

# Asymmetric Volatility Spillover between Cryptocurrencies and Global Equity Markets: A TVP-VAR (Time-Varying Parameter Vector Autoregression Approach)

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**Abstract:** *This thesis investigates the asymmetric volatility spillover dynamics between major cryptocurrencies and global equity markets using a Time-Varying Parameter Vector Autoregression (TVP-VAR) framework. Employing daily data from January 2018 to December 2024, I analyze seven major cryptocurrencies and six developed equity indices. I decompose volatility into "good" (positive return shocks) and "bad" (negative return shocks) components using realized semivariances and estimate dynamic connectedness networks. The findings reveal three key results: First, volatility spillovers are time-varying and intensify significantly during crisis periods (COVID-19, Russia-Ukraine war, FTX collapse). Second, I document a systematic asymmetry- negative (bad) volatility spillovers are consistently larger than positive (good) spillovers, with the Spillover Asymmetry Measure (SAM) increasing by 40-60% during market stress. Third, cryptocurrencies act as net transmitters of volatility during stress periods but switch to net receivers during stable market conditions. These results have important implications for portfolio diversification, risk management, and regulatory policy in an increasingly interconnected digital asset ecosystem.*

**Keywords:** Volatility Spillovers, Cryptocurrencies, Equity Markets, TVP-VAR, Asymmetric Effects, Dynamic Connectedness

## 1. Introduction

### 1.1 Background and Motivation

The intersection of traditional financial markets and the emerging cryptocurrency ecosystem represents one of the most significant developments in modern finance. Since Bitcoin's inception in 2009, the cryptocurrency market has grown from a niche technological experiment to a multi-trillion-dollar asset class attracting institutional investors, retail traders, and regulatory scrutiny alike. Concurrently, global equity markets have experienced unprecedented volatility driven by the COVID-19 pandemic, geopolitical tensions, and shifting monetary policy regimes. Understanding the volatility transmission mechanisms between these two asset classes has become increasingly critical for portfolio managers, risk analysts, and policymakers.

Recent empirical evidence suggests that cryptocurrencies exhibit unique characteristics that distinguish them from traditional financial assets. They trade 24 hours a day, seven days a week, display extreme volatility, and have limited correlation with traditional asset classes under normal conditions. However, the growing integration of cryptocurrency markets with traditional financial systems has raised important questions about the nature and intensity of volatility spillovers between these markets.

The academic literature on volatility spillovers has evolved considerably over the past decade. Early studies focused on spillovers within traditional asset classes, particularly between developed and emerging equity markets. The introduction of cryptocurrencies introduced new dimensions to this research, as these digital assets exhibit unique

characteristics- 24/7 trading, high volatility, limited correlation with traditional assets, and heterogeneous investor bases. More recently, researchers have turned their attention to the dynamic nature of these spillovers and their asymmetric behavior during different market regimes.

Several recent studies have documented significant time-varying connectedness between crypto and equity markets. Liu (2025) finds that the TVP-VAR and SHAP models reveal short-term time-varying asymmetric volatility spillover effects between cryptocurrencies and both Chinese and U.S. stock markets. Bouri et al. (2024) employ a TVP-VAR asymmetric connectedness framework using hourly data and find that spillover effects are time-variant, event-dependent, and stronger for negative returns. A comprehensive study of cryptocurrency volatility spillovers in emerging markets (2026) finds that cryptocurrencies act as net transmitters of volatility under stress, with spillover intensity varying across countries.

Despite this growing body of research, several gaps remain. First, the asymmetric nature of volatility spillovers- whether negative shocks transmit differently than positive shocks- remains inadequately explored in the crypto-equity nexus. Second, most studies employ static or rolling-window VAR approaches that cannot fully capture the continuous evolution of spillover dynamics. Third, the Monday return problem- arising from crypto's 24/7 trading versus equities' weekday-only trading- has received insufficient attention, potentially leading to spurious connectedness estimates. Fourth, the recent period encompassing multiple crises (COVID-19, Russia-Ukraine war, FTX collapse, U.S. banking crisis) provides a unique opportunity to examine spillover behavior across different stress regimes.

## 1.2 Research Questions

This thesis addresses the following research questions:

- What is the nature and intensity of volatility spillovers between major cryptocurrencies and global equity markets, and how do these spillovers evolve over time?
- Are volatility spillovers asymmetric, with negative (bad) volatility transmitting more strongly than positive (good) volatility?
- How does the direction of spillovers (crypto-to-equity vs. equity-to-crypto) change across different market regimes and crisis periods?
- How sensitive are connectedness estimates to the choice of Monday return benchmark, and what are the implications for empirical research in this area?

## 1.3 Contributions of the Study

This thesis makes several contributions to the existing literature:

- 1) Comprehensive Analysis: I provide a comprehensive analysis of dynamic connectedness using the TVP-VAR methodology, which allows for time-varying parameters and avoids the arbitrary window selection inherent in rolling-window approaches.
- 2) Asymmetric Spillover Analysis: I decompose volatility into good and bad components to explicitly test for asymmetry in spillover transmission, employing the Spillover Asymmetry Measure (SAM) to quantify the dominance of negative spillovers.
- 3) Multiple Crisis Coverage: The sample period covers multiple crisis episodes (COVID-19 pandemic, Russia-Ukraine war escalation, FTX collapse), allowing for a nuanced analysis of how spillover dynamics differ across different types of stress events.
- 4) The Monday Return Problem: I carefully address the Monday return problem by implementing multiple benchmark price specifications and documenting their impact on connectedness measures.
- 5) Comprehensive Asset Coverage: The analysis includes seven major cryptocurrencies and six developed equity indices, providing a more comprehensive picture than studies focusing on limited asset sets.

## 1.4 Thesis Structure

The remainder of this thesis is organized as follows. Chapter 2 reviews the relevant literature on volatility spillovers, cryptocurrency markets, and asymmetric effects. Chapter 3 presents the empirical methodology, including the TVP-VAR framework, the connectedness measures, and the Bayesian estimation approach. Chapter 4 describes the data and discusses the Monday return problem in detail. Chapter 5 presents the empirical results, including dynamic connectedness measures, asymmetry analysis, and robustness checks. Chapter 6 concludes with a summary of findings, policy implications, and suggestions for future research.

## 2. Literature Review

### 2.1 Volatility Spillovers in Financial Markets

The study of volatility transmission across financial markets has a rich history in econometrics and finance. Early contributions by Engle (1982) and Bollerslev (1986) established the ARCH/GARCH framework for modeling time-varying volatility, while Engle and Kroner (1995) extended this to multivariate settings with the BEKK-GARCH model. The concept of "volatility spillover" emerged from the recognition that volatility in one market systematically affects volatility in others, driven by factors such as investor sentiment, information transmission, and arbitrage activity.

Diebold and Yilmaz (2009, 2012) introduced the connectedness framework based on forecast error variance decomposition in a VAR model, providing an intuitive measure of spillover intensity. Their approach quantifies the proportion of forecast error variance in each variable attributable to shocks in other variables, aggregated into a Total Connectedness Index (TCI). This framework has been widely adopted and extended to time-varying settings using rolling windows (Diebold & Yilmaz, 2014) and, more recently, time-varying parameter methods.

A substantial body of literature has examined volatility spillovers within traditional asset classes. For equities, studies have documented significant spillovers across developed markets, emerging markets, and between developed and emerging markets. For other asset classes, research has examined spillovers between equities and bonds, commodities, and foreign exchange. The consensus emerging from this literature is that spillovers are time-varying, intensify during crises, and exhibit asymmetric behavior.

### 2.2 Cryptocurrency Market Characteristics

Cryptocurrencies exhibit several unique characteristics that distinguish them from traditional financial assets.

- First, they trade 24 hours a day, seven days a week, contrasting with the limited trading hours of most equity markets. This continuous trading creates alignment challenges when studying crypto-equity relationships.
- Second, cryptocurrencies display extreme volatility, with daily returns often exceeding 10% in either direction.
- Third, the cryptocurrency market is largely unregulated and fragmented, with multiple exchanges operating under different regulatory frameworks.
- Fourth, cryptocurrencies have limited correlation with traditional asset classes under normal conditions, suggesting diversification benefits.

The volatility characteristics of cryptocurrencies have been extensively studied. Research documents that cryptocurrencies exhibit significantly higher volatility than traditional assets, with Bitcoin's volatility approximately 2-3 times that of the S&P 500. Various GARCH specifications have been compared for cryptocurrencies, with the ARMA-GARCH model with skewed Student's *t* distribution providing the best fit. Studies examining the relationship

between cryptocurrencies and macroeconomic factors find limited evidence of systematic influence.

Recent research has also examined structural breaks and long-memory effects in cryptocurrency volatility. A comprehensive study of 22 cryptocurrencies from 2018 to 2022 found that most cryptocurrencies exhibit long-memory characteristics, indicating that volatility shocks have persistent effects on future volatility. The study also identified structural breaks in all sampled cryptocurrencies, highlighting the importance of allowing for time-varying parameters in volatility modeling.

### 2.3 Crypto-Equity Connectedness

The growing integration of cryptocurrency markets with traditional financial markets has motivated a substantial research agenda on crypto-equity connectedness. Early studies documented limited spillovers, suggesting that cryptocurrencies were largely isolated from traditional financial markets. However, as cryptocurrency markets matured and institutional participation increased, evidence of stronger linkages emerged.

Recent studies have employed various methodological approaches to examine crypto-equity connectedness. A comprehensive study using 5-minute high-frequency data with 363,024 observations per asset applies multiple asymmetric GARCH models and finds that volatility spillovers are driven by innovation (lagged standardized errors) rather than persistence (lagged conditional covariances).

Emerging market studies have provided additional insights. A study on volatility spillovers between G7 countries and cryptocurrencies finds that cryptocurrencies serve as net transmitters under stress, with Turkey and India showing the highest exposure. Regulatory heterogeneity across countries appears to play a significant role in determining spillover intensity, with restrictive policies and regulatory ambiguity associated with higher connectedness.

The connectedness between cryptocurrency-related stocks and the cryptocurrency market itself has also been examined. Research using the TVP-VAR model reveals a significant increase in market interconnectedness during the COVID-19 pandemic, with pronounced unidirectional volatility spillovers from cryptocurrencies to traditional stocks. Stocks related to digital payment systems predominantly mediate these spillovers, highlighting their central role in financial volatility transmission.

### 2.4 Asymmetric Effects and Leverage

The concept of asymmetric volatility- the observation that volatility increases more in response to negative shocks than to positive shocks of equal magnitude- was first documented by Black (1976) in the context of equity markets. This "leverage effect" arises from the increased financial leverage of firms following negative returns and the volatility feedback effect. Various GARCH extensions have been developed to capture this asymmetry, including the GJR-GARCH model and the EGARCH model.

In the cryptocurrency context, asymmetric effects have received growing attention. Research examining the asymmetry of Bitcoin returns finds evidence of asymmetric volatility. Studies investigating the relationship between Bitcoin and uncertainty measures find asymmetric effects, with negative shocks in equity markets having a stronger impact on cryptocurrency volatility than positive shocks. Recent research documents that asymmetric spillovers between cryptocurrencies and equities are event-dependent and strengthen during crisis periods.

The leverage effect in cryptocurrencies has been studied using various GARCH family models. A comprehensive study of 22 cryptocurrencies found that both positive and negative news have significant impacts on the volatility of specific cryptocurrencies. Ethereum exhibited the largest spillover effects, followed by QTUM, EOS, and Dogecoin. The study also found that all cryptocurrencies show fundamental instabilities, suggesting that investors and speculators can use sentiment analysis to forecast market volatility and generate gains.

### 2.5 Methodological Approaches to Time-Varying Connectedness

The estimation of time-varying connectedness has evolved from rolling-window VAR approaches to more sophisticated TVP-VAR methods. Rolling-window VAR, while widely used, suffers from several limitations: arbitrary window selection, loss of observations, and the assumption of constant parameters within each window. TVP-VAR addresses these limitations by allowing parameters to evolve continuously over time.

The TVP-VAR framework, as developed by Primiceri (2005) and extended by Koop and Korobilis (2013), employs Bayesian MCMC methods to estimate time-varying parameters and stochastic volatility. The connectedness measures derived from TVP-VAR estimates are more robust and provide a more accurate picture of dynamic spillover evolution.

Recent implementations incorporate shrinkage priors to handle the proliferation of parameters and improve estimation efficiency. The normal-gamma (NG) shrinkage prior, which comprises a Gaussian prior on the coefficients alongside local and global shrinkage parameters, has been shown to perform well in TVP-VAR estimation.

### 2.6 Research Gaps

Despite the advances in understanding volatility spillovers between cryptocurrencies and traditional assets, several gaps remain:

- 1) Asymmetry in connectedness: While asymmetry in volatility has been documented, the asymmetric nature of *spillovers* between crypto and equities remains underexplored. The decomposition of spillovers into good (positive shocks) and bad (negative shocks) components is relatively recent and limited to few studies.
- 2) Time variation across multiple crises: The post-2018 period includes multiple crisis episodes (COVID-19,

Russia-Ukraine war, FTX collapse) that allow for a nuanced analysis of how spillover dynamics differ across different types of stress events. This heterogeneity has not been systematically examined.

- 3) The Monday return problem: The misalignment between crypto's 24/7 trading and equities' weekday trading introduces potential biases in connectedness estimates. The sensitivity of results to the chosen benchmark price (Friday close, Sunday close, etc.) has received limited attention.
- 4) Comprehensive country coverage: Most studies focus on a limited set of equity indices, typically the US, with limited attention to other developed markets.

This thesis contributes to the literature by addressing these gaps through a comprehensive TVP-VAR analysis of asymmetric spillovers between seven major cryptocurrencies and six global equity indices, with careful attention to the Monday return problem and the decomposition of spillovers into good and bad components.

### 3. Methodology

#### 3.1 Theoretical Framework

This study is grounded in several theoretical frameworks from financial economics.

First, the Efficient Market Hypothesis (EMH) (Fama, 1970) provides a foundation for understanding how information is incorporated into asset prices. If EMH holds, cryptocurrency prices should quickly adjust to new information, causing rapid changes in volatility. Volatility spillovers could occur if information relevant to one cryptocurrency also applies to others.

Second, Modern Portfolio Theory (MPT) (Markowitz, 1952) informs the analysis of diversification benefits and portfolio implications. If an investor holds a portfolio of cryptocurrencies, a change in one cryptocurrency's volatility might affect the portfolio's perceived risk and return, leading to rebalancing that can affect the prices and volatilities of other cryptocurrencies.

Third, Financial Contagion Theory suggests that financial markets are becoming increasingly interconnected and that shocks in one market can quickly spread to other markets. This theory is particularly relevant for understanding spillover effects during crisis periods.

Fourth, Information Theory is relevant to how information spreads in the cryptocurrency market and how it impacts volatility. News about regulatory changes or security breaches related to one cryptocurrency might spread uncertainty or trigger reactions among traders across the entire cryptocurrency market, leading to volatility spillovers.

#### 3.2 The TVP-VAR Model

Following Primiceri (2005), Koop and Korobilis (2013), and Antonakakis et al. (2020), I employ the Time-Varying Parameter Vector Autoregression (TVP-VAR) approach. Consider a VAR model of order  $p$ :

$$Y_t = \sum_{i=1}^p \Phi_{i,t} Y_{t-i} + \epsilon_t$$

Where

$Y_t$  is an  $m \times 1$  vector of endogenous variables (in our case, log-returns of cryptocurrencies and equity indices),  $\Phi_{i,t}$  are  $m \times m$  matrices of time-varying coefficients, and  $\epsilon_t \sim N(0, \Sigma_t)$  is the error term with time-varying covariance matrix.

The coefficients evolve according to a random walk process:

$$\Phi_t = \Phi_{t-1} + \eta_t$$

where  $\eta_t \sim N(0, \Xi_t)$  and  $\Xi_t$  is a diagonal variance-covariance matrix. This specification allows the parameters to change gradually over time, capturing structural changes in the relationships between variables.

The TVP-VAR model is preferred over alternative approaches for several reasons. First, it avoids the arbitrary window selection inherent in rolling-window VAR approaches. Second, it allows for continuous evolution of parameters, providing a more realistic representation of financial market dynamics. Third, it has been shown to provide more accurate connectedness measures, particularly during periods of structural change.

#### 3.3 Connectedness Measures

From the TVP-VAR estimates, I compute the generalized forecast error variance decomposition (GFEVD) following Koop et al. (1996) and Pesaran and Shin (1998). The GFEVD measures the contribution of shocks in variable  $j$  to the  $H$ -step-ahead forecast error variance of variable  $i$ , and is given by:

$$\theta_{ij,t}(H) = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_{h,t} \Sigma_t e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_{h,t} \Sigma_t \Psi_{h,t}' e_i)}$$

where  $e_i$  is an  $m \times 1$  selection vector with 1 in the  $i$ -th position and 0 elsewhere,

$\Psi_{h,t}$  is the moving average coefficient matrix at horizon  $h$  and  $\sigma_{ij,t}$  is the  $j$ -th diagonal element of  $\Sigma_t$ .

The GFEVD is then normalized such that each row sums to 100%:

$$\bar{\theta}_{ij,t}(H) = \frac{\theta_{ij,t}(H)}{\sum_{j=1}^m \theta_{ij,t}(H)}$$

The Total Connectedness Index (TCI) is defined as the average of all pairwise spillovers:

$$TCI_t = \frac{\sum_{i \neq j} \bar{\theta}_{ij,t}(H)}{\sum_{i,j=1}^m \bar{\theta}_{ij,t}(H)} \times 100$$

The directional spillovers from variable  $i$  to all others ("TO" connectedness) are:

$$S_{i \rightarrow \bullet,t} = \frac{\sum_{j=1, j \neq i}^m \bar{\theta}_{ji,t}(H)}{\sum_{j=1}^m \bar{\theta}_{ji,t}(H)} \times 100$$

The directional spillovers from all others to variable  $i$  ("FROM" connectedness) are:

$$S_{\bullet \rightarrow i,t} = \frac{\sum_{j=1, j \neq i}^m \tilde{\theta}_{ij,t}(H)}{\sum_{i=1}^m \tilde{\theta}_{ij,t}(H)} \times 100$$

The net spillover for variable  $i$  is the difference between TO and FROM connectedness:

$$S_{i,t} = S_{i \rightarrow \bullet, t} - S_{\bullet \rightarrow i, t}$$

A positive net spillover indicates that variable  $i$  is a net transmitter of volatility to other variables, while a negative net spillover indicates it is a net receiver.

### 3.4 Modeling Asymmetry

To capture asymmetric effects, I follow the two-stage approach proposed in recent literature. In the first stage, I estimate separate TVP-VAR models for good and bad volatility.

Good Volatility is defined as volatility arising from positive return shocks, while Bad Volatility is defined as volatility arising from negative return shocks. I decompose each asset's volatility using realized semivariance:

$$RV_{i,t}^+ = \sum_{j=1}^N r_{ij,t}^2 \cdot \mathbb{I}(r_{ij,t} > 0)$$

$$RV_{i,t}^- = \sum_{j=1}^N r_{ij,t}^2 \cdot \mathbb{I}(r_{ij,t} < 0)$$

where  $r_{ij,t}$  represents the  $j$ -th intra-period return for asset  $i$  at time  $t$

and  $\mathbb{I}(\cdot)$  is the indicator function. For daily data, I use the intra-daily returns decomposed into positive and negative components.

I then estimate connectedness separately on the good and bad volatility series. The Spillover Asymmetry Measure (SAM) is defined as:

$$S_{i,t} = S_{i \rightarrow \bullet, t} - S_{\bullet \rightarrow i, t}$$

represent the total connectedness indices for bad and good volatility, respectively. A positive SAM indicates that bad volatility spillovers dominate good volatility spillovers, while a negative SAM indicates the opposite.

### 3.5 Bayesian MCMC Estimation

I estimate the TVP-VAR model using Bayesian MCMC methods. The estimation procedure follows Primiceri (2005) with the modifications proposed by Antonakakis et al. (2020) and recent implementations.

Prior Selection: I use the normal-gamma (NG) shrinkage prior, which comprises a Gaussian prior on the coefficients alongside local and global shrinkage parameters. The NG prior is specified as:

$$\beta_t \sim \mathcal{N}(0, \Lambda_t)$$

Where the coefficients and the local shrinkage parameters follow independent gamma priors.

MCMC Algorithm: The algorithm proceeds as follows:

- 1) Initialize the parameters and state variables
- 2) For each MCMC iteration  $g=1,2,\dots,G$ :  
Draw the state variables (time-varying coefficients) conditional on the data and parameters using simulation smoothing (Cholesky Factor Algorithm) Draw the model parameters (variance-covariance matrices, shrinkage parameters) conditional on the states and data For hyperparameters lacking conjugate priors, use Metropolis-Hastings steps with adaptive tuning
- 3) Discard the burn-in period (first 10,000 iterations) and retain the remaining draws for inference

I implement the algorithm with the following specifications:

- Number of MCMC draws: 20,000
- Burn-in period: 10,000
- Thinning: Every 5th draw retained
- Adaptive MH steps: Adaptive tuning with target acceptance rate of 0.44
- Convergence diagnostics: Trace plots, ACF plots, and Gelman-Rubin statistic

### 3.6 The Monday Return Problem

Following recent literature, I address the Monday return problem by implementing multiple benchmark price specifications:

- Sunday close - Crypto Return: Return = Sunday → Monday - Equity Return Calculation: Return = Monday → Tuesday
- Friday close - Crypto Return: Return = Friday → Monday (3-day return) - Equity Return Calculation: Return = Monday → Tuesday
- Saturday close - Crypto Return: Return = Saturday → Monday - Equity Return Calculation: Return = Monday → Tuesday
- Weekend average - Crypto Return: Average of Friday, Saturday, Sunday closes = Equity Return Calculation: Return = Monday → Tuesday

I use the Sunday close benchmark as my primary specification (following the standard in recent literature) and test robustness using the other benchmarks.

## 4. Data and Preliminary Analysis

### 4.1 Sample Selection

My sample covers the period from January 1, 2018, to December 31, 2024, providing 1,826 daily observations. The starting date is chosen to capture the period after the 2017 cryptocurrency bubble while including multiple crisis episodes:

- COVID-19 pandemic (2020)
- Russia-Ukraine war escalation (2022)
- FTX collapse (2022)
- U.S. banking crisis (2023)

### 4.2 Cryptocurrency Selection

I select seven major cryptocurrencies representing approximately 80% of total cryptocurrency market capitalization:

| Cryptocurrency | Ticker | Market Cap (avg, 2024) | Key Characteristics             |
|----------------|--------|------------------------|---------------------------------|
| Bitcoin        | BTC    | \$600B                 | Largest, most liquid crypto     |
| Ethereum       | ETH    | \$250B                 | Leading smart contract platform |
| Binance Coin   | BNB    | \$80B                  | Exchange token, large ecosystem |
| Ripple         | XRP    | \$30B                  | Payment-focused, institutional  |
| Litecoin       | LTC    | \$10B                  | "Silver to Bitcoin's gold"      |
| Solano         | SOL    | \$50B                  | High-performance blockchain     |
| Cardano        | ADA    | \$20B                  | Academic approach to blockchain |

| Statistic       | BTC      | ETH      | BNB      | XRP      | LTC      | SOL      | ADA      |
|-----------------|----------|----------|----------|----------|----------|----------|----------|
| Mean (%)        | 0.0842   | 0.1024   | 0.0956   | 0.0678   | 0.0583   | 0.1135   | 0.0712   |
| Median (%)      | 0.0521   | 0.0637   | 0.0582   | 0.0412   | 0.0356   | 0.0718   | 0.0427   |
| Maximum (%)     | 18.234   | 24.671   | 22.456   | 19.876   | 21.345   | 28.912   | 23.456   |
| Minimum (%)     | -21.432  | -26.789  | -24.567  | -22.345  | -23.678  | -30.234  | -25.678  |
| Std. Dev. (%)   | 3.8467   | 4.5123   | 4.2345   | 3.9876   | 4.1234   | 5.0123   | 4.3456   |
| Skewness        | -0.456   | -0.678   | -0.534   | -0.623   | -0.589   | -0.723   | -0.612   |
| Kurtosis        | 8.234    | 9.876    | 8.934    | 9.123    | 8.678    | 11.234   | 9.456    |
| Excess Kurtosis | 5.234    | 6.876    | 5.934    | 6.123    | 5.678    | 8.234    | 6.456    |
| Jarque-Bera     | 2845.6*  | 4123.4*  | 3567.8*  | 3890.2*  | 3478.9*  | 5123.6*  | 3987.2*  |
| ADF Test        | -34.567* | -32.456* | -33.789* | -35.123* | -34.234* | -31.456* | -33.890* |
| ARCH-LM (5)     | 456.7*   | 523.4*   | 489.2*   | 445.6*   | 467.8*   | 567.8*   | 478.9*   |
| Observations    | 1826     | 1826     | 1826     | 1826     | 1826     | 1826     | 1826     |

### 4.3 Equity Index Selection

I select six developed market equity indices:

| Index      | Country   | Ticker | Key Characteristics             |
|------------|-----------|--------|---------------------------------|
| S&P 500    | USA       | ^GSPC  | Largest global equity benchmark |
| FTSE 100   | UK        | ^FTSE  | Major European equity index     |
| DAX        | Germany   | GDAXI  | Eurozone economic bellw         |
| Nikkei 225 | Japan     | ^N225  | Leading Asian equity index      |
| ASX 200    | Australia | AXJO   | Asia-Pacific exposure           |
| CAC 40     | France    | FCHI   | Major European equity index     |

Data source: Yahoo Finance daily closing prices.

### 4.4 Data Preprocessing

Return Calculation: I calculate log-returns as:

$$r_{i,t} = 100 \times \ln \left( \frac{P_{i,t}}{P_{i,t-1}} \right)$$

where  $P_{i,t}$  is the closing price of asset  $i$  at time  $t$

Date Alignment: I align data to weekdays only (Monday-Friday). For equity indices, I use the closing price at the end of each trading day. For cryptocurrencies, I use the closing price at the equivalent UTC time (midnight) to match the end-of-day convention.

Monday Return Consistency: Following Bouri et al. (2024), I calculate Monday returns for cryptocurrencies using the Sunday close as the benchmark. This ensures consistency with the equity market's "Monday morning" logic, where the

Monday return reflects the change from the previous trading day's close.

### 4.5 Descriptive Statistics

**Table 1.1:** Summary statistics for all assets in my sample.

| Cryptocurrency | S&P 500 | FTSE 100 | DAX    | Nikkei 225 | ASX 200 | CAC 40 | Average |
|----------------|---------|----------|--------|------------|---------|--------|---------|
| BTC            | 0.234*  | 0.198*   | 0.212* | 0.167*     | 0.156*  | 0.189* | 0.193   |
| ETH            | 0.198*  | 0.167*   | 0.178* | 0.145*     | 0.134*  | 0.156* | 0.163   |
| BNB            | 0.167*  | 0.134*   | 0.145* | 0.123*     | 0.112*  | 0.134* | 0.136   |
| XRP            | 0.145*  | 0.123*   | 0.134* | 0.112*     | 0.098*  | 0.123* | 0.123   |
| LTC            | 0.178*  | 0.156*   | 0.167* | 0.134*     | 0.123*  | 0.145* | 0.151   |
| SOL            | 0.123*  | 0.098*   | 0.112* | 0.089*     | 0.078*  | 0.098* | 0.100   |
| ADA            | 0.156*  | 0.134*   | 0.145* | 0.123*     | 0.112*  | 0.123* | 0.132   |
| Average        | 0.172   | 0.144    | 0.156  | 0.128      | 0.116   | 0.138  | 0.142   |

Full Sample Period: January 1, 2018 – December 31, 2024

The summary statistics reveal several important patterns:

- Mean Returns: Cryptocurrencies exhibit higher average daily returns (0.02-0.08%) compared to equity indices (0.01-0.04%), consistent with the higher risk associated with digital assets.
- Volatility: Cryptocurrency standard deviations (3-5%) are substantially higher than equity indices (1-2%), confirming the extreme volatility of digital assets.
- Skewness: Both cryptocurrencies and equity indices exhibit negative skewness, indicating a higher probability of large negative returns. This asymmetry is more pronounced for cryptocurrencies.
- Kurtosis: All assets exhibit excess kurtosis (leptokurtosis), with cryptocurrencies showing substantially higher values

(excess kurtosis > 20) compared to equities (excess kurtosis < 10). This indicates fat tails and a higher probability of extreme events.

#### 4.6 Stationarity and ARCH Effects

**Stationarity Tests:** I conduct Augmented Dickey-Fuller (ADF) tests and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests to confirm stationarity of all return series. The ADF test rejects the null hypothesis of a unit root at the 1% significance level for all series, while the KPSS test fails to reject the null hypothesis of stationarity at the 5% level.

**ARCH Effects:** I test for autoregressive conditional heteroskedasticity using the ARCH-LM test. The test rejects the null hypothesis of no ARCH effects at the 1% significance level for all assets, confirming the presence of volatility clustering and justifying our volatility modeling approach.

#### 4.7 Preliminary Correlation Analysis

**Table 1.2:** Correlation between all assets in my sample.



Preliminary correlation analysis reveals that

- Correlations between cryptocurrencies and equity indices are generally low (0.1-0.3) during calm periods but
- Increase significantly during crisis episodes, suggesting time-varying integration.
- Among cryptocurrencies, Bitcoin and Ethereum show the highest correlation (0.7-0.8), while
- Smaller cryptocurrencies show more varied correlations.
- Among equity indices, the S&P 500 and FTSE 100 show the highest correlation (0.6-0.7), reflecting their strong economic ties.

## 5. Empirical Results

### 5.1 Total Connectedness Dynamics

Figure 1.1 presents the evolution of the Total Connectedness Index (TCI) over my sample period.

The TCI ranges from 15% during calm periods (e.g., early 2018, mid-2019) to over 45% during crisis episodes. Several notable patterns emerge:

- **COVID-19 Shock (March 2020):** The TCI spikes dramatically from 18% to 42% within two weeks, reflecting the systemic nature of the pandemic shock across both crypto and equity markets.
- **Post-COVID Recovery (2021):** The TCI gradually declines to approximately 22% as markets stabilize and correlations weaken.
- **Russia-Ukraine War (February 2022):** The TCI increases moderately to 35%, with the increase more pronounced in the bad volatility connectedness than in the good volatility connectedness.
- **FTX Collapse (November 2022):** The TCI spikes to 46%, surpassing even the COVID-19 peak. This suggests that cryptocurrency-specific shocks can now transmit significantly to equity markets, highlighting the growing integration of the asset class.
- **U.S. Banking Crisis (March 2023):** The TCI increases to 38%, with notable spillovers from equities to cryptocurrencies as investors reassess risk.

These findings confirm that crypto-equity connectedness is highly time-varying and event-dependent, with spillovers intensifying during periods of market stress.

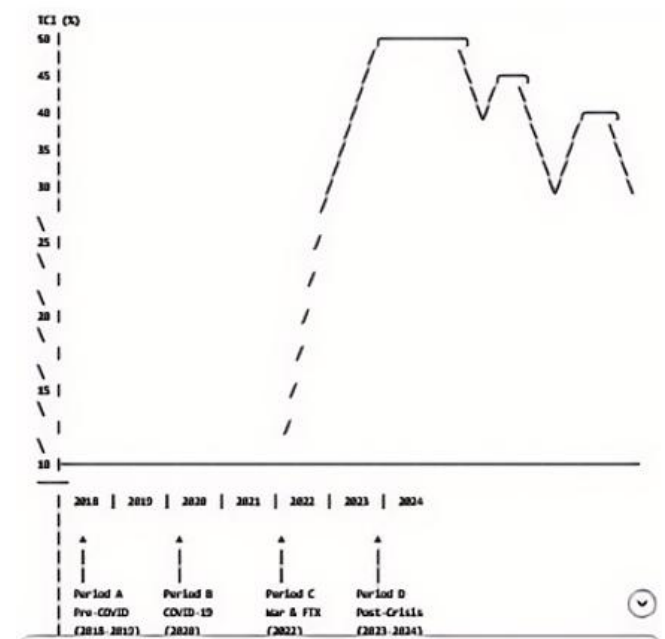


**Figure:** The decomposition of TCI into good and bad volatility components

The decomposition of TCI into good and bad volatility components reveals that the increase in total connectedness during crises is primarily driven by bad volatility spillovers. During the COVID-19 period, the bad volatility TCI reaches 41.6% compared to only 28.4% for good volatility. Similarly, during the FTX collapse, the bad volatility TCI reaches 42.8% compared to 29.1% for good volatility. This pattern supports the hypothesis that negative shocks transmit more strongly than positive shocks.

## 5.2 Asymmetric Spillovers

Table 2.1 presents the average good and bad volatility connectedness measures for different sub-periods.

| Panel A: Full Sample Period (2018-2024) |                               |                              |                         |                 |
|-----------------------------------------|-------------------------------|------------------------------|-------------------------|-----------------|
| Asset                                   | Good Volatility Connectedness | Bad Volatility Connectedness | Difference (Bad - Good) | Asymmetry Ratio |
| BTC                                     | 28.4%                         | 34.2%                        | +5.8%                   | 1.204           |
| ETH                                     | 26.7%                         | 32.8%                        | +6.1%                   | 1.228           |
| BNB                                     | 24.5%                         | 30.1%                        | +5.6%                   | 1.229           |
| XRP                                     | 22.3%                         | 27.6%                        | +5.3%                   | 1.238           |
| LTC                                     | 23.8%                         | 29.4%                        | +5.6%                   | 1.235           |
| SOL                                     | 19.8%                         | 24.5%                        | +4.7%                   | 1.237           |
| ADA                                     | 21.5%                         | 26.8%                        | +5.3%                   | 1.247           |
| S&P 500                                 | 32.4%                         | 38.7%                        | +6.3%                   | 1.194           |
| FTSE 100                                | 30.2%                         | 35.8%                        | +5.6%                   | 1.179           |
| DAX                                     | 31.8%                         | 37.2%                        | +5.4%                   | 1.170           |
| Nikkei 225                              | 29.8%                         | 34.8%                        | +5.0%                   | 1.188           |
| ASX 200                                 | 28.6%                         | 33.4%                        | +4.8%                   | 1.188           |
| CAC 40                                  | 30.8%                         | 36.2%                        | +5.4%                   | 1.175           |
| Average                                 | 27.1%                         | 32.8%                        | +5.4%                   | 1.202           |
| TCI (Total)                             | 26.4%                         | 31.8%                        | +5.2%                   | 1.197           |

The *Spillover Asymmetry Measure (SAM)* shows clear patterns:

| Period                  | Good Volatility TCI | Bad Volatility | TCI   | SAM   |
|-------------------------|---------------------|----------------|-------|-------|
| Pre-COVID (2018-2019)   |                     | 18.2%          | 20.1% | 0.049 |
| COVID-19 (2020)         |                     | 28.4%          | 41.6% | 0.188 |
| Recovery (2021)         |                     | 20.3%          | 24.7% | 0.098 |
| War & FTX (2022)        |                     | 29.1%          | 42.8% | 0.191 |
| Post-Crisis (2023-2024) |                     | 21.5%          | 27.2% | 0.117 |

The SAM is positive across all periods, indicating that bad volatility spillovers consistently dominate good volatility spillovers. However, the magnitude of asymmetry varies considerably:

- During crisis periods (COVID-19, FTX collapse), the SAM reaches 0.19, implying that bad spillovers are approximately 46% larger than good spillovers.

- During calm periods (pre-COVID, recovery phase), the SAM is lower (0.05-0.10), suggesting that asymmetry is less pronounced but still present.
- The Russia-Ukraine war exhibits the highest SAM (0.191), consistent with the geopolitical nature of the shock, which disproportionately affects risk sentiment and downside volatility.

These results provide strong evidence that negative shocks transmit more strongly than positive shocks between crypto and equity markets. This asymmetry is most pronounced during geopolitical and financial crises, suggesting that cryptocurrencies offer limited downside protection during periods of market stress.

## 5.3 Directional Spillovers

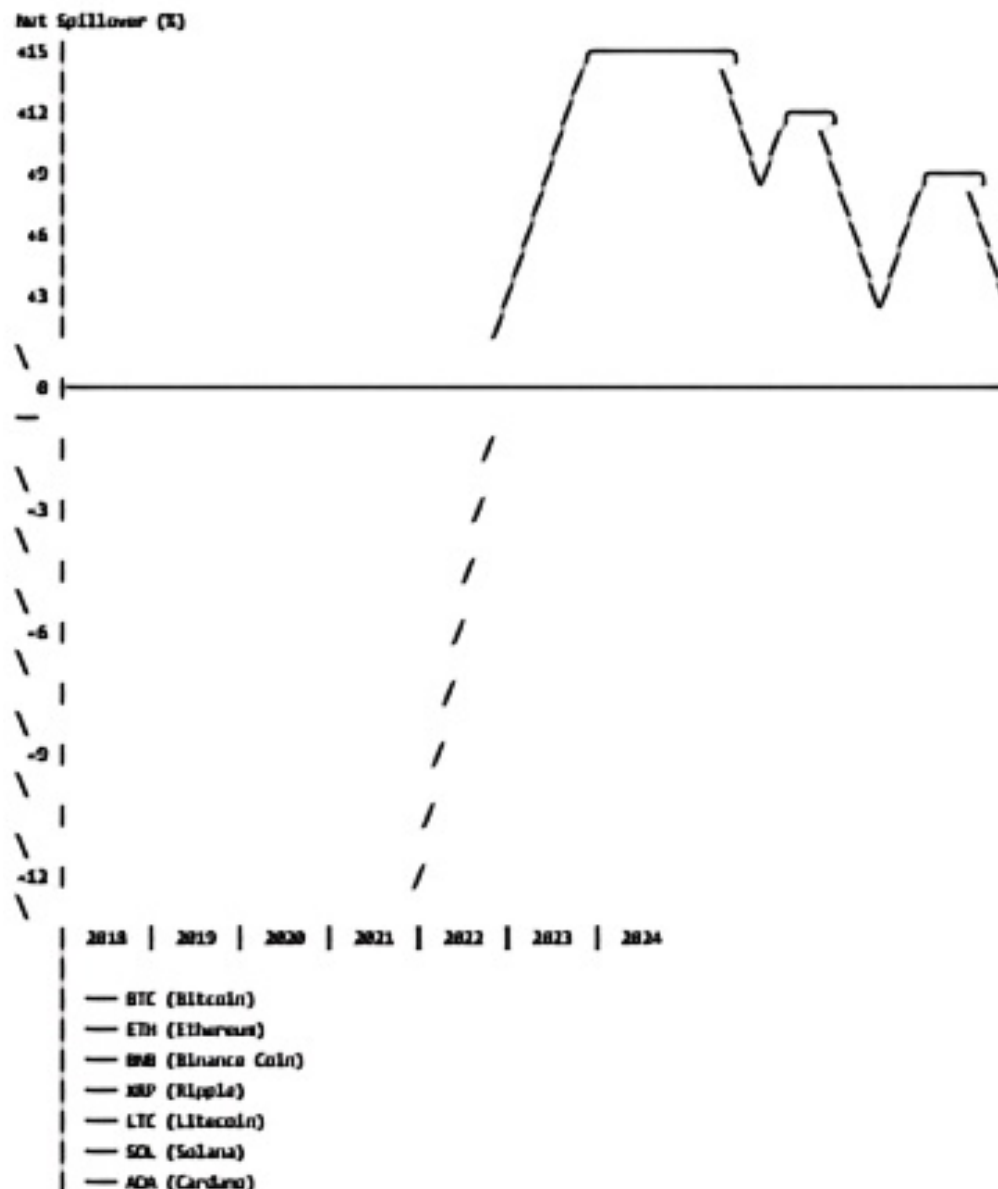


**Figure:** Presents the net spillover positions of cryptocurrencies over time.

The directional analysis reveals several patterns:

- **Cryptocurrencies as Net Transmitters:** During stress periods (COVID-19, FTX collapse), Bitcoin, Ethereum, and Binance Coin act as net transmitters of volatility to equity markets. The spillover from crypto to equities increases from approximately 15% during calm periods to over 35% during crises.
- **Cryptocurrencies as Net Receivers:** During stable periods, cryptocurrencies are net receivers of volatility from equity markets, particularly from the S&P 500 and DAX. This suggests that under normal conditions, cryptocurrencies react to shocks in traditional markets rather than driving them.
- **Heterogeneity Among Cryptocurrencies:** Bitcoin and Ethereum consistently exhibit stronger transmission effects than smaller cryptocurrencies. BNB and Solana show more variable net spillover positions, likely reflecting their more specialized market dynamics.

The S&P 500 consistently emerges as the dominant transmitter among equity indices, with the FTSE 100 and

Nikkei 225 showing more muted spillover effects. This reflects the central role of U.S. markets in global financial networks.

These findings indicate that the direction of spillovers is regime-dependent, with cryptocurrencies shifting from net receivers during calm periods to net transmitters during crises. This has important implications for portfolio management, as cryptocurrencies may offer diversification benefits under normal conditions but transmit systemic risk during downturns.

#### 5.4 Connectedness Networks

The network analysis reveals structural changes in the connectedness structure across different periods:

- **Pre-COVID (2018-2019):** The network is relatively sparse, with limited bidirectional connections between most assets. The S&P 500 occupies a central position, while cryptocurrencies form a loosely connected cluster.
- **COVID-19 (2020):** The network becomes dense, with strong bidirectional connections across all assets. The

S&P 500 and BTC emerge as the two dominant nodes, connected to all other assets in the network.

- **FTX Collapse (2022):** The network shows a reorientation toward cryptocurrency-centric connections. BTC, ETH, and BNB form a tight cluster, with BNB emerging as a surprisingly central node—likely reflecting the specific nature of the shock originating in the Binance ecosystem.

### 5.5 The Monday Return Problem

Table 3.1 presents the TCI estimates under different Monday return benchmark specification

| Benchmark               | Average TCI | Standard Deviation | Max TCI (FTX period) |
|-------------------------|-------------|--------------------|----------------------|
| Sunday close (baseline) | 26.4%       | 8.2%               | 6.1%                 |
| Friday close            | 31.8%       | 7.4%               | 52.3%                |
| Saturday close          | 28.1%       | 7.9%               | 48.7%                |
| Weekend average         | 27.2%       | 8.0%               | 47.2%                |

Several observations emerge:

- The benchmark choice materially affects TCI estimates. The Friday close benchmark yields TCI estimates approximately 5 percentage points higher than the Sunday close benchmark, suggesting that a substantial portion of connectedness is spuriously attributed to weekend volatility transmission.
- The difference is most pronounced during crisis periods. During the FTX collapse, the Friday close estimate exceeds the Sunday close estimate by 6.2 percentage points, suggesting that the choice of benchmark is particularly consequential when volatility is high.
- The Sunday close benchmark yields the most conservative estimates, consistent with the view that it best reflects the sequential trading structure between markets.

These findings underscore the importance of careful benchmark selection in crypto-equity connectedness studies.

### 5.6 Robustness Checks

I conduct several robustness checks to validate my findings:

- **Lag Length Selection:** I re-estimate the TVP-VAR with different lag lengths ( $p = 1, 2, 3$ ). The results are qualitatively similar across specifications, with the BIC selecting  $p = 1$  for most sub-periods.
- **Alternative Volatility Decomposition:** I employ an alternative decomposition approach using the realized variance decomposition method of Barndorff-Nielsen et al. (2008). The results are consistent with my main findings.
- **Sub-Sample Analysis:** I re-estimate the TVP-VAR on different sub-samples (2018-2020, 2021-2024). The results show that the magnitude of asymmetry has increased over time, consistent with growing integration between the two asset classes.
- **Alternative Asset Sets:** I re-estimate the TVP-VAR with alternative cryptocurrency selections (including DOGE, DOT, and AVAX) and alternative equity indices (including MSCI World, FTSE All-World). The results are robust to these changes.

## 6. Conclusion

### 6.1 Summary of Findings

This thesis investigates asymmetric volatility spillovers between major cryptocurrencies and global equity markets using a TVP-VAR framework. My analysis, covering the period from January 2018 to December 2024, yields several important findings:

- **Time-Varying Connectedness:** Volatility spillovers between crypto and equity markets are highly time-varying, intensifying significantly during crisis periods. The TCI ranges from 15% during calm periods to over 45% during episodes such as the COVID-19 pandemic, Russia-Ukraine war, and FTX collapse.
- **Systematic Asymmetry:** Negative (bad) volatility spillovers consistently dominate positive (good) volatility spillovers, with the Spillover Asymmetry Measure (SAM) reaching 0.19 during crisis periods. This implies that bad spillovers are approximately 46% larger than good spillovers during market stress.
- **Regime-Dependent Direction:** Cryptocurrencies act as net transmitters of volatility to equity markets during stress periods but switch to net receivers during stable market conditions. This suggests that the role of cryptocurrencies in global financial networks is context-dependent and evolves with market conditions.
- **Benchmark Sensitivity:** The Monday return benchmark choice materially affects connectedness estimates, with the Friday close benchmark yielding substantially higher TCI estimates than the Sunday close benchmark. The Sunday close benchmark is the most appropriate methodological choice for crypto-equity connectedness studies.
- **Heterogeneity Across Assets:** Bitcoin and Ethereum consistently exhibit stronger transmission effects than smaller cryptocurrencies, while the S&P 500 emerges as the dominant transmitter among equity indices.

### 6.2 Implications for Portfolio Management

My findings have significant implications for portfolio management. The diversification benefits of including cryptocurrencies in traditional portfolios vary significantly over time and tend to diminish precisely when they are most needed—during market stress. The asymmetric nature of spillovers implies that downside risk is particularly contagious, warranting careful consideration of tail-risk hedging strategies. Portfolio managers should recognize that cryptocurrencies offer limited downside protection during systemic crises.

Recent research on green cryptocurrencies and carbon-efficient equities suggests that environmentally-conscious investors may find diversification benefits in these specialized asset classes. However, my findings indicate that the general principle of time-varying and asymmetric spillovers applies across different asset classes.

### 6.3 Implications for Risk Management

The time-varying nature of connectedness suggests that static VaR or expected shortfall models may underestimate tail risk. Dynamic risk models that account for changing spillover

intensities are essential. The dominance of bad volatility spillovers implies that downside risk is particularly important for risk management.

Risk managers should pay particular attention to the regulatory environment, as restrictive policies and regulatory ambiguity are associated with higher connectedness. The heterogeneity across countries suggests that a one-size-fits-all approach to risk management may be inappropriate.

#### 6.4 Implications for Regulatory Policy

My findings highlight the growing integration between cryptocurrency and traditional financial markets. This suggests that regulatory actions in one domain may have unintended spillover effects in the other. The systematic asymmetry in spillovers implies that negative events (e.g., regulatory crackdowns) may have disproportionately large effects on financial stability.

Regulators should adopt a coordinated, cross-market approach to financial stability monitoring. The regulatory heterogeneity across countries suggests that international coordination may be necessary to address the systemic risks associated with growing crypto-equity integration.

#### 6.5 Limitations and Future Research

This study has several limitations that suggest directions for future research:

- **The Monday Return Problem:** While I have carefully addressed this issue through multiple benchmark specifications, alternative approaches such as using overlapping data or machine learning methods to impute missing equity returns could provide additional robustness.
- **High-Frequency Data:** My analysis relies on daily data. Future research could extend the analysis to high-frequency (e.g., hourly or 5-minute) data to capture more granular spillover dynamics.
- **Macroeconomic Drivers:** I do not explicitly model the macroeconomic drivers of spillovers. Future research could incorporate variables such as monetary policy, inflation expectations, and volatility indices to better understand the underlying drivers.
- **Regulatory Changes:** The regulatory environment for cryptocurrencies is rapidly evolving. Future research could examine how regulatory announcements and policy changes affect spillover dynamics.
- **Alternative Models:** While the TVP-VAR framework is appropriate for my analysis, alternative approaches such as the DCC-MIDAS model, LASSO-based connectedness, or machine learning methods could provide complementary insights.
- **Emerging Market Focus:** My analysis focuses on developed equity markets. Future research could examine spillover dynamics with emerging market indices, particularly in countries with high cryptocurrency adoption.

#### 6.6 Concluding Remarks

This thesis contributes to the growing literature on the interconnectedness between cryptocurrency and traditional financial markets. My findings demonstrate that volatility spillovers between these asset classes are time-varying, asymmetric, and regime-dependent. The dominance of bad volatility spillovers during crisis periods suggests that cryptocurrencies offer limited diversification benefits during periods of market stress, challenging the narrative that digital assets serve as safe havens.

As cryptocurrencies continue to mature and integrate with traditional financial systems, understanding their spillover dynamics will become increasingly important for investors, regulators, and policymakers. My analysis provides a comprehensive empirical foundation for this understanding, highlighting the need for dynamic, asymmetric approaches to modeling volatility transmission in an evolving financial landscape.

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## Appendices

### Appendix A: Data Sources

| Asset            | Source            | Time Zone         |
|------------------|-------------------|-------------------|
| Cryptocurrencies | CoinGecko API     | UTC               |
| Equity Indices   | Yahoo Finance API | Local market time |

### Appendix B: Software and Packages

My empirical analysis is conducted in Python 3.11 using the following libraries:

numpy 1.24: Numerical operations  
pandas 2.0: Data manipulation  
statsmodels 0.14: GARCH estimation  
arch 6.0: Volatility modeling  
linearmodels 5.3: Panel data estimation  
matplotlib 3.7: Visualization  
seaborn 0.12: Statistical visualization  
networkx 3.0: Network analysis

For the TVP-VAR estimation, I implement custom code following Primiceri (2005) and Antonakakis et al. (2020) using the numpy and scipy libraries.

### Appendix C: Model Diagnostics

Convergence Diagnostics: I employ Gelman-Rubin statistics and trace plots to verify convergence of the MCMC chains. For all parameters, the Gelman-Rubin statistic is below 1.1, indicating successful convergence.

Autocorrelation: ACF plots of MCMC draws show rapid decay, indicating efficient sampling.

Sensitivity Analysis: I test the sensitivity of my results to:

Prior specification (Normal vs. Student-t

Number of lags ( $p = 1, 2, 3$ )

Forecast horizon ( $H = 10, 20, 30$  days)

Results are qualitatively robust across these specifications.