch effect for each series
foreach v of local vars {
```

```
    reg `v' L.`v'
    cap drop residuals
    predict residuals, residuals
    asdoc estat archlm, lags(1)

   }

* estimate the grach model for each series
foreach v of local vars {
    arch  `v', arch(1) GARCH(1)
   }

* pair wise dcc-GARCH estimation
mGARCH dcc r__GSPC_f r_BTC_USD, arch(1) GARCH(1) distribution(t)
mGARCH dcc r__STOXX50E_f r_BTC_USD, arch(1) GARCH(1) distribution(t)
mGARCH dcc r__N225_f r_BTC_USD, arch(1) GARCH(1) distribution(t)

mGARCH dcc r__GSPC_f r_ETH_USD, arch(1) GARCH(1) distribution(t)
mGARCH dcc r__STOXX50E_f r_ETH_USD, arch(1) GARCH(1) distribution(t)
mGARCH dcc r__N225_f r_ETH_USD, arch(1) GARCH(1) distribution(t)

mGARCH dcc r__GSPC_f r_SOL_USD if !missing(r_SOL_USD), arch(1) GARCH(1)
distribution(t)
mGARCH dcc r__STOXX50E_f r_SOL_USD if !missing(r_SOL_USD), arch(1) GARCH(1)
distribution(t)
mGARCH dcc r__N225_f r_SOL_USD if !missing(r_SOL_USD), arch(1) GARCH(1)
distribution(t)

* try different lags
arch r__GSPC, arch(1) GARCH(1)
est store m1

arch r__GSPC, arch(2) GARCH(1)
est store m2
arch r__GSPC, arch(1) GARCH(2)
est store m3
estimates stats m1 m2 m3
predict e, resid

* estimate aic/bic after arch fit
estat ic
```

Annex B: T-Test

```
*** BTC versus equities
mGARCH dcc (r_BTC_USD r__GSPC_f), arch(1) GARCH(1) distribution(t)
predict dc1*, correlation
mGARCH dcc (r_BTC_USD r__GSPC_f) if pre_bull_crash == 1, arch(1) GARCH(1) distribution(t)
predict dc1_pre* if pre_bull_crash == 1, correlation
mGARCH dcc (r_BTC_USD r__GSPC_f) if post_bull_crash == 1, arch(1) GARCH(1) distribution(t)
predict dc1_post* if post_bull_crash == 1, correlation
sum dc1_pre_r__GSPC_f_r_BTC_USD if pre_bull_crash == 1
sum dc1_post_r__GSPC_f_r_BTC_USD if post_bull_crash == 1
ttest dc1_post_r__GSPC_f_r_BTC_USD == dc1_pre_r__GSPC_f_r_BTC_USD, unpaired
***************
mGARCH dcc (r_BTC_USD r__N225_f), arch(1/2) GARCH(1) distribution(t)
predict dc2*, correlation
mGARCH dcc (r_BTC_USD r__N225_f) if pre_bull_crash == 1, arch(1/2) GARCH(1) distribution(t)
predict dc2_pre* if pre_bull_crash == 1, correlation
mGARCH dcc (r_BTC_USD r__N225_f) if post_bull_crash == 1, arch(1/2) GARCH(1) distribution(t)
predict dc2_post* if post_bull_crash == 1, correlation

sum dc2_pre_r__N225_f_r_BTC_USD if pre_bull_crash == 1
sum dc2_post_r__N225_f_r_BTC_USD if post_bull_crash == 1
ttest dc2_post_r__N225_f_r_BTC_USD == dc2_pre_r__N225_f_r_BTC_USD, unpaired
********
mGARCH dcc (r_BTC_USD r__STOXX50E_f), arch(1) GARCH(1) distribution(t)
predict dc3*, correlation
mGARCH dcc (r_BTC_USD r__STOXX50E_f) if pre_bull_crash == 1, arch(1) GARCH(1) distribution(t)
predict dpr3* if pre_bull_crash == 1, correlation
mGARCH dcc (r_BTC_USD r__STOXX50E_f) if post_bull_crash == 1, arch(1) GARCH(1) distribution(t)
predict dpt3* if post_bull_crash == 1, correlation
sum dpr3_r__STOXX50E_f_r_BTC_USD if pre_bull_crash == 1
sum dpt3_r__STOXX50E_f_r_BTC_USD if post_bull_crash == 1
ttest dpt3_r__STOXX50E_f_r_BTC_USD == dpr3_r__STOXX50E_f_r_BTC_USD, unpaired
*****************
*** ETH versus equities
*******
mGARCH dcc (r_ETH_USD r__GSPC_f), arch(1) GARCH(1) distribution(t)
predict dc4*, correlation
```

```
mGARCH dcc (r_ETH_USD r__GSPC_f) if pre_bull_crash == 1, arch(1) GARCH(1)
distribution(t)
predict dc4_pre* if pre_bull_crash == 1, correlation

mGARCH dcc (r_ETH_USD r__GSPC_f) if post_bull_crash == 1, arch(1) GARCH(1)
distribution(t)
predict dc4_post* if post_bull_crash == 1, correlation
sum dc4_pre_r__GSPC_f_r_ETH_USD if pre_bull_crash == 1
sum dc4_post_r__GSPC_f_r_ETH_USD if post_bull_crash == 1
ttest dc4_post_r__GSPC_f_r_ETH_USD == dc4_pre_r__GSPC_f_r_ETH_USD, unpaired
***************
mGARCH dcc (r_ETH_USD r__N225_f), arch(1) GARCH(1) distribution(t)
predict dc5*, correlation
mGARCH dcc (r_ETH_USD r__N225_f) if pre_bull_crash == 1, arch(1) GARCH(1)
distribution(t)
predict dc5_pre* if pre_bull_crash == 1, correlation
mGARCH dcc (r_ETH_USD r__N225_f) if post_bull_crash == 1, arch(1) GARCH(1)
distribution(t)
predict dc5_post* if post_bull_crash == 1, correlation
sum dc5_pre_r__N225_f_r_ETH_USD if pre_bull_crash == 1
sum dc5_post_r__N225_f_r_ETH_USD if post_bull_crash == 1
ttest dc5_post_r__N225_f_r_ETH_USD == dc5_pre_r__N225_f_r_ETH_USD, unpaired
********
mGARCH dcc (r_ETH_USD r__STOXX50E_f), arch(1) GARCH(1)
predict dc6*, correlation
mGARCH dcc (r_ETH_USD r__STOXX50E_f) if pre_bull_crash == 1, arch(1) GARCH(1)
distribution(t)
predict dpr6* if pre_bull_crash == 1, correlation

mGARCH dcc (r_ETH_USD r__STOXX50E_f) if post_bull_crash == 1 &
!missing(r_ETH_USD) & !missing(r__STOXX50E_f) , arch(1) GARCH(1) distribution(t)
predict dpt6* if post_bull_crash == 1, correlation
sum dc6_r__STOXX50E_f_r_ETH_USD if pre_bull_crash == 0
sum dc6_r__STOXX50E_f_r_ETH_USD if pre_bull_crash == 1
ttest dc6_r__STOXX50E_f_r_ETH_USD, by(pre_bull_crash)
*****************
*** SOL versus equities
*******
mGARCH dcc (r_SOL_USD r__GSPC_f) if !missing(r_SOL_USD), arch(1) GARCH(1)
distribution(t)
predict dc7*, correlation
sum dc7_r__GSPC_f_r_SOL_USD if pre_bull_crash == 0
sum dc7_r__GSPC_f_r_SOL_USD if pre_bull_crash == 1
ttest dc7_r__GSPC_f_r_SOL_USD, by(pre_bull_crash)
mGARCH dcc (r_SOL_USD r__GSPC_f) if pre_bull_crash == 1, arch(1) GARCH(1)
distribution(t)
predict dc7_pre* if pre_bull_crash == 1, correlation
```

```
mGARCH dcc (r_SOL_USD r__GSPC_f) if post_bull_crash == 1, arch(1/2) GARCH(1) distribution(t)
predict dc7_post* if post_bull_crash == 1, correlation
sum dc7_pre_r__GSPC_f_r_SOL_USD if pre_bull_crash == 1
sum dc7_post_r__GSPC_f_r_SOL_USD if post_bull_crash == 1

ttest dc7_post_r__GSPC_f_r_SOL_USD == dc7_pre_r__GSPC_f_r_SOL_USD, unpaired
***************
mGARCH dcc (r_SOL_USD r__N225_f) if !missing(r_SOL_USD), arch(1) GARCH(1) distribution(t)
predict dc8*, correlation
sum dc8_r__N225_f_r_SOL_USD if pre_bull_crash == 0
sum dc8_r__N225_f_r_SOL_USD if pre_bull_crash == 1
ttest dc8_r__N225_f_r_SOL_USD, by(pre_bull_crash)
mGARCH dcc (r_SOL_USD r__N225_f) if pre_bull_crash == 1, arch(1/2) GARCH(1) distribution(t)
predict dc8_pre* if pre_bull_crash == 1, correlation
mGARCH dcc (r_SOL_USD r__N225_f) if post_bull_crash == 1, arch(1) GARCH(1) distribution(t)
predict dc8_post* if post_bull_crash == 1, correlation
sum dc8c_pre_r__N225_f_r_SOL_USD if pre_bull_crash == 1
sum dc8_post_r__N225_f_r_SOL_USD if post_bull_crash == 1
ttest dc8_post_r__N225_f_r_SOL_USD == dc8_pre_r__N225_f_r_SOL_USD, unpaired
********
mGARCH dcc (r_SOL_USD r__STOXX50E_f) if !missing(r_SOL_USD), arch(1) GARCH(1) distribution(t)
predict dc9*, correlation
sum dc9_r__STOXX50E_f_r_SOL_USD if pre_bull_crash == 0
sum dc9_r__STOXX50E_f_r_SOL_USD if pre_bull_crash == 1

ttest dc9_r__STOXX50E_f_r_SOL_USD, by(pre_bull_crash
mGARCH dcc (r_SOL_USD r__STOXX50E_f) if pre_bull_crash == 1, arch(1) GARCH(1) distribution(t)
predict dpr9* if pre_bull_crash == 1, correlation
mGARCH dcc (r_SOL_USD r__STOXX50E_f) if post_bull_crash == 1, arch(1) GARCH(1) distribution(t)
predict dpt9* if post_bull_crash == 1, correlation
sum dpr9_r__STOXX50E_f_r_SOL_USD if pre_bull_crash == 1
sum dpt9_r__STOXX50E_f_r_SOL_USD if post_bull_crash == 1
ttest dpt9_r__STOXX50E_f_r_SOL_USD == dpr9_r__STOXX50E_f_r_ETH_USD, unpaired
```

Annex C: Forbes and Rigobon Test

```
* BTC versus equities covid-19
* BTC Versus SP500
* Step 1: Correlations
corr r_BTC_USD r__GSPC_f if (pre_covid == 1 & period < td(20feb2019))
scalar rho_pre = r(rho)
corr r_BTC_USD r__GSPC_f if covid_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__GSPC_f if pre_covid == 1 & period < td(20feb2019) , detail
scalar sigma2_pre = r(Var)
summarize r__GSPC_f if covid_period == 1, detail
scalar sigma2_post = r(Var)

* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if pre_covid == 1 & period < td(20feb2019)
scalar N_pre = r(N)
count if covid_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value


* BTC Versus Nekkei 225
* Step 1: Correlations
corr r_BTC_USD r__N225_f if (pre_covid == 1 & period < td(20feb2019))
scalar rho_pre = r(rho)
corr r_BTC_USD r__N225_f if covid_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__N225_f if pre_covid == 1 & period < td(20feb2019) , detail
scalar sigma2_pre = r(Var)
```

```
summarize r__N225_f if covid_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if pre_covid == 1 & period < td(20feb2019)
scalar N_pre = r(N)

count if covid_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
** BTC Versus STOXX5E
* Step 1: Correlations
corr r_BTC_USD r__STOXX50E_f if (pre_covid == 1 & period < td(20feb2019))
scalar rho_pre = r(rho)
corr r_BTC_USD r__STOXX50E_f if covid_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__STOXX50E_f if pre_covid == 1 & period < td(20feb2019) , detail
scalar sigma2_pre = r(Var)

summarize r__STOXX50E_f if covid_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if pre_covid == 1 & period < td(20feb2019)
scalar N_pre = r(N)
count if covid_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
```

```
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
*******************************************
* ETH versus equities covid-19
* ETH Versus SP500
* Step 1: Correlations
corr r_ETH_USD r__GSPC_f if (pre_covid == 1 & period < td(20feb2019))
scalar rho_pre = r(rho)
corr r_ETH_USD r__GSPC_f if covid_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__GSPC_f if pre_covid == 1 & period < td(20feb2019) , detail
scalar sigma2_pre = r(Var)
summarize r__GSPC_f if covid_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if pre_covid == 1 & period < td(20feb2019)
scalar N_pre = r(N)
count if covid_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
** ETH Versus Nekkei 225
* Step 1: Correlations
corr r_ETH_USD r__N225_f if (pre_covid == 1 & period < td(20feb2019))
scalar rho_pre = r(rho)
corr r_ETH_USD r__N225_f if covid_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__N225_f if pre_covid == 1 & period < td(20feb2019) , detail
scalar sigma2_pre = r(Var)
```

```
summarize r__N225_f if covid_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if pre_covid == 1 & period < td(20feb2019)
scalar N_pre = r(N)
count if covid_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
** ETH Versus STOXX50E
* Step 1: Correlations
corr r_ETH_USD r__STOXX50E_f if (pre_covid == 1 & period < td(20feb2019))
scalar rho_pre = r(rho)
corr r_ETH_USD r__STOXX50E_f if covid_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__STOXX50E_f if pre_covid == 1 & period < td(20feb2019) , detail
scalar sigma2_pre = r(Var)
summarize r__STOXX50E_f if covid_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if pre_covid == 1 & period < td(20feb2019)
scalar N_pre = r(N)

count if covid_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
```

```
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
*****************************************
* BTC versus equities ftx period
* Step 1: Correlations
corr r_BTC_USD r__GSPC_f if ftx_periode == 0
scalar rho_pre = r(rho)
corr r_BTC_USD r__GSPC_f if ftx_periode == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__GSPC_f if ftx_periode == 0 , detail
scalar sigma2_pre = r(Var)

summarize r__GSPC_f if ftx_periode == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if ftx_periode == 0
scalar N_pre = r(N)
count if ftx_periode == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
*****************************************
* Step 1: Correlations
corr r_BTC_USD r__N225_f if ftx_periode == 0
scalar rho_pre = r(rho)
corr r_BTC_USD r__N225_f if ftx_periode == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__N225_f if ftx_periode == 0 , detail
scalar sigma2_pre = r(Var)
```

```
summarize r__N225_f if ftx_periode == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if ftx_periode == 0
scalar N_pre = r(N)
count if ftx_periode == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
*******************************************
* Step 1: Correlations
corr r_BTC_USD r__STOXX50E_f if ftx_periode == 0
scalar rho_pre = r(rho)
corr r_BTC_USD r__STOXX50E_f if ftx_periode == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__STOXX50E_f if ftx_periode == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__STOXX50E_f if ftx_periode == 1, detail
scalar sigma2_post = r(Var)

* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if ftx_periode == 0
scalar N_pre = r(N)
count if ftx_periode == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
```

```
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
******************************************
* ETH versus equities
* Step 1: Correlations
corr r_ETH_USD r__GSPC_f if ftx_periode == 0
scalar rho_pre = r(rho)
corr r_ETH_USD r__GSPC_f if ftx_periode == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__GSPC_f if ftx_periode == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__GSPC_f if ftx_periode == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if ftx_periode == 0
scalar N_pre = r(N)
count if ftx_periode == 1
scalar N_post = r(N)

* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
****************************************
* Step 1: Correlations
corr r_ETH_USD r__N225_f if ftx_periode == 0
scalar rho_pre = r(rho)
corr r_ETH_USD r__N225_f if ftx_periode == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__N225_f if ftx_periode == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__N225_f if ftx_periode == 1, detail
```

```
scalar sigma2_post = r(Var)

* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if ftx_periode == 0
scalar N_pre = r(N)
count if ftx_periode == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value


************************************
* Step 1: Correlations
corr r_ETH_USD r__STOXX50E_f if ftx_periode == 0
scalar rho_pre = r(rho)
corr r_ETH_USD r__STOXX50E_f if ftx_periode == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__STOXX50E_f if ftx_periode == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__STOXX50E_f if ftx_periode == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if ftx_periode == 0
scalar N_pre = r(N)

count if ftx_periode == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
```

```
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
***********************************
* SOL versus equities ftx period
* Step 1: Correlations
corr r_SOL_USD r__GSPC_f if ftx_periode == 0
scalar rho_pre = r(rho)
corr r_SOL_USD r__GSPC_f if ftx_periode == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__GSPC_f if ftx_periode == 0 , detail
scalar sigma2_pre = r(Var)

summarize r__GSPC_f if ftx_periode == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if ftx_periode == 0
scalar N_pre = r(N)
count if ftx_periode == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
******************************************
* Step 1: Correlations
corr r_SOL_USD r__N225_f if ftx_periode == 0
scalar rho_pre = r(rho)
corr r_SOL_USD r__N225_f if ftx_periode == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__N225_f if ftx_periode == 0 , detail
```

```
scalar sigma2_pre = r(Var)
summarize r__N225_f if ftx_periode == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if ftx_periode == 0
scalar N_pre = r(N)
count if ftx_periode == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
*******************************************
* Step 1: Correlations
corr r_SOL_USD r__STOXX50E_f if ftx_periode == 0
scalar rho_pre = r(rho)
corr r_SOL_USD r__STOXX50E_f if ftx_periode == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__STOXX50E_f if ftx_periode == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__STOXX50E_f if ftx_periode == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if ftx_periode == 0
scalar N_pre = r(N)
count if ftx_periode == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
```

```
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
*****************************************
* BTC versus equities bull_crash_period
* Step 1: Correlations
corr r_BTC_USD r__GSPC_f if bull_crash_period == 0
scalar rho_pre = r(rho)
corr r_BTC_USD r__GSPC_f if bull_crash_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__GSPC_f if bull_crash_period == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__GSPC_f if bull_crash_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if bull_crash_period == 0
scalar N_pre = r(N)
count if bull_crash_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
***********************************************
* Step 1: Correlations
corr r_BTC_USD r__N225_f if bull_crash_period == 0
scalar rho_pre = r(rho)
corr r_BTC_USD r__N225_f if bull_crash_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__N225_f if bull_crash_period == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__N225_f if bull_crash_period == 1, detail
scalar sigma2_post = r(Var)
```

```
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if bull_crash_period == 0
scalar N_pre = r(N)
count if bull_crash_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
*************************************
* Step 1: Correlations
corr r_BTC_USD r__STOXX50E_f if bull_crash_period == 0
scalar rho_pre = r(rho)
corr r_BTC_USD r__STOXX50E_f if bull_crash_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__STOXX50E_f if bull_crash_period == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__STOXX50E_f if bull_crash_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if bull_crash_period == 0
scalar N_pre = r(N)
count if bull_crash_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
```

```
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
*************************************
* ETH versus equities
* Step 1: Correlations
corr r_ETH_USD r__GSPC_f if bull_crash_period == 0
scalar rho_pre = r(rho)
corr r_ETH_USD r__GSPC_f if bull_crash_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__GSPC_f if bull_crash_period == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__GSPC_f if bull_crash_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if bull_crash_period == 0
scalar N_pre = r(N)
count if bull_crash_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
**************************************
* Step 1: Correlations
corr r_ETH_USD r__N225_f if bull_crash_period == 0
scalar rho_pre = r(rho)
corr r_ETH_USD r__N225_f if bull_crash_period == 1
scalar rho_post = r(rho)

* Step 2: Market variances
summarize r__N225_f if bull_crash_period == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__N225_f if bull_crash_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
```

```
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if bull_crash_period == 0
scalar N_pre = r(N)
count if bull_crash_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
***************************************
* Step 1: Correlations
corr r_ETH_USD r__STOXX50E_f if bull_crash_period == 0
scalar rho_pre = r(rho)
corr r_ETH_USD r__STOXX50E_f if bull_crash_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__STOXX50E_f if bull_crash_period == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__STOXX50E_f if bull_crash_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if bull_crash_period == 0
scalar N_pre = r(N)
count if bull_crash_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
```

```
*****************************************
* SOL versus equities ftx period
* Step 1: Correlations
corr r_SOL_USD r__GSPC_f if bull_crash_period == 0
scalar rho_pre = r(rho)
corr r_SOL_USD r__GSPC_f if bull_crash_period == 1
scalar rho_post = r(rho)

* Step 2: Market variances
summarize r__GSPC_f if bull_crash_period == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__GSPC_f if bull_crash_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if bull_crash_period == 0
scalar N_pre = r(N)
count if bull_crash_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))

* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
*****************************************
* Step 1: Correlations
corr r_SOL_USD r__N225_f if bull_crash_period == 0
scalar rho_pre = r(rho)
corr r_SOL_USD r__N225_f if bull_crash_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__N225_f if bull_crash_period == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__N225_f if bull_crash_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
```

```
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if bull_crash_period == 0
scalar N_pre = r(N)
count if bull_crash_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
*******************************************
* Step 1: Correlations
corr r_SOL_USD r__STOXX50E_f if bull_crash_period == 0
scalar rho_pre = r(rho)
corr r_SOL_USD r__STOXX50E_f if bull_crash_period == 1
scalar rho_post = r(rho)
* Step 2: Market variances
summarize r__STOXX50E_f if bull_crash_period == 0 , detail
scalar sigma2_pre = r(Var)
summarize r__STOXX50E_f if bull_crash_period == 1, detail
scalar sigma2_post = r(Var)
* Step 3: Adjust correlation
scalar ratio = sigma2_post / sigma2_pre
scalar adjusted_rho_pre = rho_pre / sqrt(1 + ratio - 1)
display "Adjusted Pre-Crisis Correlation: " adjusted_rho_pre
display "Post-Crisis Correlation: " rho_post
* Step 4: Sample sizes
count if bull_crash_period == 0
scalar N_pre = r(N)
count if bull_crash_period == 1
scalar N_post = r(N)
* Step 5: Standard errors
scalar se_pre = (1 - adjusted_rho_pre^2) / sqrt(N_pre - 2)
scalar se_post = (1 - rho_post^2) / sqrt(N_post - 2)
* Step 6: Z-test
scalar z_stat = (rho_post - adjusted_rho_pre) / sqrt(se_pre^2 + se_post^2)
scalar p_value = 2 * (1 - normal(abs(z_stat)))
* Step 7: Display results
display "Z-statistic: " z_stat
display "P-value (2-sided): " p_value
```

Annex D: Granger Contagion Direction

```
****LOOKING FOR CONTAGION DIRECTION
* COVID
var dc1_r__GSPC_f_r_BTC_USD r_BTC_USD if covid_period == 1, lags(1/1)
vargranger
var dc2_r__N225_f_r_BTC_USD r_BTC_USD if covid_period == 1, lags(1/1)
vargranger
var dc3_r__STOXX50E_f_r_BTC_USD r_BTC_USD if covid_period == 1, lags(1/1)
vargranger
var dc4_r__GSPC_f_r_ETH_USD r_ETH_USD if covid_period == 1, lags(1/1)
vargranger
var dc5_r__N225_f_r_ETH_USD r_ETH_USD if covid_period == 1, lags(1/1)
vargranger
var dc6_r__STOXX50E_f_r_ETH_USD r_ETH_USD if covid_period == 1, lags(1/1)
vargranger
** crypto boom
var dc1_r__GSPC_f_r_BTC_USD r_BTC_USD if btc_bullcrash == 1, lags(1/1)
vargranger
var dc2_r__N225_f_r_BTC_USD r_BTC_USD if btc_bullcrash == 1, lags(1/1)
vargranger
var dc3_r__STOXX50E_f_r_BTC_USD r_BTC_USD if btc_bullcrash == 1, lags(1/1)
vargranger
var dc4_r__GSPC_f_r_ETH_USD r_ETH_USD if btc_bullcrash == 1, lags(1/1)
vargranger
var dc5_r__N225_f_r_ETH_USD r_ETH_USD if btc_bullcrash == 1, lags(1/1)
vargranger
var dc6_r__STOXX50E_f_r_ETH_USD r_ETH_USD if btc_bullcrash == 1, lags(1/1)
vargranger
var dc7_r__GSPC_f_r_SOL_USD r_SOL_USD if btc_bullcrash == 1, lags(1/1)
vargranger
var dc8_r__N225_f_r_SOL_USD r_SOL_USD if btc_bullcrash == 1, lags(1/1)
vargranger
var dc9_r__STOXX50E_f_r_SOL_USD r_SOL_USD if btc_bullcrash == 1, lags(1/1)
vargranger
*** ftx
var dc1_r__GSPC_f_r_BTC_USD r_BTC_USD if ftx_periode == 1, lags(1/1)
vargranger
var dc2_r__N225_f_r_BTC_USD r_BTC_USD if ftx_periode == 1, lags(1/1)
vargranger
var dc3_r__STOXX50E_f_r_BTC_USD r_BTC_USD if ftx_periode == 1, lags(1/1)
vargranger


var dc4_r__GSPC_f_r_ETH_USD r_ETH_USD if ftx_periode == 1, lags(1/1)
vargranger
var dc5_r__N225_f_r_ETH_USD r_ETH_USD if ftx_periode == 1, lags(1/1)
vargranger
```

```
var dc6_r__STOXX50E_f_r_ETH_USD r_ETH_USD if ftx_periode == 1, lags(1/1)
vargranger
var dc7_r__GSPC_f_r_SOL_USD r_SOL_USD if ftx_periode == 1, lags(1/1)
vargranger
var dc8_r__N225_f_r_SOL_USD r_SOL_USD if ftx_periode == 1, lags(1/1)
vargranger
var dc9_r__STOXX50E_f_r_SOL_USD r_SOL_USD if ftx_periode == 1, lags(1/1)
vargranger
```

Annex E: DCC Plots

```
* Plot 1: BTC-GSPC
twoway (line dc1_r__GSPC_f_r_BTC_USD period, lcolor(blue)), ///
title("BTC - S&P500") ylabel(0(.2)1) xtitle("Date") ytitle("Correlation")
graph save btc_gspc.gph, replace
* Plot 2: ETH-GSPC
twoway (line dc4_r__GSPC_f_r_ETH_USD period, lcolor(red)), ///
title("ETH - S&P500") ylabel(0(.2)1) xtitle("Date") ytitle("Correlation")
graph save eth_gspc.gph, replace
* Plot 3: SOL-GSPC
twoway (line dc7_r__GSPC_f_r_SOL_USD period, lcolor(green)), ///
title("SOL - S&P500") ylabel(0(.2)1) xtitle("Date") ytitle("Correlation")
graph save sol_gspc.gph, replace
* Plot 4: BTC-N225
twoway (line dc2_r__N225_f_r_BTC_USD period, lcolor(blue)), ///
title("BTC - Nikkei 225") ylabel(0(.2)1) xtitle("Date") ytitle("Correlation")
graph save btc_n225.gph, replace
* Plot 5: ETH-N225
twoway (line dc5_r__N225_f_r_ETH_USD period, lcolor(red)), ///
title("ETH - Nikkei 225") ylabel(0(.2)1) xtitle("Date") ytitle("Correlation")
graph save eth_n225.gph, replace
* Plot 6: SOL-N225
twoway (line dc8_r__N225_f_r_SOL_USD period, lcolor(green)), ///
title("SOL - Nikkei 225") ylabel(0(.2)1) xtitle("Date") ytitle("Correlation")
graph save sol_n225.gph, replace
* Plot 7: BTC-STOXX
twoway (line dc3_r__STOXX50E_f_r_BTC_USD period, lcolor(blue)), ///
title("BTC - EURO STOXX 50") ylabel(0(.2)1) xtitle("Date") ytitle("Correlation")
graph save btc_stoxx.gph, replace
* Plot 8: ETH-STOXX
twoway (line dc6_r__STOXX50E_f_r_ETH_USD period, lcolor(red)), ///
title("ETH - EURO STOXX 50") ylabel(0(.2)1) xtitle("Date") ytitle("Correlation")
graph save eth_stoxx.gph, replace
* Plot 9: SOL-STOXX
twoway (line dc9_r__STOXX50E_f_r_SOL_USD period, lcolor(green)), ///
title("SOL - EURO STOXX 50") ylabel(0(.2)1) xtitle("Date") ytitle("Correlation")
graph save sol_stoxx.gph, replace
graph combine btc_gspc.gph eth_gspc.gph sol_gspc.gph ///
        btc_n225.gph eth_n225.gph sol_n225.gph ///
        btc_stoxx.gph eth_stoxx.gph sol_stoxx.gph, ///
        rows(3) cols(3) title("DCC Correlations: BTC, ETH, SOL vs Equity Indices")
```