



Flickering safe havens: Time-varying properties in global equity markets during COVID-19 and the Russia–Ukraine war

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Abstract

Prior research on safe-haven assets has addressed crisis-type and horizon dependence only in a fragmented fashion. This study examines whether gold, U.S. Treasuries, the Swiss franc, and Bitcoin exhibit safe-haven properties conditional on crisis type and investment horizon. Using daily data from January 2015 to November 2025, we assess safe-haven effectiveness for four equity markets (S&P 500, FTSE 100, MSCI Emerging Markets, and Shanghai Composite) across two distinct crises: COVID-19, a global demand shock, and the Russia–Ukraine war, marked by supply-side and inflationary pressures. The framework combines Wavelet Quantile Correlation with Time-Varying Parameter VAR connectedness analysis, with structural breaks identified via the Bai–Perron procedure. Results show strongly regime-dependent behavior. During COVID-19, gold offered limited protection, benefiting only China at specific horizons, while Treasuries hedged the UK but not the U.S. The Swiss franc was the most stable hedge, particularly for U.S. and emerging markets, while Bitcoin’s positive co-movement with equities disqualified it as a safe haven. During the Russia–Ukraine war, gold and Treasuries weakened further amid inflationary pressures, whereas the Swiss franc remained resilient, shifting from net receiver to net transmitter of shocks. Safe-haven status is thus crisis-specific, with implications for portfolio allocation and risk management.

Keywords: Financial market connectedness, Global equity markets, Gold, Safe-haven assets, TVP-VAR connectedness, Wavelet quantile correlation.

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Contribution of this paper to the literature

This study demonstrates that safe-haven effectiveness depends on crisis type, investment horizon, and market-specific dynamics. It shows that COVID-19 and the Russia-Ukraine war produced distinct safe-haven patterns, identifies horizon-dependent protection overlooked by time-domain methods, and reveals the Swiss franc's transition from shock receiver to transmitter while retaining selective lower-tail protection.

1. Introduction

Safe-haven assets are fundamental to financial risk management, providing portfolio protection during market turmoil through zero or negative correlation with equities during downturns (Baur & Lucey, 2010; Cheema, Ryan, & Sarwar, 2025; Paltrinieri, Perdichizzi, & Piserà, 2026). While traditional safe havens such as gold and government bonds have demonstrated defensive capabilities during crises such as the 2008 Global Financial Crisis, their effectiveness varies considerably across time and market environments (Gao, Bei, Wu, Guo, & Wei, 2026). Recent literature has extended this inquiry to digital assets, with findings ranging from support for Bitcoin's conditional defensive properties (Xu & Kinkyo, 2023) to sustained skepticism regarding its safe-haven capacity (Cheng, Wang, Wang, & Shi, 2025; Conlon & McGee, 2020).

The empirical landscape is characterized by contradiction. Gold's safe-haven properties may disappear under liquidity stress (Baur & McDermott, 2016); the Swiss franc's effectiveness varies across crisis regimes (Tronzano, 2023); and U.S. Treasury safe-haven behavior has become increasingly unstable in recent financial regimes, particularly following the Federal Reserve's April 2022 rate cycle (Zhang, 2025). Financial Market Integration Theory suggests these properties reflect the conditional interconnectedness of global financial markets rather than intrinsic asset attributes (Höfler & Schertler, 2024). A central implication motivating this study is that whether an asset qualifies as a safe haven cannot be determined from full-sample, time-domain analysis alone. Crisis type, investment horizon, and market-specific dynamics must all be considered simultaneously.

A review of the empirical literature reveals a persistent gap: no existing study systematically examines all four major safe-haven candidates across two structurally distinct crisis types using a unified time-frequency and dynamic connectedness framework, applied simultaneously to four major equity markets. Studies that examine a single asset (e.g., gold in Akhtaruzzaman, Boubaker, Lucey, and Sensoy (2021); Bitcoin in Conlon and McGee (2020)) cannot reveal cross-asset comparative evidence. Studies that focus on a single crisis episode cannot establish whether the crisis transmission channel (demand-side versus supply-side inflationary) determines safe-haven effectiveness. Studies that use time-domain correlation methods cannot separate short-horizon from long-horizon dynamics, and therefore cannot identify the horizon-specificity of safe-haven properties predicted by the Fractal Market Hypothesis (Niveditha, 2025; Peters, 1994). This study addresses all three limitations simultaneously.

The empirical contribution can be stated precisely. First, the study establishes that the COVID-19 demand shock and the Russia-Ukraine supply shock generated systematically different safe-haven patterns across assets and markets, confirming that the crisis transmission channel is a first-order moderator. Second, it demonstrates that safe-haven properties are horizon-dependent in ways that existing time-domain analyses cannot detect, showing that an asset may qualify as a safe haven at trading frequencies (2-8 days) but not at institutional investment horizons (128-256 days), or vice versa. Third, it documents a previously uncharacterized phenomenon: the Swiss franc shifted from a net receiver of shocks during COVID-19 to a primary net transmitter during Russia-Ukraine, illustrating how geographically concentrated supply-side shocks can transform the network role of a traditional refuge currency without eliminating its lower-tail protective properties for some markets.

This study addresses three research questions. First, do safe-haven properties of gold, U.S. Treasuries, the Swiss franc, and Bitcoin vary across investment horizons and market conditions, as the Fractal Market Hypothesis predicts? Second, do these properties differ systematically between the COVID-19 demand shock and the Russia-Ukraine supply shock? Third, which assets function as net transmitters versus net receivers of financial shocks across the two crisis regimes, and does this network position change between crises? The remainder of the paper is organized as follows: Section 2 reviews the theoretical and empirical literature; Section 3 describes the data and methodology; Section 4 presents and discusses the empirical results; Section 5 reports robustness checks; Sections 6-8 conclude with policy implications and limitations.

2. Literature Review

2.1. Theoretical Foundations of Safe-Haven Assets

This study adopts the classification framework introduced by Baur and Lucey (2010), which distinguishes three asset roles. A hedge is an asset that is uncorrelated or negatively correlated with equities on average. A diversifier is an asset that is positively but imperfectly correlated with equities on average. A safe haven is an asset that is uncorrelated or negatively correlated with equities specifically during periods of market stress, that is, at extreme negative equity quantiles. In this study, the lower quantile range (5th to 30th percentile) of the equity return distribution is used as the proxy for stress conditions, consistent with the wavelet quantile correlation approach introduced by Kumar and Padakandla (2022), who combined quantile-based dependence at extreme negative equity returns with wavelet decomposition across investment horizons to operationalize the safe-haven definition of Baur and Lucey (2010). An asset is classified as a safe haven when its wavelet quantile correlation with equities is negative in this range. Where an asset satisfies this criterion in at least three of the four equity markets at a given horizon, it is described as a broad safe haven at that horizon; this cross-market consistency requirement follows the logic used by Mensi, Hammoudeh, and Tiwari (2016) who applied a wavelet-based quantile approach across multiple Gulf Cooperation Council equity markets and distinguished safe-haven properties that held consistently across markets from those that were market-specific, treating cross-market consistency as the marker of a genuine rather than an idiosyncratic result. This threshold approach is further supported by Cheema et al. (2025), who tested 11 candidate assets against 13 distinct stock market downturns specifically to reduce the likelihood that an identified safe haven reflects the idiosyncrasies of a single event or market, classifying an asset as a robust safe haven only when it

performed as such across multiple, non-idiosyncratic episodes rather than in an isolated instance. Where evidence is horizon-specific or market-specific, the classification is reported conditionally.

Flight-to-Quality Theory posits that during periods of heightened economic uncertainty, investors deliberately reallocate capital from higher-risk investments toward perceived safer assets, prioritizing capital preservation over return maximization (Baur & Lucey, 2010). This behavior manifests in compressed yields on government securities and widening credit spreads during crisis episodes. The Federal Reserve Board's research has documented how investors systematically seek the safety of U.S. Treasury securities during systemic shocks, with demand intensifying despite rapidly expanding supply of these instruments (Active Flight-to-Quality: Meaning Criticisms & Real-World Uses, 2024).

Financial Market Integration Theory provides a complementary framework for understanding the conditional nature of safe-haven properties. Höfler and Schertler (2024) demonstrate that hedging and safe-haven characteristics are significantly moderated by the degree of global financial integration. Their evidence from 24 countries' sovereign bonds reveals that industrial metals provide stronger safe-haven characteristics when sovereign bond markets are more globally integrated, whereas precious metals do not exhibit this integration-dependent behavior. This finding suggests that safe-haven status is not an intrinsic asset attribute but rather a conditional property shaped by the interconnectedness of global financial markets.

The Fractal Market Hypothesis (FMH) addresses a critical limitation of efficient market frameworks by positing that markets comprise heterogeneous agents operating across diverse investment horizons (Peters, 1994). Niveditha (2025) demonstrates that under FMH, market stability depends on the diversity of these horizons; when all participants converge on the same time scale during a crisis, markets become fragile and prone to sharp, correlated dislocations. An asset may provide effective protection to short-term traders operating at 2-to-8-day horizons while offering no such benefit to institutional investors operating over 128-to-256-day horizons, and vice versa. The present study employs the Maximal Overlap Discrete Wavelet Transform, which overcomes the boundary and shift-variance limitations of prior wavelet specifications, to examine whether this horizon-dependence of safe-haven status holds across both crisis types and all four candidate assets simultaneously.

2.2. Empirical Review

2.2.1. Empirical Evidence on Gold as a Safe-Haven Asset

Gold has long been regarded as the archetypal safe-haven asset. Seminal work by Baur and Lucey (2010) formally identified gold as both a hedge and a safe haven against equity market downturns, a finding supported by Ji, Zhang, and Zhao (2020). Compared with other precious metals such as silver, palladium, and platinum, gold is generally viewed as superior, as these metals exhibit defensive properties mainly over short horizons (Bredin, Conlon, & Potì, 2017; Lahiani, Mefteh-Wali, & Vasbieva, 2021). Historical analysis further confirms gold's defensive appeal during extreme uncertainty, including wartime episodes (Oosterlinck, Reyns, & Szafarz, 2023).

Recent evidence, however, reveals that gold's safe-haven role is not unconditional. Several studies affirm its effectiveness during market stress. Duan, Ren, Wen, and Chen (2023) show that gold functions as a hedge in normal periods and as a safe haven during turmoil, while Widjaja, Gaby, and Havidz (2024) and Manzli and Jeribi (2024) report robust protection under bearish and crisis regimes. A growing literature emphasizes time variation and crisis specificity. Gold's defensive properties are found to be time-varying (Akhtaruzzaman et al., 2021) and market-specific (Beckmann, Berger, & Czudaj, 2015). Kumar and Padakandla (2022) argue that its safe-haven status evolves across macroeconomic regimes. During COVID-19, gold's effectiveness weakened (Będowska-Sójka & Kliber, 2021; Tarchella, Khalfaoui, & Hammoudeh, 2024), although it re-emerged as a defensive asset during the Russia-Ukraine conflict (Le Thi Thuy, Oanh, & Ha, 2024). Additional evidence suggests that its performance depends on crisis catalysts and sectoral exposure (Kinatader, Gurrib, & Choudhury, 2024; Ryan, Corbet, & Oxley, 2024) and may even break down during extreme turbulence (Flavin & Sheenan, 2025). Earlier critiques likewise question its consistent safe-haven function (Dee, Li, & Zheng, 2013; Klein, 2017).

2.2.2. Empirical Evidence on the Swiss Franc as a Safe-Haven Currency

The Swiss franc is widely regarded as one of the most prominent safe-haven currencies due to Switzerland's political stability, strong financial institutions, and large net foreign asset position. Empirical research consistently shows that the currency appreciates during periods of global financial stress. Early evidence by Ranaldo and Söderlind (2010) demonstrates that the Swiss franc appreciates when global equity markets decline and volatility rises, confirming its safe-haven characteristics. Similarly, Habib and Stracca (2012) show that currencies issued by countries with strong external balances, particularly the Swiss franc, tend to perform well during global risk-off episodes.

More recent studies confirm that the safe-haven role of the Swiss franc persists in modern financial markets but may vary across crises. Using exchange rate dynamics and global risk indicators, Grisse and Nitschka (2015) find that the Swiss franc appreciates in response to increases in financial market uncertainty and equity market downturns. Recent evidence confirms that the Swiss franc retains its defensive characteristics in modern portfolio settings, though with important nuances. Tronzano (2023) reassesses major safe-haven currencies over 1999 to 2022 and finds that the Swiss franc continues to provide diversification benefits in global equity portfolios during periods of heightened financial stress. However, a growing body of evidence documents that the strength and consistency of this protection vary across crisis episodes. Siemaszkiewicz (2021) finds that while the Swiss franc functioned reliably during the Global Financial Crisis, its protective role was less pronounced during the COVID-19 shock, a finding consistent with this study's results showing weaker haven performance in the UK and Chinese markets during that period. Feder-Sempach, Szczepocki, and Bogotebska (2024) further characterize the Swiss franc as providing strong safe-haven properties for major equity markets during periods of geopolitical uncertainty, aligning with this study's finding that it served as a consistent safe haven for emerging markets during the Russia-Ukraine conflict.

Collectively, the evidence suggests that the Swiss franc's safe-haven effectiveness is not homogeneous. It tends to be strongest in U.S. and emerging market contexts and during financially driven crises, but weakens when the shock is inflationary in nature or when the Swiss National Bank intervenes in currency markets. This conditionality,

and in particular whether the franc's performance is consistent across both the demand-side COVID shock and the supply-side Russia-Ukraine shock, remains insufficiently documented in the literature and is directly addressed in this study.

2.2.3. Empirical Evidence on U.S. Treasuries as a Safe-Haven Asset

U.S. Treasury securities are widely regarded as benchmark safe-haven assets due to their high liquidity, low credit risk, and historically negative correlation with equities. During periods of financial stress, investors typically engage in “flight-to-quality” behavior by reallocating capital from risky assets to government bonds. Empirical evidence shows that Treasury securities tend to experience price increases when equity markets decline sharply, reinforcing their role as defensive assets.

Earlier research by Baele, Bekaert, and Inghelbrecht (2010) demonstrates that government bonds, including U.S. Treasuries, exhibit strong safe-haven characteristics because their returns increase during extreme stock market downturns. Similarly, Campbell, Sunderam, and Viceira (2017) show that nominal government bonds provide significant hedging benefits against equity market risk, particularly in low-inflation environments where the stock-bond correlation is negative.

More recent research confirms that Treasuries continued to function as safe-haven assets during global crises. Using wavelet-based time-frequency analysis, Gubareva, Umar, Teplova, and Vo (2023) find strong evidence of flight-to-quality flows from emerging market bonds toward U.S. Treasury securities during both the Global Financial Crisis and the COVID-19 pandemic, highlighting their diversification and risk-mitigation properties.

However, the safe-haven effectiveness of U.S. Treasuries may depend on broader macroeconomic conditions. Campbell et al. (2017) note that rising inflation expectations can weaken the negative correlation between stocks and bonds, thereby reducing their hedging effectiveness. As a result, while Treasuries remain central to global safe-haven strategies, their protective role may vary across macroeconomic regimes, particularly during inflation-driven crises.

Overall, empirical evidence consistently supports the role of U.S. Treasury securities as key safe-haven assets, although their effectiveness can vary depending on inflation dynamics, monetary policy conditions, and the nature of financial shocks.

2.2.4. Empirical Evidence on Bitcoin as a Safe-Haven Asset

Bitcoin has increasingly been examined as a potential safe-haven asset, yet its defensive role remains highly contested. Early studies argued that cryptocurrencies, particularly Bitcoin, could serve as safe havens due to their detachment from the traditional financial system (Dyhrberg, 2016). Empirical evidence identified Bitcoin as a portfolio diversifier (Dyhrberg, 2016; Guesmi, Saadi, Abid, & Ftiti, 2019) and, in some cases, a short-term hedge (Bouri, Jalkh, Molnár, & Roubaud, 2017; Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017). These findings fueled the “digital gold” narrative, suggesting that Bitcoin could offer protection during systemic shocks (Bouri et al., 2017).

Recent crisis-based evidence, however, is far from unanimous. A number of studies support Bitcoin's conditional safe-haven properties. Xu and Kinkyo (2023) report that Bitcoin played a robust short-term safe-haven role during both COVID-19 and the Russia-Ukraine war. Similarly, Theiri, Nekhili, and Sultan (2023) argue that Bitcoin gained recognition as a defensive instrument due to its weak correlation with bonds. Liu and Yuan (2024) find stronger safe-haven capabilities during periods of heightened market turmoil, while Manzli and Jeribi (2024) conclude that Bitcoin functioned effectively as a safe haven during crisis episodes.

Yet mounting evidence highlights heterogeneity across markets and time. Huang, Duan, and Mishra (2021) show that Bitcoin's safe-haven attributes vary across economic regions. Le Thi Thuy et al. (2024) document robust safe-haven behavior in European markets but significantly weaker performance in China. Feder-Sempach et al. (2024) further characterize Bitcoin as, at best, a weak safe-haven asset during financial distress.

A substantial body of literature rejects the safe-haven classification altogether. Ji et al. (2020) conclude that Bitcoin fails to serve as an effective hedge in diversified portfolios. During the COVID-19 crash, when Bitcoin prices plunged nearly 39 percent in a single day in March 2020 before recovering later that year, its vulnerability to systemic shocks raised doubts about its protective capacity. Empirical analyses during this period find limited safe-haven performance (Conlon & McGee, 2020; Syuhada, Suprijanto, & Hakim, 2022), with Nagy and Benedek (2021) identifying only weak defensive properties. More recent studies suggest that Bitcoin lost its ability to hedge equities following the pandemic outbreak (Cheng et al., 2025) and failed to provide safe-haven benefits in Asian emerging markets (Nguyen & Pham, 2025).

In summary, recent evidence shows that gold, Bitcoin, the Swiss franc, and U.S. Treasuries exhibit safe-haven properties only under specific conditions. Their effectiveness varies by crisis type, market, horizon, and macroeconomic regime, highlighting the limitations of static analyses. This underscores the need for a systematic reassessment of these assets using time-varying and frequency-based approaches to determine whether they act as universal or conditional safe havens.

3. Methods

3.1. Empirical Data and Initial Examination

The study employs daily financial data spanning January 1, 2015, to November 30, 2025, covering both global equity indices and candidate safe-haven assets. Equity indices include the S&P 500 (U.S.), FTSE 100 (UK), MSCI Emerging Markets, and the Shanghai Composite (China). Safe-haven assets include gold (XAU/USD spot price), U.S. 10-Year Treasury bonds (ICE Total Return Index), the Swiss franc (CHF/USD exchange rate), and Bitcoin (daily closing price).

All series are converted to logarithmic daily returns to ensure stationarity and facilitate comparison across asset classes. For consistency across asset classes, the datasets were merged using common trading days only. Given that Bitcoin trades continuously throughout the week while equity and bond markets operate only on business days, observations corresponding to non-trading days in the conventional financial markets were excluded from the merged dataset. Consequently, the final sample retains only those dates on which all assets have simultaneously observed returns. This alignment procedure avoids asynchronous trading biases and ensures comparability in the

estimation of dependence and connectedness dynamics across assets. The use of common trading days is particularly important for WQC and TVP-VAR analyses because both methods are sensitive to temporal misalignment and unequal information arrival across series. By restricting the sample to synchronized observations, the analysis preserves the integrity of the estimated safe-haven relationships without relying on artificial interpolation or imputation procedures.

The safe-haven properties of assets are examined over two distinct sub-periods: the COVID-19 pandemic (December 31, 2019, to December 9, 2022), and the Russia-Ukraine war (February 24, 2022, to November 30, 2025). These sub-periods overlap by approximately nine months (February 24 to December 9, 2022). This overlap reflects a deliberate design consistent with crisis demarcation standards in the literature (Su, Ding, Wang, & Wang, 2026; Wen, Tong, & Ren, 2022; Xu & Kinkyo, 2023; Zhang, Liu, Qin, & Gao, 2025) rather than an oversight. The two crises differ fundamentally in their shock transmission channels, with COVID-19 representing a demand-side collapse and the Russia-Ukraine conflict representing a supply-side inflationary shock. Treating them as equivalent would therefore misidentify their distinct conditional safe-haven dynamics.

To address the potential concern that the overlapping window attenuates the contrast between crisis regimes, robustness checks are conducted using strictly non-overlapping sub-periods. In these alternative specifications, the COVID-19 period is restricted to December 31, 2019, to February 23, 2022, and the Russia-Ukraine period begins on February 24, 2022. Results under these non-overlapping windows, reported in Section 5, confirm that the main qualitative conclusions are not sensitive to the sub-period demarcation.

3.2. Data Sources and Relevance

All data are sourced from Investing.com, which provides comprehensive, daily market prices for equities, commodities, currencies, bonds, and cryptocurrencies. Investing.com is widely used in empirical finance research due to its timeliness, reliability, and coverage across global markets (Frimpong & Siaw, 2026). Its data allow consistent measurement of price dynamics for both traditional and modern safe-haven assets, ensuring comparability across asset classes and geographical regions.

3.3. Variable Justification

Gold (XAU/USD) is included as a conventional safe-haven asset, historically providing protection against equity market downturns (Hillier, Draper, & Faff, 2006). U.S. 10-Year Treasuries serve as benchmark government bonds, reflecting flight-to-quality behavior and exhibiting negative correlations with equities during periods of market stress. The Swiss franc (CHF/USD) represents a defensive currency due to Switzerland's political stability and strong external balance, often appreciating during global risk-off episodes, making it a reliable short-term hedge (Ranaldo & Söderlind, 2010). Bitcoin (BTC) is included as a modern, digital safe-haven candidate, potentially independent of traditional financial markets and offering short-term hedging and portfolio diversification benefits (Conlon & McGee, 2020). Finally, the equity indices (S&P 500, FTSE 100, MSCI Emerging Markets, and Shanghai Composite) are selected to capture major developed and emerging markets, enabling assessment of safe-haven effectiveness across heterogeneous economic and regional contexts.

3.4. Wavelet Quantile Correlation

Earlier research on safe-haven assets typically assumed that the relationship between assets is uniform across investment horizons, characterizing dependence using quantile correlation (QC; Li, Li, and Tsai (2015)). While QC captures local and asymmetric dependence at different quantile levels, it does not distinguish short-run from long-run dynamics and therefore cannot fully characterize safe-haven behavior across heterogeneous investor horizons (Kristoufek, 2013). The Wavelet Quantile Correlation (WQC) approach, developed by Kumar and Padakandla (2022), extends QC into the time-frequency domain by first decomposing the series using wavelet analysis before computing quantile-based correlations at each decomposition level.

3.4.1. Wavelet Family Selection

This study employs the Maximal Overlap Discrete Wavelet Transform (MODWT) with the Daubechies least-asymmetric wavelet of length 8 (LA8), following the established practice in financial time-series analysis (Percival & Walden, 2000). The choice of the LA8 wavelet is motivated by three considerations. First, it achieves a good balance between time and frequency localization, making it well suited for financial return series that exhibit both smooth trends and sharp discontinuities. Second, unlike the Haar wavelet, which is the simplest wavelet but imposes abrupt transitions, the LA8 produces smoother decompositions that align better with the gradual dynamics observed in asset co-movements. Third, unlike Daubechies wavelets of shorter length, the LA8 minimizes phase shift, which is important for computing lead-lag relationships across frequency bands. The MODWT is preferred over the standard Discrete Wavelet Transform (DWT) because it does not require dyadic sample lengths, is shift invariant, and uses all available observations at each decomposition level, thereby improving statistical efficiency for financial series of arbitrary length (Gençay, Selçuk, & Whitcher, 2002).

To assess the robustness of results to this choice, the analysis is also replicated using the Daubechies D4 wavelet (a four-coefficient filter with lower smoothness). Results are reported in the robustness section and do not materially affect the qualitative conclusions.

3.4.2. Frequency Band Mapping

With daily data, the wavelet decomposition levels correspond to the following approximate investment horizons: Levels 1-2 (2-4 and 4-8 days): short-term, corresponding to intraday-to-weekly traders. Levels 3-5 (8-16, 16-32, and 32-64 days): medium-term, corresponding to swing traders and tactical asset allocators. Levels 6-8 (64-128, 128-256, and 256-512 days): long-term, corresponding to strategic and institutional investors. This mapping is grounded in the Fractal Market Hypothesis (Niveditha, 2025; Peters, 1994) and follows the frequency band structure adopted by Nguyen, Naeem, Balli, Balli, and Vo (2021) and Su et al. (2026). The selection of eight decomposition levels, rather

than a smaller number, ensures that the long-term dynamics, which have received less attention in prior WQC studies are captured alongside the shorter-horizon effects.

3.4.3. Formal Specification

This approach combines two concepts: Quantile Correlation (QC) and the Maximal Overlap Discrete Wavelet Transform (MODWT).

Let $Q_{\tau,X}$ be the τ -th quantile of a random variable X and $Q_{\tau,Y}(X)$ be the τ -th quantile of Y conditional on X . For $0 < \tau < 1$, the quantile covariance is defined as:

$$qcov_{\tau}(Y, X) = cov\{I(Y - Q_{\tau,Y} > 0), X\} = E\left(\phi_{\tau}(Y - Q_{\tau,Y})(X - E(X))\right) \quad (1)$$

Where

$$\phi_{\tau}(w) = \tau - I(w < 0) \quad (2)$$

The quantile correlation is then:

$$qcor_{\tau}(X, Y) = \frac{qcov_{\tau}(Y, X)}{\sqrt{var(\phi_{\tau}(Y - Q_{\tau,Y}))var(X)}} \quad (3)$$

Maximal Overlap Discrete Wavelet Transform (MODWT): We decompose each time series X_t and Y_t using MODWT. Let $h_1[i]$ and $g_1[i]$ be the low-pass and high-pass wavelet filters. At the first level, the approximation coefficients $a_1[i]$ and detail coefficients $d_1[i]$ are obtained by convolution.

$$d_1[i] = g_1[i] * s[i] = \sum_k g_1[i - k]s[k] \quad (5)$$

$$a_{j+1}[i] = h_{j+1}[i] * a_j[i] = \sum_k h_{j+1}[i - k]a_j[k] \quad (6)$$

For higher levels $j = 1, 2, \dots, J_0 - 1$, the coefficients are computed recursively using up-sampled filters.

$$d_{j+1}[i] = g_{j+1}[i] * a_j[i] = \sum_k g_{j+1}[i - k]a_j[k] \quad (7)$$

Where $h_{j+1}[i] = U(h_j[i])$ and $g_{j+1}[i] = U(g_j[i])$, and U is the up-sampling operator that inserts zeros between adjacent elements.

Wavelet Quantile Correlation (WQC): After obtaining the detail coefficients $d_j[X]$ and $d_j[Y]$ for each decomposition level j , we compute the Quantile Correlation between them. The WQC at level j and quantile τ is:

$$WQC_{\tau}(d_j[X], d_j[Y]) = \frac{qcov_{\tau}(d_j[Y], d_j[X])}{\sqrt{var(\phi_{\tau}(d_j[Y] - Q_{\tau,d_j[Y]})var(d_j[X]))}} \quad (8)$$

A key advantage of WQC over DCC-GARCH or simple rolling-window correlations is that it does not impose any parametric distributional assumptions on the joint density of returns, making it suitable for the fat-tailed, asymmetric return distributions observed across the heterogeneous asset classes in this study.

3.5. Time Domain TVP-VAR Connectedness

The research employs TVP-VAR methods to examine the dynamic interconnections among bond, currency, commodity, cryptocurrency, and equity markets. The TVP-VAR framework, established by Antonakakis, Chatziantoniou, and Gabauer (2020) and further refined by Chatziantoniou, Gabauer, and Gupta (2021) provides substantial benefits compared to conventional VAR models by permitting temporal variation in parameters and elucidating dynamic interrelationships across variables.

3.5.1. Lag Order and Forgetting Factor

The TVP-VAR model is estimated with a lag order of $p = 1$, consistent with the Bayesian Information Criterion applied to each sub-sample and with the standard specification in daily financial data studies employing TVP-VAR (Ahad, Imran, & Shahzad, 2024; Padhan, Kocoglu, Tiwari, & Haouas, 2024). The model is estimated using the Kalman filter with exponentially weighted moving average (EWMA) forgetting factors, following Koop and Korobilis (2014). The forgetting factor governs the speed at which the model discounts past observations; a value close to 1 implies slow adaptation, while lower values allow more rapid parameter evolution. The benchmark specification employs a forgetting factor of 0.99, consistent with the literature.

The TVP-VAR model is estimated as:

$$y_t = B_t z_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \Omega_t) \quad (9)$$

$$\text{vec}(B_t) = \text{vec}(B_{t-1}) + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \Lambda_t) \quad (10)$$

Where, y_t and z_{t-1} , and ε_t are $K \times 1$ dimensional vectors. B_t and Ω_t are $K \times K$ dimensional matrices. $\text{vec}(B_t)$ and η_t are $K^2 \times 1$ dimensional vectors. Ω_t and Λ_t are time varying variance covariance matrices and Λ_t is $K^2 \times K^2$ dimension matrix.

3.5.2. Generalized Forecast Error Variance Decomposition

The connectedness measures are computed from the Generalized Forecast Error Variance Decomposition (GFEVD) of Diebold and Yilmaz (2014) using a forecast horizon of $H = 20$ days. The GFEVD does not require orthogonalization of shocks, making results invariant to variable ordering, an important advantage when working with a heterogeneous set of assets. The forecast horizon $H = 20$ is standard in daily financial data studies and broadly corresponds to a three-week trading period.

This GFEVD analysis is used in converting the TVP-VAR to TVP-VMA. To convert the TVP-VAR into the TVP-VMA form, $y_t = \sum_{h=0}^{\infty} B_{h,t} f_{t-h}$ where $B_{0,t} = I_K$. Hence, the effect of a shock originating from variable s on variable r is calculated as:

$$\Phi_{rs,t}^{\text{gen}}(H) = \frac{\sum_{h=0}^{H-1} (f_r^T B_{h,t} \Omega_t f_s)^2}{(f_r^T \Omega_t f_s) \sum_{h=0}^{H-1} (f_r^T B_{h,t} \Omega_t B_{h,t}^T f_r B)} \quad (11)$$

Where, $\sum_{s=1}^n \Phi_{rs,t}^{\text{gen}}(H) = 1$ and $\sum_{s=1}^n \Phi_{rs,t}^{\text{gen}}(H) = K$. Following the work of Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014), the connected measures computed from the GFEVD are as follows:

$$TO_{st}(H) = \sum_{r=1, r \neq s}^K \Phi_{rs,t}^{\text{gen}}(H) \quad (12)$$

$$FROM_{st}(H) = \sum_{r=1, r \neq s}^K \Phi_{sr,t}^{\text{gen}}(H) \quad (13)$$

$$NET_{st}(H) = TO_{st} - FROM_{st} = \sum_{r=1, r \neq s}^K \Phi_{rs,t}^{\text{gen}}(H) - \sum_{r=1, r \neq s}^K \Phi_{sr,t}^{\text{gen}}(H) \quad (14)$$

$$TCI_t(H) = K^{-1} \sum_{s=1}^K TO_{st} \equiv K^{-1} \sum_{s=1}^K FROM_{st} \quad (15)$$

$$NPDC_{rs,t}(H) = \Phi_{rs,t}^{\text{gen}}(H) - \Phi_{sr,t}^{\text{gen}}(H) \quad (16)$$

The connected measures show the shocks from variable r to variable s as total directional connectedness, which is Equation (15). The shocks transferred from variable r to s are the TO directional connectedness in Equation (12), and the shocks transmitted from variable s to variable r are the FROM directional connectedness specified in Equation (13). The Equation (14) displays the NET directional connectedness, which is difference between the TO and FROM directional connectedness. Equation (16) demonstrates the net pairwise directional connectivity between variable r and s .

It is important to note that the connectedness measures derived from the Generalized Forecast Error Variance Decomposition (GFEVD), specifically the TO, FROM, NET, and TCI indices, reflect the proportion of the forecast error variance of one variable attributable to shocks from another variable in a linear VAR approximation. These measures should therefore be interpreted as indicators of statistical interdependence and co-movement, not as evidence of structural causation. The connectedness analysis complements the safe-haven classification derived from WQC but does not serve as its basis. Safe-haven status is determined solely by lower-tail quantile correlations; the TVP-VAR connectedness results inform understanding of how shocks propagate across the system and how network positions evolve across crisis regimes.

4. Results and Discussion of Results

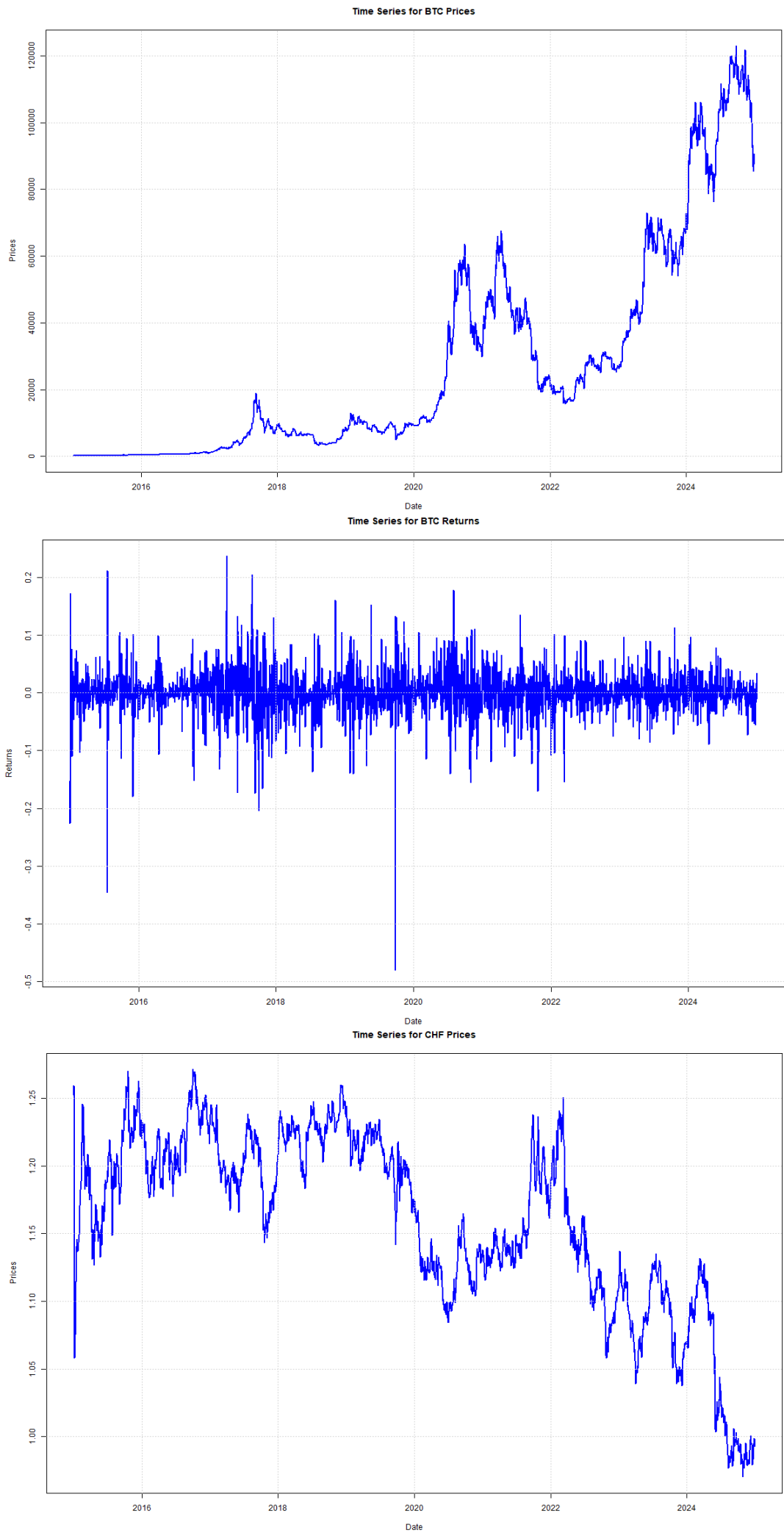
4.1. Preliminary Analysis

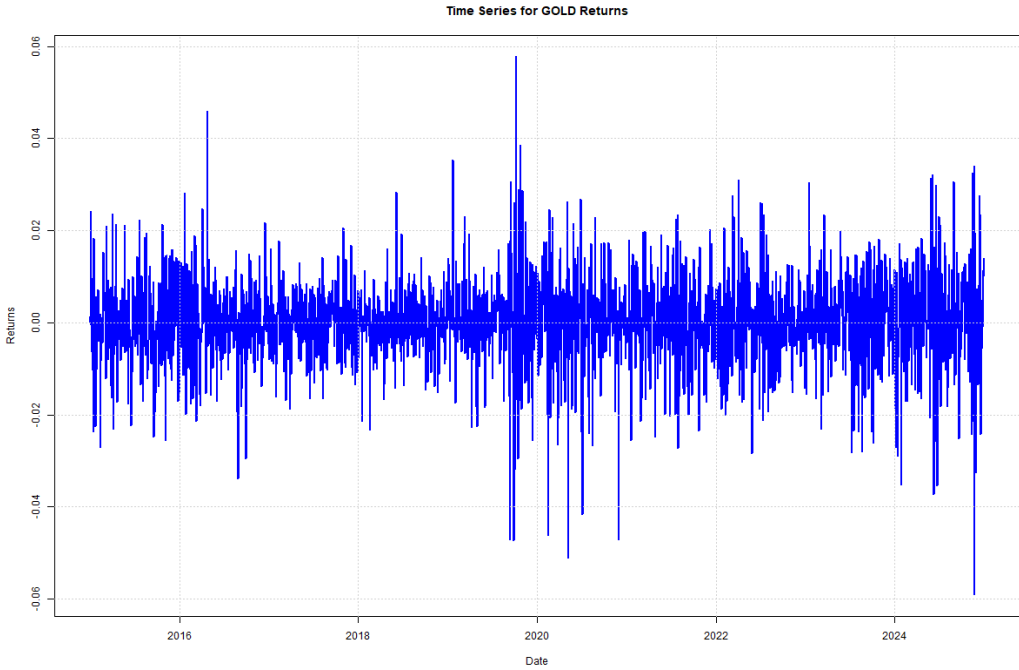
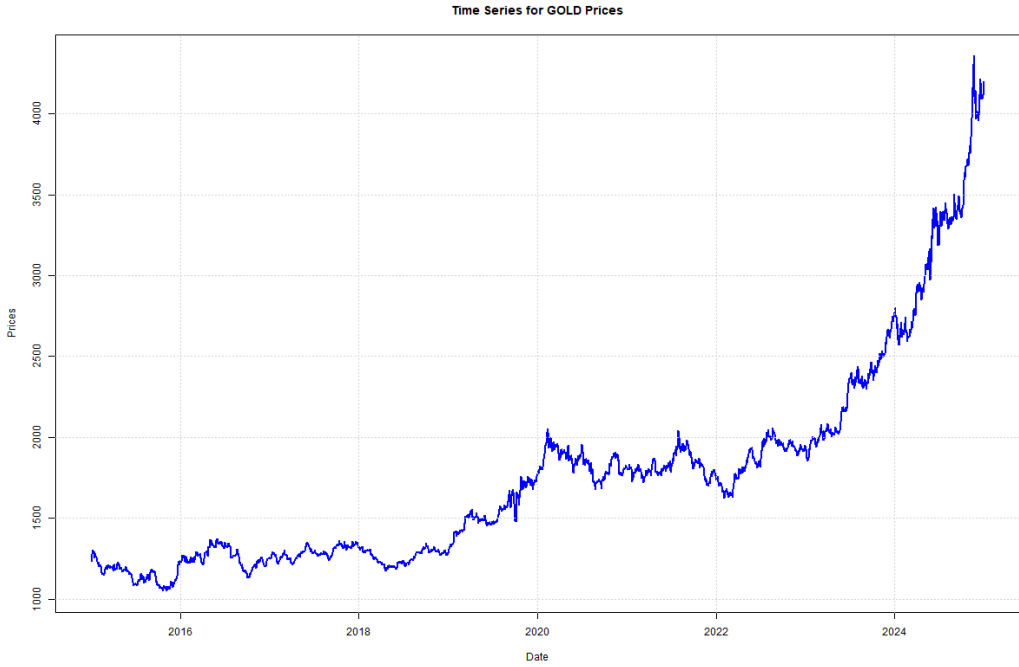
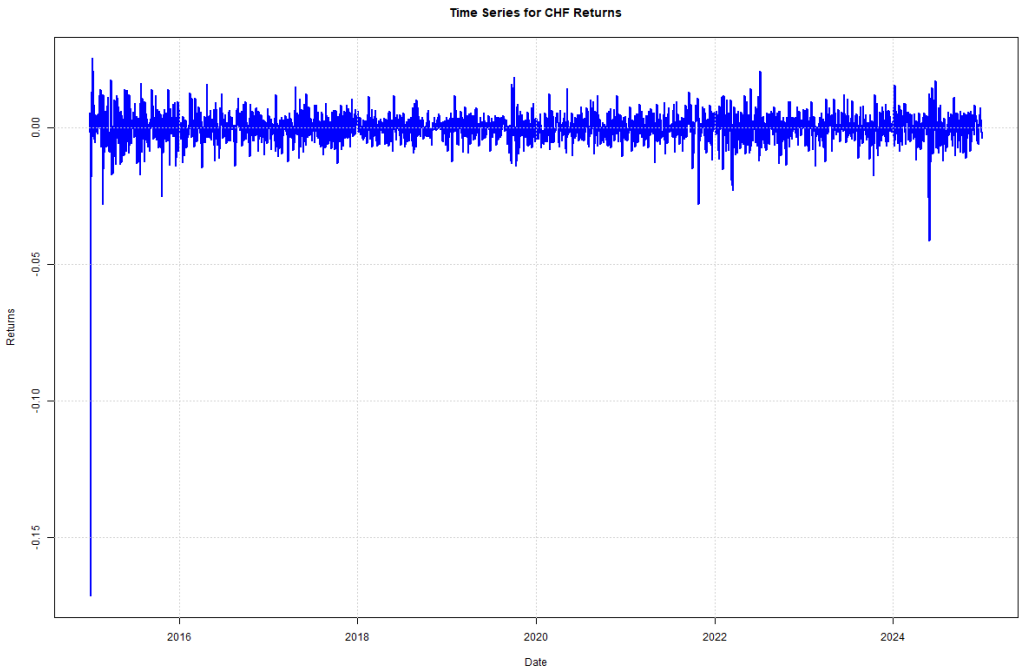
From January 2015 to November 2025, the dataset shown in Figures 1 and 2 spans a transformative decade in global finance. This period is marked by the emergence of Bitcoin as a major financial asset, rising from relatively low valuations to levels exceeding 100,000 US dollars, accompanied by substantial volatility. The Swiss franc experienced a sharp appreciation against the US dollar following the removal of its exchange rate peg, reinforcing its status as a traditional safe haven. Gold exhibited a strong upward trajectory in the latter part of the sample, surpassing 4,000 US dollars and reflecting renewed demand under heightened macroeconomic and geopolitical uncertainty.

Equity market performance over the same period is notably heterogeneous. The S&P 500 achieved sustained growth and reached successive record highs, largely supported by accommodative monetary policy and strong performance in technology sectors. In contrast, several emerging markets displayed weaker dynamics, with China's Shanghai Composite Index showing prolonged stagnation and limited recovery over the decade. US Treasury prices generally trended downward until around 2023, consistent with rising yields amid monetary policy tightening, before stabilizing as expectations of policy easing began to emerge.

The COVID-19 pandemic in 2020 represents a critical inflection point within the sample. It intensified risk aversion and triggered a pronounced reallocation of capital toward perceived safe-haven assets such as gold, while simultaneously accelerating equity market gains in technology-driven sectors. The period from 2024 to 2025 appears as a distinct phase characterized by concurrent strength across Bitcoin, gold, and US equities, suggesting a shift in market structure and investor behavior under evolving macro-financial conditions.

It is important to recognize that the broad cross-asset co-movements observed throughout the sample may be driven by common exogenous factors rather than purely bilateral relationships between assets. Changes in monetary policy regimes, including episodes of quantitative easing, tapering, and interest rate normalization, played a central role in shaping global financial conditions. Fluctuations in global liquidity and shifts in risk sentiment acted as pervasive systemic forces. These factors introduce potential confounding effects in the interpretation of pairwise correlations and connectedness measures and should be considered when evaluating the underlying transmission mechanisms. Accordingly, the results presented below are interpreted as descriptive of conditional statistical co-movement rather than as evidence of direct structural causation.





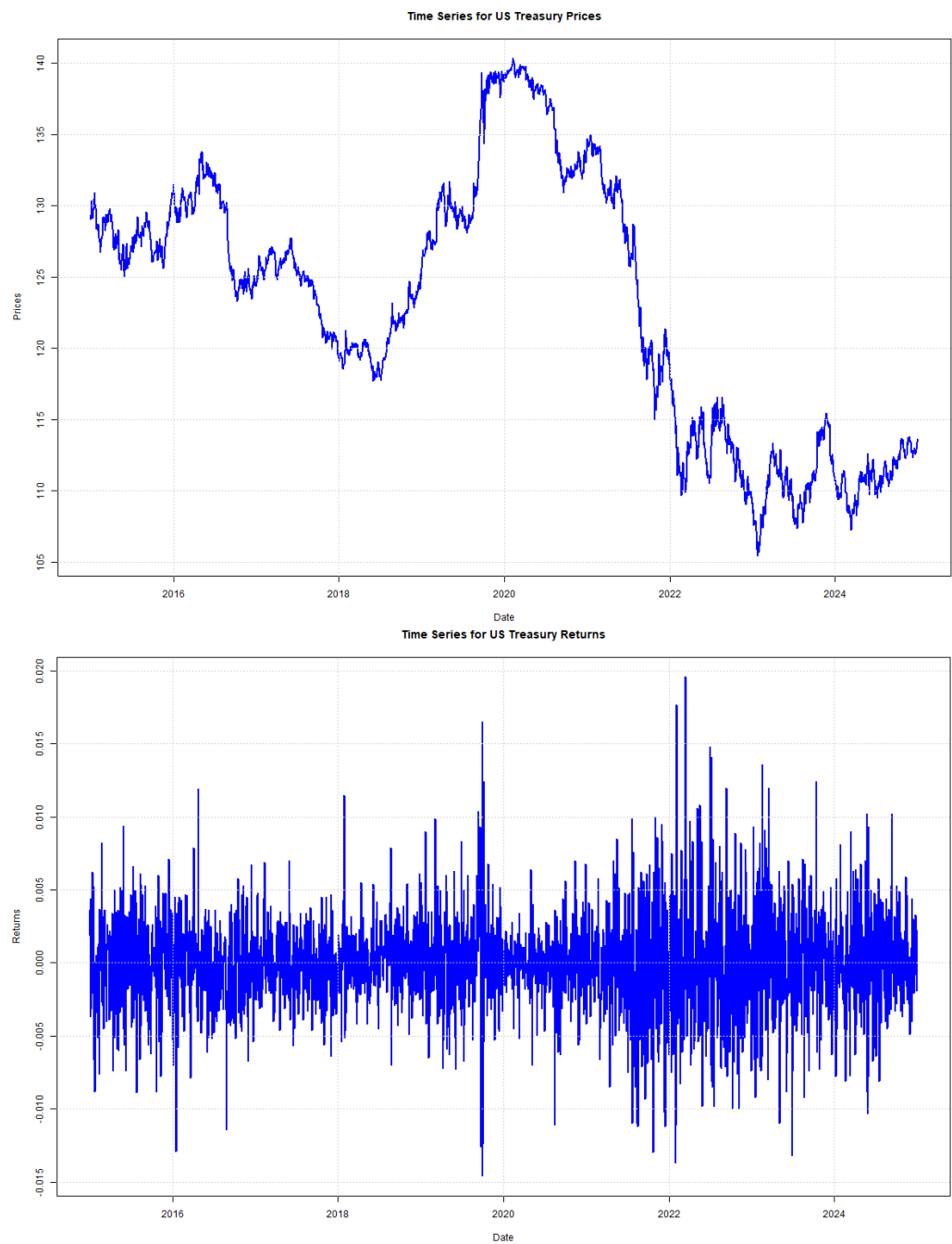
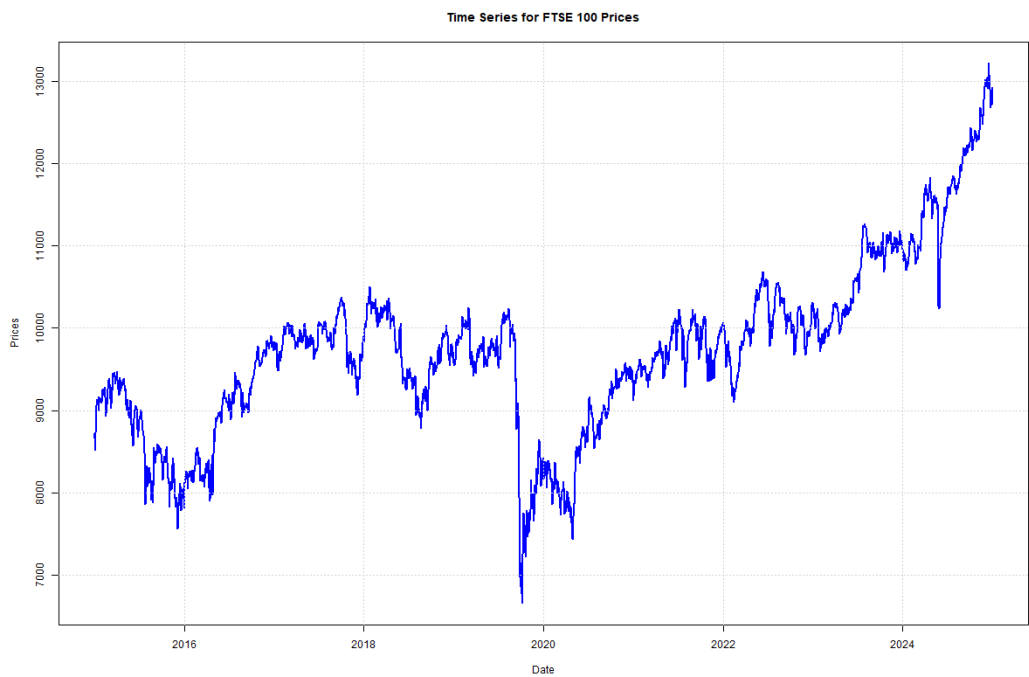
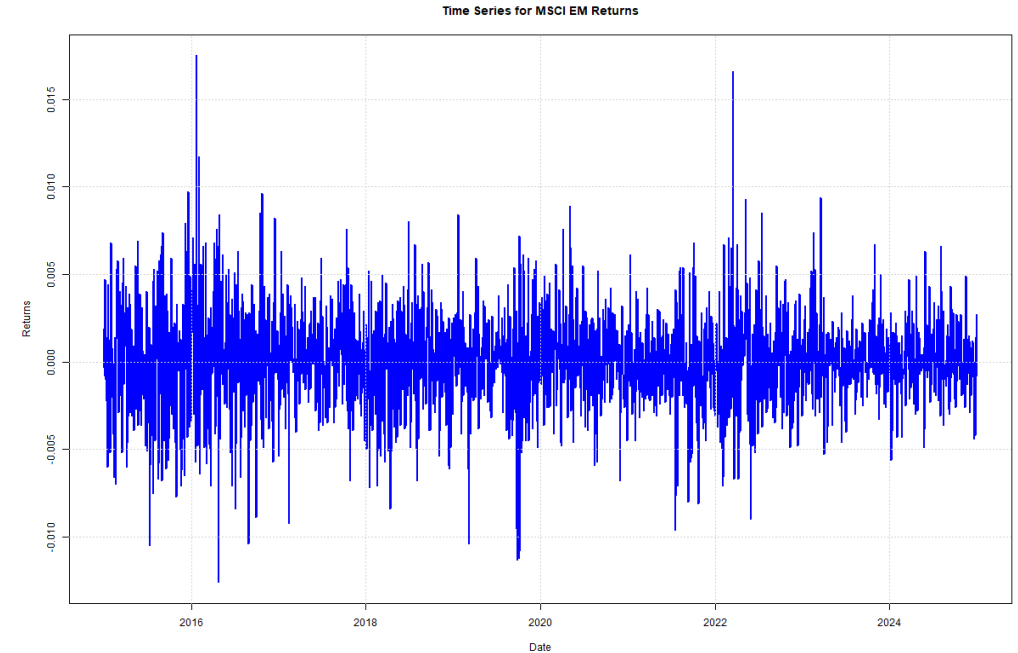
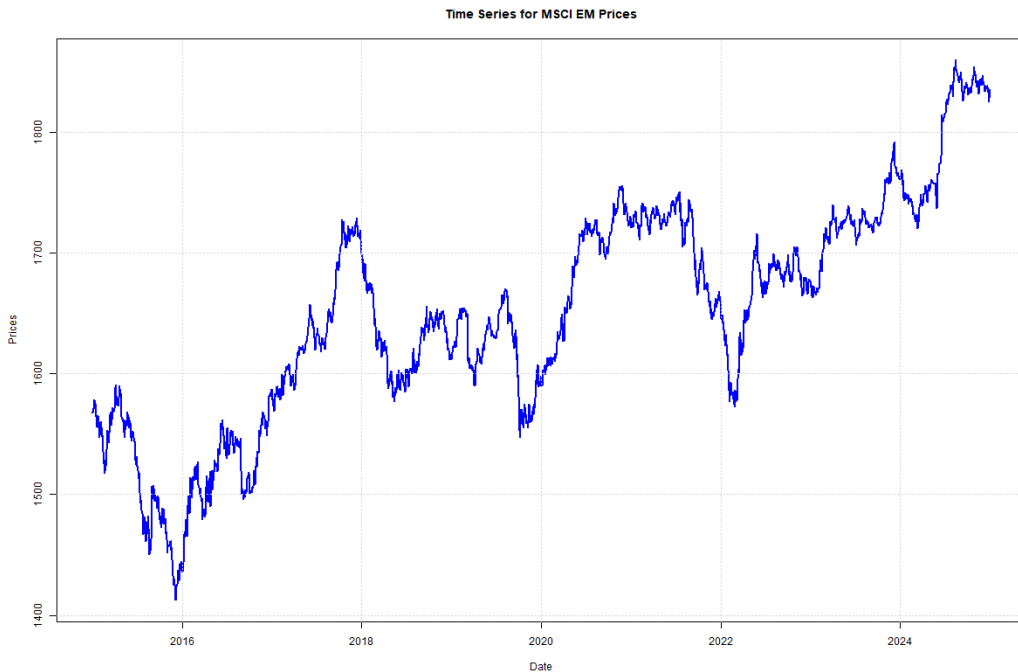
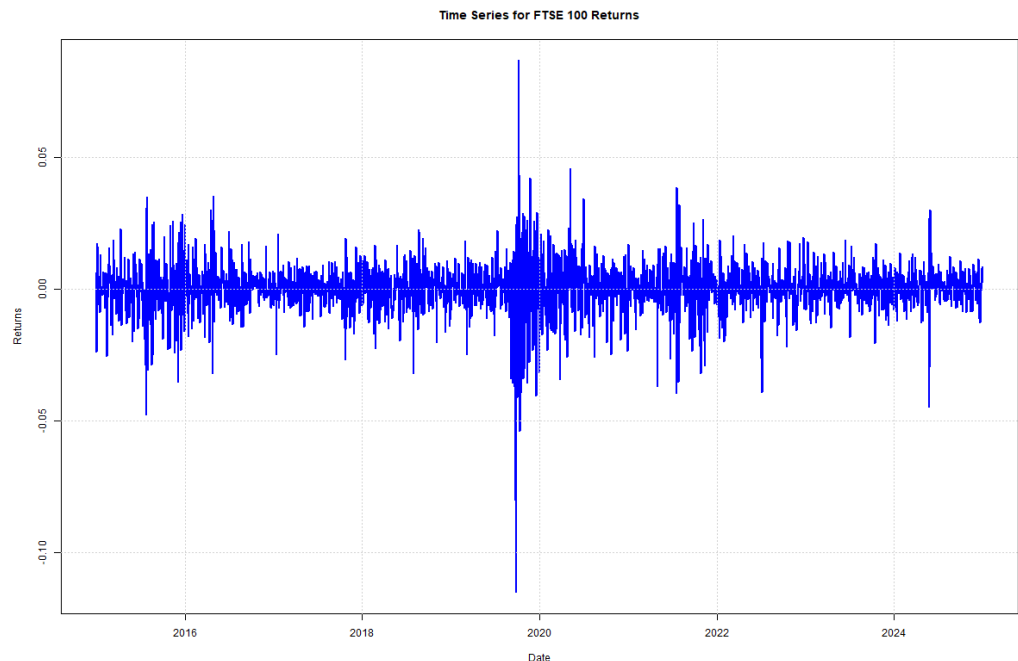
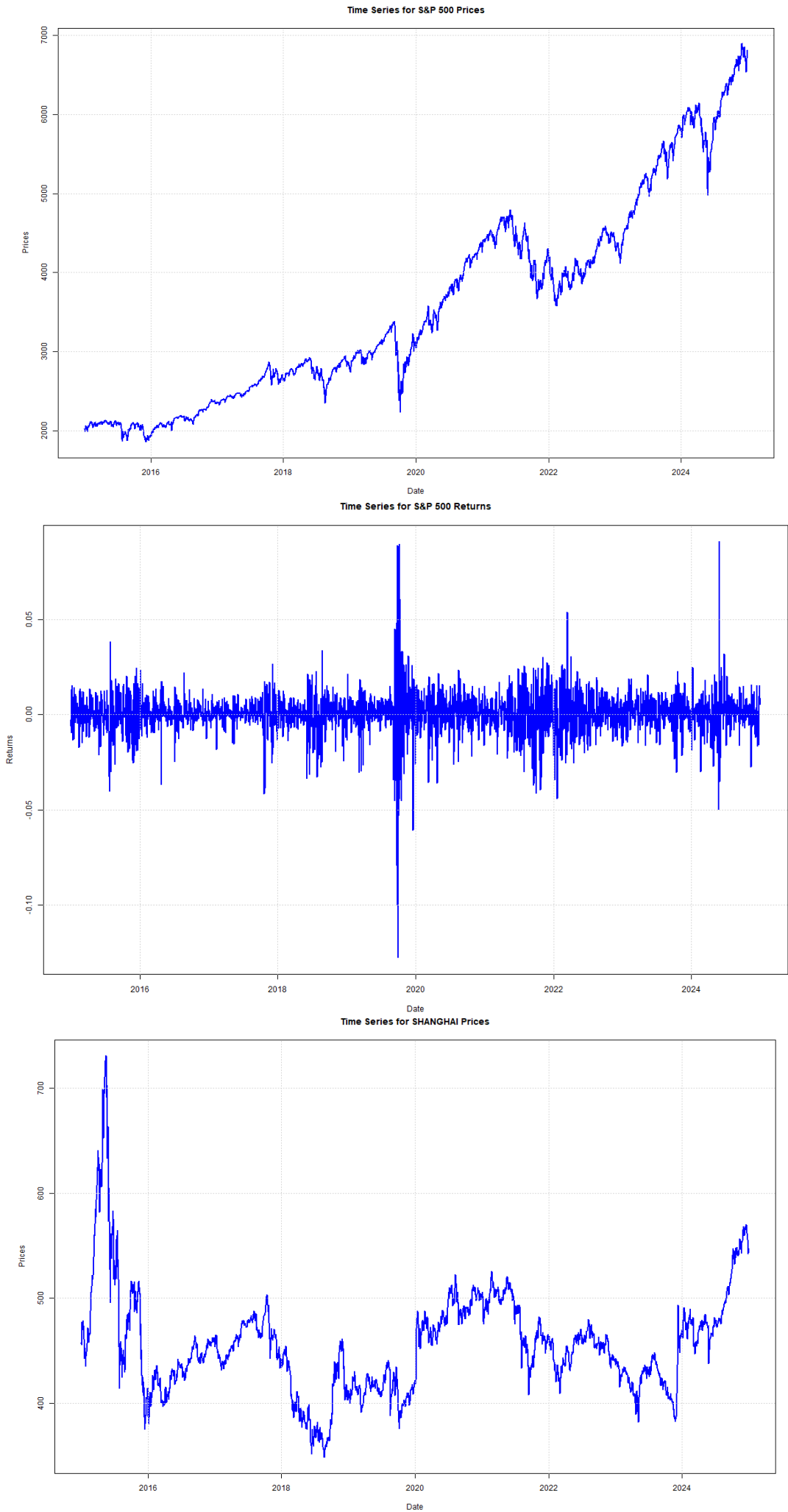


Figure 1. Prices and return series for safe haven assets.







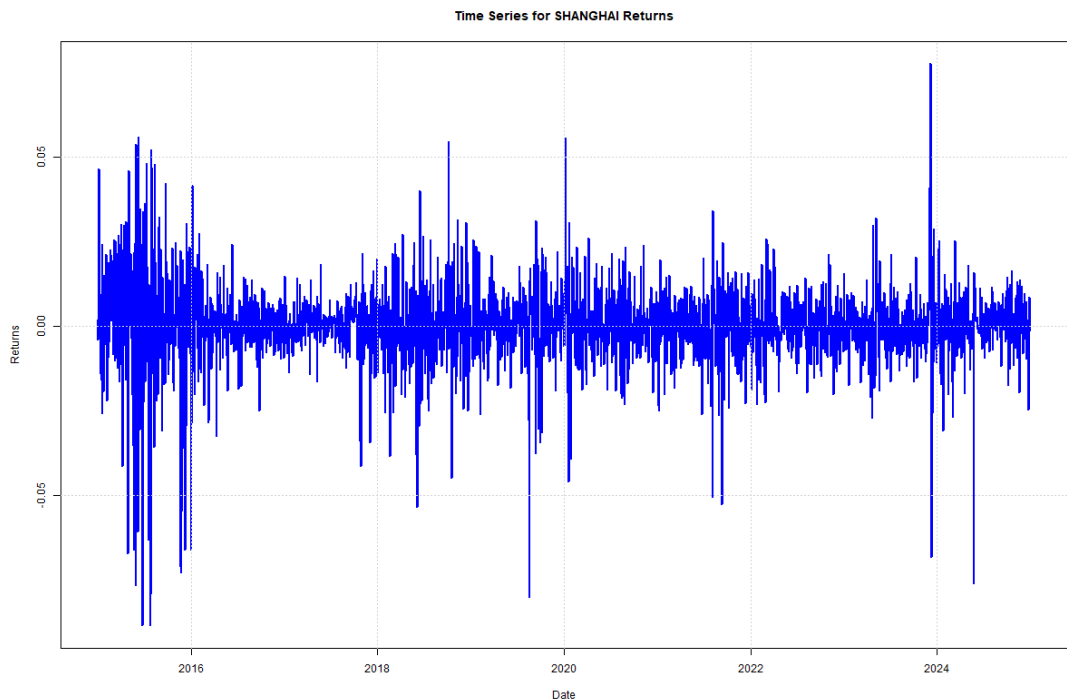


Figure 2. Prices and return series for equity markets.

Table 1. Summary statistics in the full sample (Full Sample).

Variable	Mean	Std. Dev	Skewness	Kurtosis	ADF	KPSS	JB
GOLD	0.000	0.010	-0.253	6.785	-13.818**	0.447*	1519.414***
UST	-0.000	0.003	0.152	5.183	-14.017**	0.099*	506.415***
CHF	-0.000	0.006	-8.896	244.840	-15.029**	0.025*	6127793.363***
BTC	0.001	0.040	-0.981	16.573	-13.070**	0.094*	19598.239***
S&P	0.000	0.011	-0.753	19.612	-13.167**	0.099*	28995.181***
FTSE	0.000	0.010	-0.981	17.445	-13.303**	0.074*	22144.711***
EM	0.000	0.003	0.009	5.476	-12.111**	0.044*	638.707***
SSE	-0.000	0.013	-0.992	11.725	-14.296**	0.041*	8343.784***

Note: Std. Dev. denotes standard deviation, ADF (Dickey & Fuller, 1979) denotes the Augmented Dickey–Fuller unit root test, KPSS (Kwiatkowski, Phillips, Schmidt, & Shin, 1992) denotes the Kwiatkowski–Phillips–Schmidt–Shin stationarity test, and JB (Jarque & Bera, 1987) denotes the Jarque–Bera normality test. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The descriptive statistics in Table 1 reveal that most assets exhibit mean returns of approximately zero over the sample period, with the exception of Bitcoin (BTC), which shows a marginally higher average return of 0.001, indicating slightly better performance and UST (US Treasuries), Swiss Franc (CHF), and Shanghai (SSE) recording negative means denoting poor performance. In terms of volatility, BTC is the riskiest asset with the highest standard deviation (0.040), while UST (US Treasuries) and EM are the most stable, displaying the lowest volatility. The distribution of returns for all assets is non-normal, as confirmed by the highly significant Jarque-Bera statistics. Most assets exhibit negative skewness, indicating a tendency toward extreme downside returns, while excess kurtosis across all series reflects fat tails and a higher likelihood of extreme movements than implied by normality. The Swiss franc (CHF) is a clear outlier, exhibiting exceptionally high negative skewness (-8.896) and kurtosis (244.840), indicating a highly asymmetric distribution with an unusually heavy left tail and the presence of extreme observations. These characteristics distinguish the CHF from the other assets and suggest that its return distribution deviates substantially from normality. Although these extreme observations influence the distributional moments, they do not alter the qualitative safe-haven findings because the WQC framework focuses on lower-tail dependence and is robust to isolated outliers. Finally, the stationarity tests (ADF and KPSS) confirm that the return series are stationary and suitable for further time-series econometric analysis.

Table 2. Summary statistics in the COVID-19 period (COVID).

Variable	Mean	Std. Dev	Skewness	Kurtosis	ADF	KPSS	JB
GOLD	0.000	0.011	-0.287	7.052	-10.261**	0.089*	474.466***
UST	-0.000	0.004	0.140	6.038	-8.643**	0.383*	263.651***
CHF	-0.000	0.005	-0.523	5.800	-9.447**	0.08*	253.162***
BTC	0.001	0.045	-1.895	23.553	-8.921**	0.734**	12376.207***
S&P	0.000	0.016	-0.884	14.416	-7.875**	0.156*	3780.756***
FTSE	-0.000	0.013	-1.134	15.673	-8.581**	0.113*	4696.096***
EM	-0.000	0.003	-0.019	5.898	-8.433**	0.223*	237.939***
SSE	-0.000	0.011	-0.817	8.602	-9.586**	0.082*	964.752***

Note: ***, ** and * shows significance at the 1%, 5% and the 10% levels respectively.

The descriptive statistics for this sample in Table 2 confirm that all return series exhibit near-zero means, consistent with typical financial return behavior characterized by minimal drift, with Bitcoin (BTC) standing out as the only asset with a slightly positive average return (0.001), alongside being the most volatile with a standard deviation of 0.045. In contrast, the Emerging Markets variable (EM) and US Treasuries (UST) remain the safest havens, exhibiting the lowest volatility. The distribution of returns is overwhelmingly non-normal for every series, as evidenced by the statistically significant Jarque-Bera (JB) tests. A consistent theme of negative skewness persists across most assets, including GOLD, BTC, and the equity indices, indicating a bias towards large negative movements. Bitcoin, in particular, displays a sharp increase in negative skew (-1.895) and extreme kurtosis (23.553),

suggesting the sample period captured more severe downside tail events for the cryptocurrency. The stationarity tests (ADF and KPSS) confirm that all return series are stationary and suitable for econometric modelling.

Table 3. Summary statistics in the Russia-Ukraine war period (RUSSIA-UKRAINE WAR).

Variable	Mean	Std. Dev	Skewness	Kurtosis	ADF	KPSS	JB
GOLD	0.001	0.010	-0.350	5.129	-10.363**	0.387*	181.083***
UST	0.000	0.004	0.217	3.952	-9.580**	0.172*	39.435***
CHF	-0.000	0.005	-0.918	8.293	-10.248**	0.063*	1131.292***
BTC	0.000	0.030	-0.192	6.555	-8.163**	0.265*	460.705***
S&P	0.001	0.011	0.233	9.610	-8.926**	0.25*	1582.511***
FTSE	0.000	0.008	-0.599	7.695	-9.912**	0.159*	846.145***
EM	0.000	0.002	0.369	6.662	-8.561**	0.296*	503.073***
SSE	-0.000	0.010	-0.376	13.534	-9.704**	0.292*	4019.511***

Note: ***, ** and * shows significance at the 1%, 5% and the 10% levels respectively.

The descriptive statistics from Table 3 indicate that, on average, all assets delivered near-zero returns over the sample period, with only GOLD and the S&P 500 showing a slightly positive mean of 0.001. Bitcoin (BTC) exhibits the highest volatility, with a standard deviation of 0.030, making it the riskiest asset in this set, while the Emerging Markets variable (EM) is the most stable, displaying the lowest standard deviation at just 0.002. The distribution of returns for every asset is non-normal, as confirmed by the highly significant Jarque-Bera (JB) statistics. Most assets are negatively skewed, meaning they have a tendency for extreme negative returns; this is particularly evident for the Swiss Franc (CHF) with a skewness of -0.918 and the FTSE with -0.599. However, the S&P 500 and EM stand out with positive skewness (0.233 and 0.369), indicating a bias towards positive outlier returns during this period. Excess kurtosis is present across all series, with the Shanghai Composite (SSE) showing the highest value (13.534), suggesting a significant frequency of extreme market movements. Finally, the stationarity tests (ADF) confirm that all return series are stationary and suitable for time-series analysis.

4.1.1. Structural Break Section

To formally assess the stability of safe-haven-equity relationships within each sub-sample, the Bai and Perron (2003) multiple structural break test is applied to the pairwise lower-tail quantile correlations between each safe-haven candidate and each equity market. The Bai-Perron procedure identifies unknown breakpoints endogenously by minimizing the sum of squared residuals across candidate break dates, with the number of breaks determined by the sequential F-test under the null of no structural change. The maximum number of breaks is set to three, and the minimum segment length is set to 15 percent of the sub-sample, consistent with the trimming convention proposed by Bai and Perron (2003).

This analysis serves two purposes. First, it confirms whether the demarcation of the COVID-19 and Russia-Ukraine sub-periods aligns with statistically identified breaks in the correlation and connectedness structure, thereby validating the sub-sample design. Second, it allows us to assess whether the findings are sensitive to the precise timing of sub-period boundaries.

The structural break results in Table 4 indicate that safe-haven–equity relationships are highly time-varying and characterized by regime shifts that largely align with major global stress episodes. Breaks cluster prominently around early 2020, coinciding with the onset of the COVID-19 pandemic (e.g., GOLD–SP500, BTC across markets, CHF–MSCIEM), confirming that asset–equity linkages reconfigure sharply during systemic crises and supporting the sub-sample demarcation. Additional breaks around February 2022 reflect the impact of the Russian invasion of Ukraine, while a further shift in late 2022, particularly for U.S. Treasury pairings, is consistent with changes in Federal Reserve monetary policy and aligns with Zhang (2025) evidence of a post-April 2022 regime change in Treasury safe-haven behavior. Across assets, gold exhibits earlier and more dispersed breaks (2016–2019), suggesting a more gradual evolution in its safe-haven role, whereas CHF shows episodic shifts tied to currency stress, and Bitcoin displays synchronized breaks during crisis periods, indicating sensitivity to systemic shocks.

Table 4. Structural break test.

Safe Haven	Equity	Break Dates
GOLD	S&P 500	2018-01-11, 2019-02-19, 2020-03-10
GOLD	FTSE 100	2017-11-06, 2018-11-21, 2020-02-27
GOLD	MSCI_EM	2016-09-29, 2019-08-01, 2020-09-02
GOLD	SSE	2016-09-27, 2018-10-10, 2019-12-06
UST	S&P 500	2020-09-22, 2022-08-11, 2024-08-05
UST	FTSE	2018-10-24, 2022-06-10, 2023-07-11
UST	MSCI EM	2016-11-08, 2018-02-27, 2022-06-09
UST	SSE	2016-05-24, 2018-08-23, 2020-08-10
CHF	S&P 500	2020-06-11, 2022-09-14, 2024-07-16
CHF	FTSE	2020-09-08, 2022-09-14, 2024-03-25
CHF	MSCI_EM	2016-05-13, 2018-09-26, 2020-03-18
CHF	SSE	2017-01-05, 2018-09-27, 2019-12-10
BTC	S&P 500	2020-03-11, 2023-04-24, 2024-08-02
BTC	FTSE	2017-07-03, 2020-03-11, 2023-03-10
BTC	MSCI EM	2017-09-08, 2020-03-11, 2024-07-16
BTC	SSE	2018-07-03, 2023-06-28, 2024-07-19

4.2. Main Results

4.2.1. Wavelet Quantile Correlation

The Wavelet Quantile Correlation (WQC) approach is employed to examine the dependence between potential safe-haven assets and major global equity markets across different market conditions and investment horizons. By combining wavelet decomposition with quantile-based correlation, the method captures relationships across short-, medium-, and long-term frequencies while also accounting for variations in bearish, normal, and bullish market states. This framework is particularly useful during periods of financial turbulence such as the COVID-19 Pandemic and the ongoing Russia–Ukraine War. In this study, WQC is used to assess the dynamic relationships between safe-haven candidates, namely Gold, Bitcoin, the Swiss Franc, and U.S. Treasury securities and major equity indices including the S&P 500, FTSE 100, Shanghai Composite Index, and the MSCI Emerging Markets Index, providing insights into their hedging and safe-haven properties during crisis periods.

Before reporting the WQC results, the criteria for safe-haven classification are stated explicitly. An asset is classified as a safe haven at a given horizon and for a given equity market if its WQC is negative at quantiles in the 5th to 30th percentile range. An asset whose WQC is positive in the lower quantile range is disqualified as a safe haven regardless of its behavior at other quantiles. Where evidence is consistent across at least three of the four equity markets at a given horizon, the asset is described as a broad safe haven at that horizon; otherwise, the classification is reported conditionally by market.

In the WQC heatmaps, negative coefficients are represented by blue and indicate an inverse relationship between the safe-haven asset and the equity market, suggesting potential safe-haven behavior. Positive coefficients are represented by red and indicate positive co-movement, implying the absence of safe-haven properties. Following Baur and Lucey (2010), lower quantiles (0.10 to 0.30) represent bearish market conditions, middle quantiles (0.40 to 0.60) capture normal market conditions, and upper quantiles (0.70 to 0.90) reflect bullish market conditions.

Since the objective of this study is to evaluate safe-haven properties, the analysis focuses primarily on the lower quantiles. Particular attention is therefore given to whether the estimated correlations become negative and statistically significant during bearish market states, as this provides evidence of safe-haven behavior during episodes of market stress.

4.2.1.1. WQC In COVID-19 Period

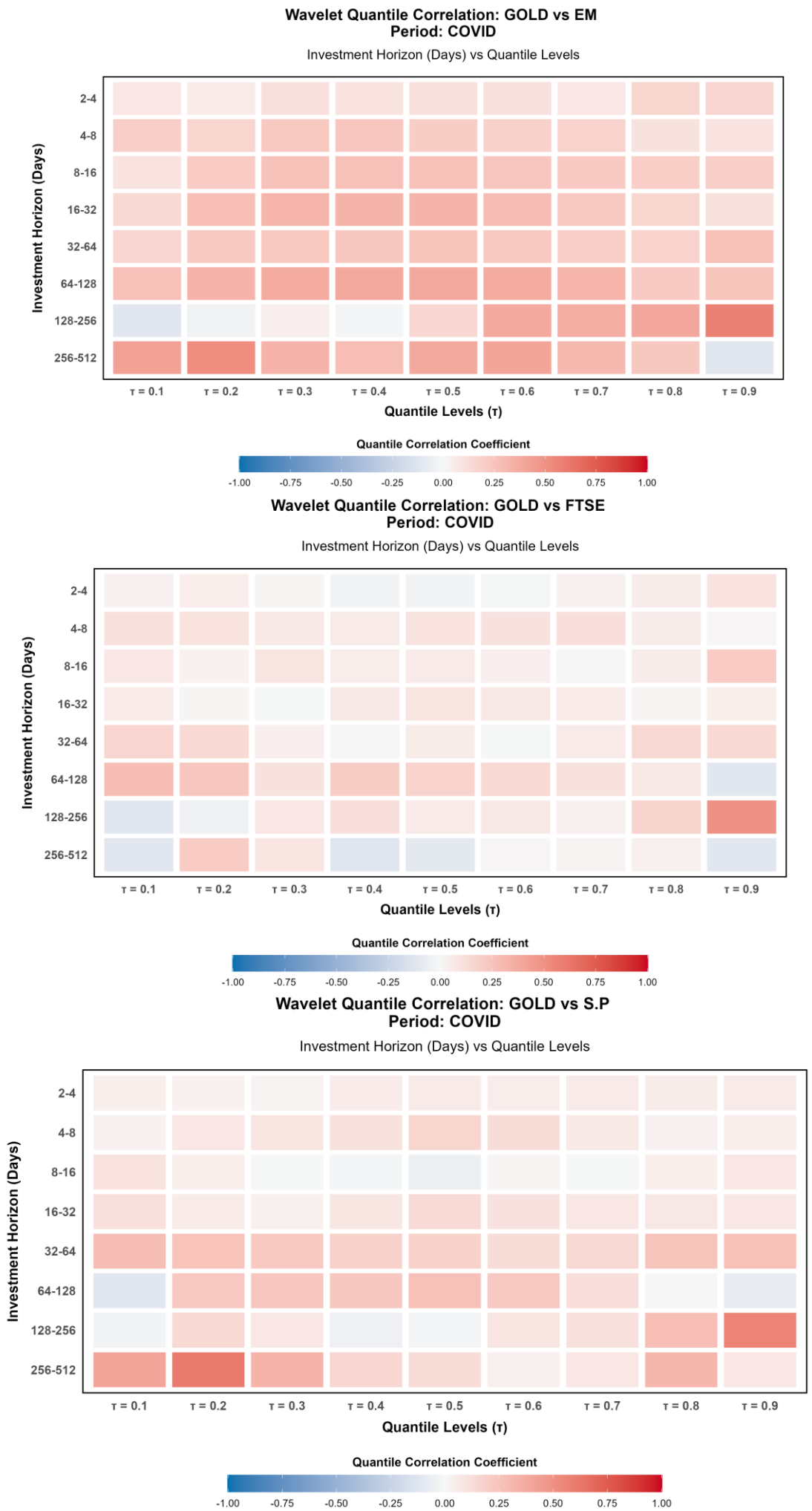
The WQC results for the COVID-19 period reveal a striking pattern of market specificity in safe-haven effectiveness that neither time-domain correlation nor full-sample analysis could detect. Gold's failure to provide downside protection (Figure 3) in the U.S., UK, and emerging markets reflects the well-documented liquidity spiral of March 2020, during which forced liquidation of long gold positions to cover equity margin calls temporarily disrupted the traditionally negative gold-equity co-movement (Baur & McDermott, 2016). The exception, namely gold's safe-haven properties in the Chinese market at the 2 to 4-day and 128-to-256-day frequencies, likely reflects the sequencing of the pandemic shock: Chinese equity markets experienced their most acute stress in January and February 2020, weeks before Western markets, creating a period in which gold served as a crisis-period refuge specifically for Chinese investors before the global liquidity event contaminated cross-market correlations. This horizon heterogeneity, observable only through wavelet decomposition, would be averaged out and therefore masked in any purely time-domain analysis.

U.S. Treasury securities failed to provide safe-haven protection in their domestic market (Figure 4), consistent with the March 2020 “dash-for-cash” episode where Treasuries were sold to meet liquidity needs, temporarily disrupting the stock–bond diversification link (He, Nagel, & Song, 2022). However, their effectiveness in the UK across all horizons suggests a global rather than domestic refuge role, driven by foreign demand for dollar-denominated safety.

The Swiss franc shows broad safe-haven effectiveness (Figure 5), particularly against U.S. equities, reflecting its role as a currency-based refuge. In contrast, Bitcoin exhibits persistent positive co-movement with equities across markets and horizons (Figure 6), indicating risk-asset behavior during the pandemic and contradicting the “digital gold” narrative, consistent with Conlon and McGee (2020).

The findings align with prior safe-haven literature. Gold serves as a safe haven mainly during extreme market stress (Baur & Lucey, 2010), while its role during COVID-19 is time-varying and market-specific (Ji et al., 2020), consistent with the limited and frequency-dependent effectiveness observed in this study. The weak performance of U.S. Treasuries in the domestic market supports the liquidity-driven “dash-for-cash” dynamics documented by Conlon and McGee (2020), whereas their effectiveness in the UK aligns with the international diversification benefits highlighted by Baur and McDermott (2016). The Swiss franc's uneven regional performance is also consistent with the findings of Grisse and Nitschka (2015). Finally, Bitcoin's failure as a safe haven corroborates the evidence of weak and unstable safe-haven properties reported by Bouri et al. (2017).

More broadly, these findings emphasize that safe-haven effectiveness is not only asset-specific but also sensitive to crisis structure, market integration, and investment horizon. Overall, safe-haven characteristics are crisis-dependent and vary systematically across markets and time scales, underscoring the need for dynamic rather than static portfolio allocation strategies.



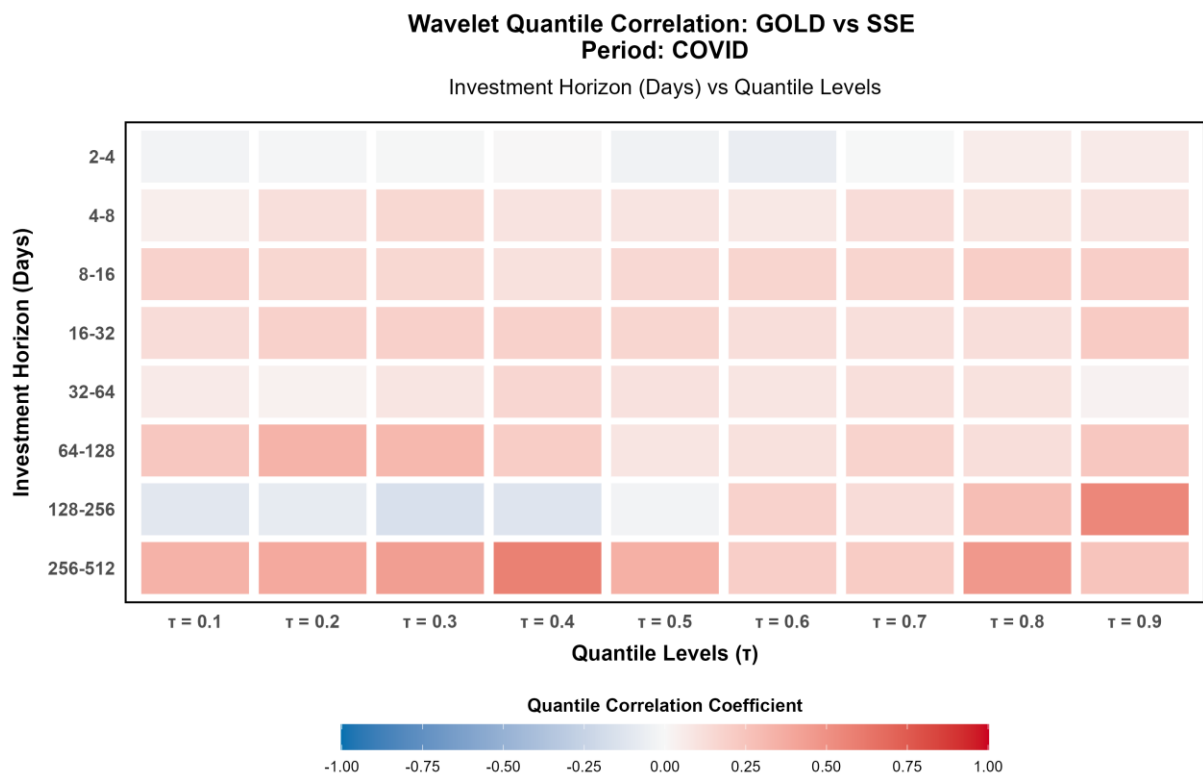
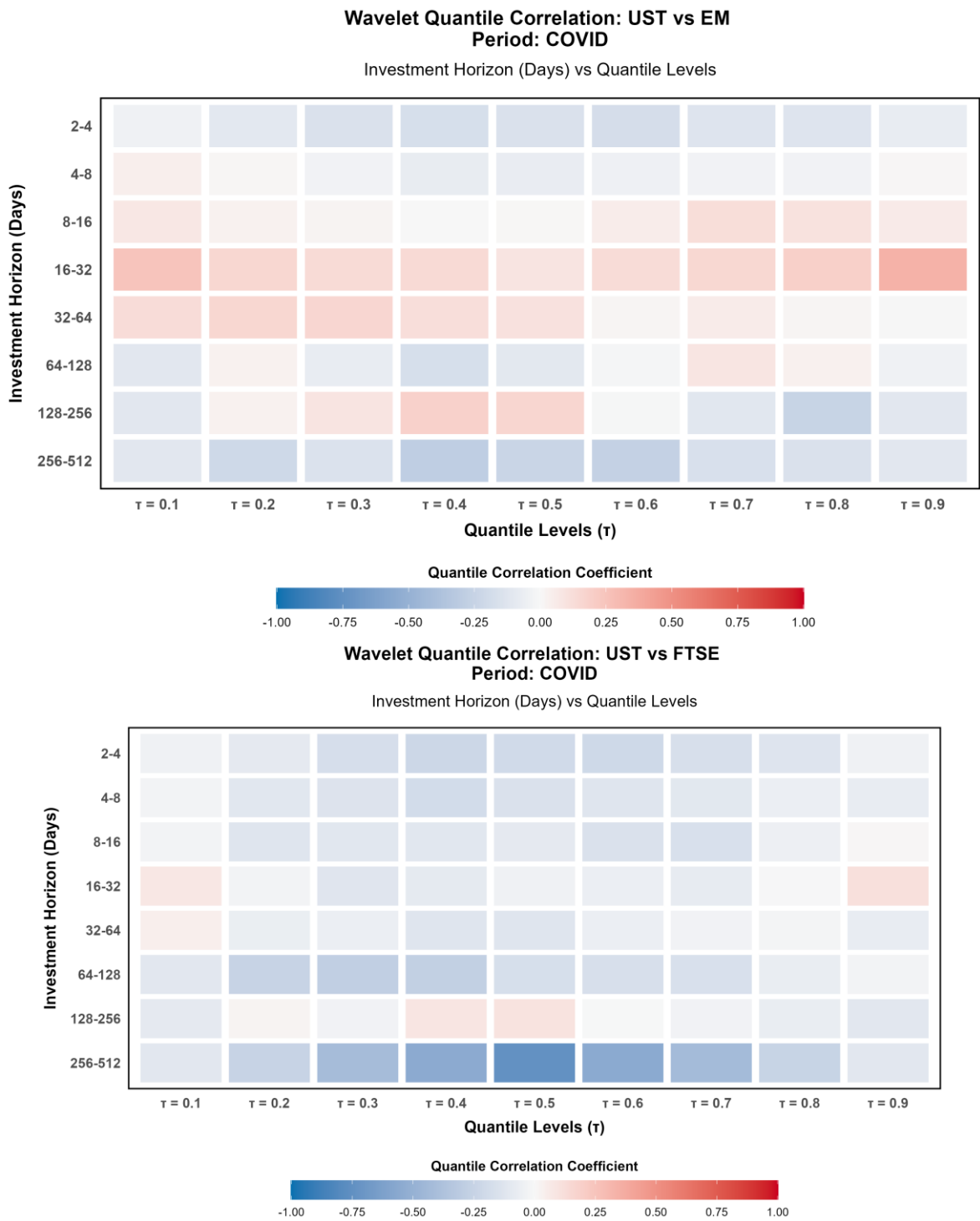


Figure 3. Wavelet Quantile Correlation between Gold and equities during the COVID- 19 period.



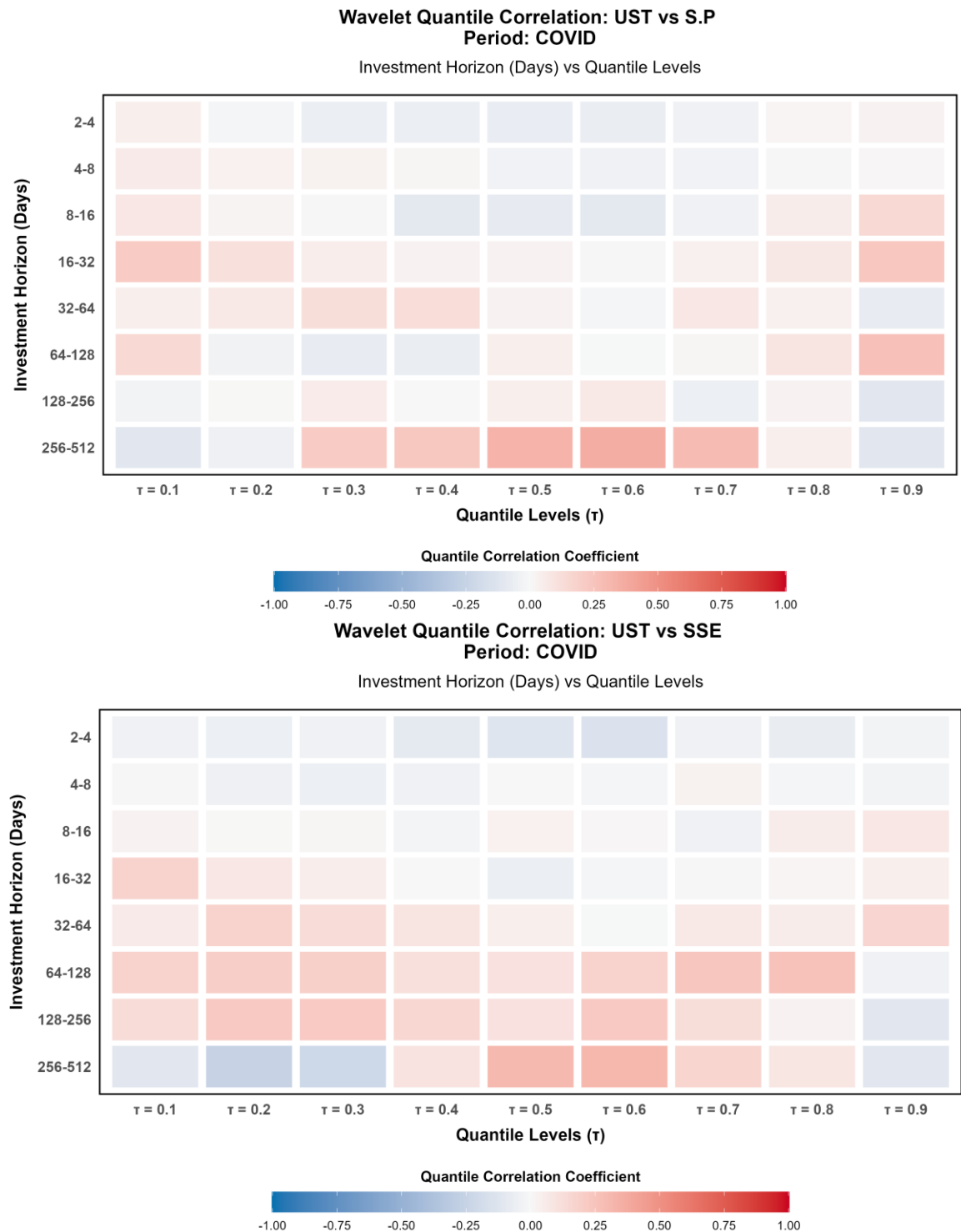
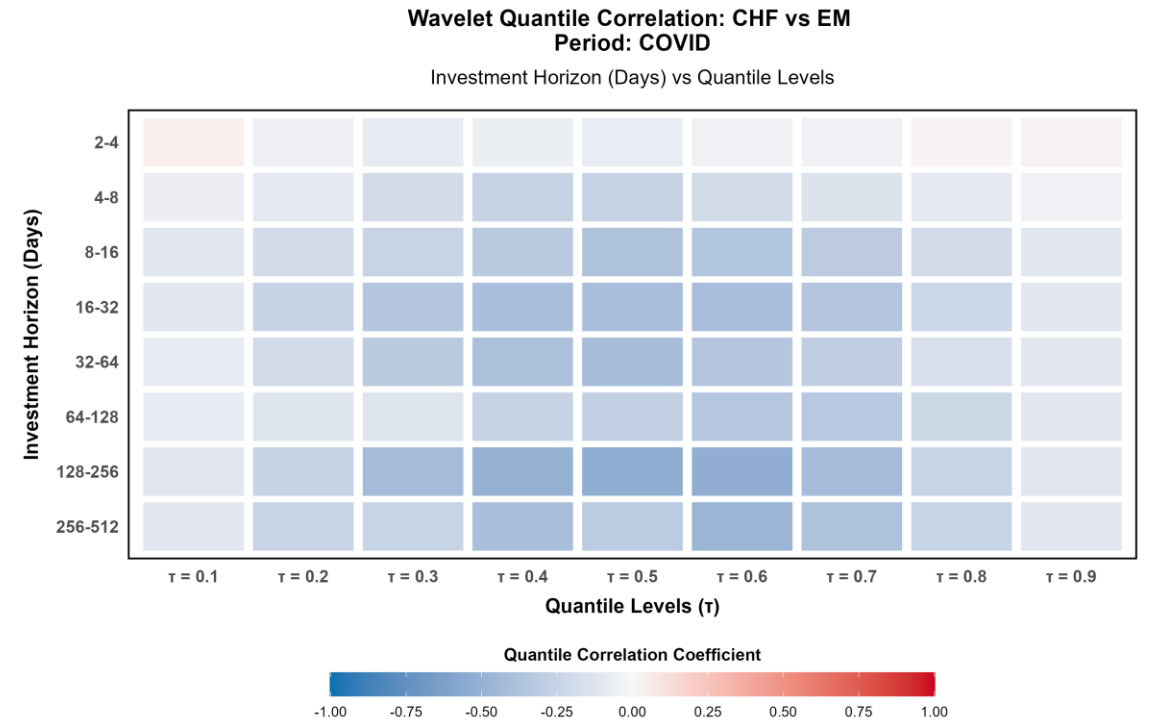


Figure 4. Wavelet Quantile Correlation between US Treasury and equities during the COVID- 19 period.



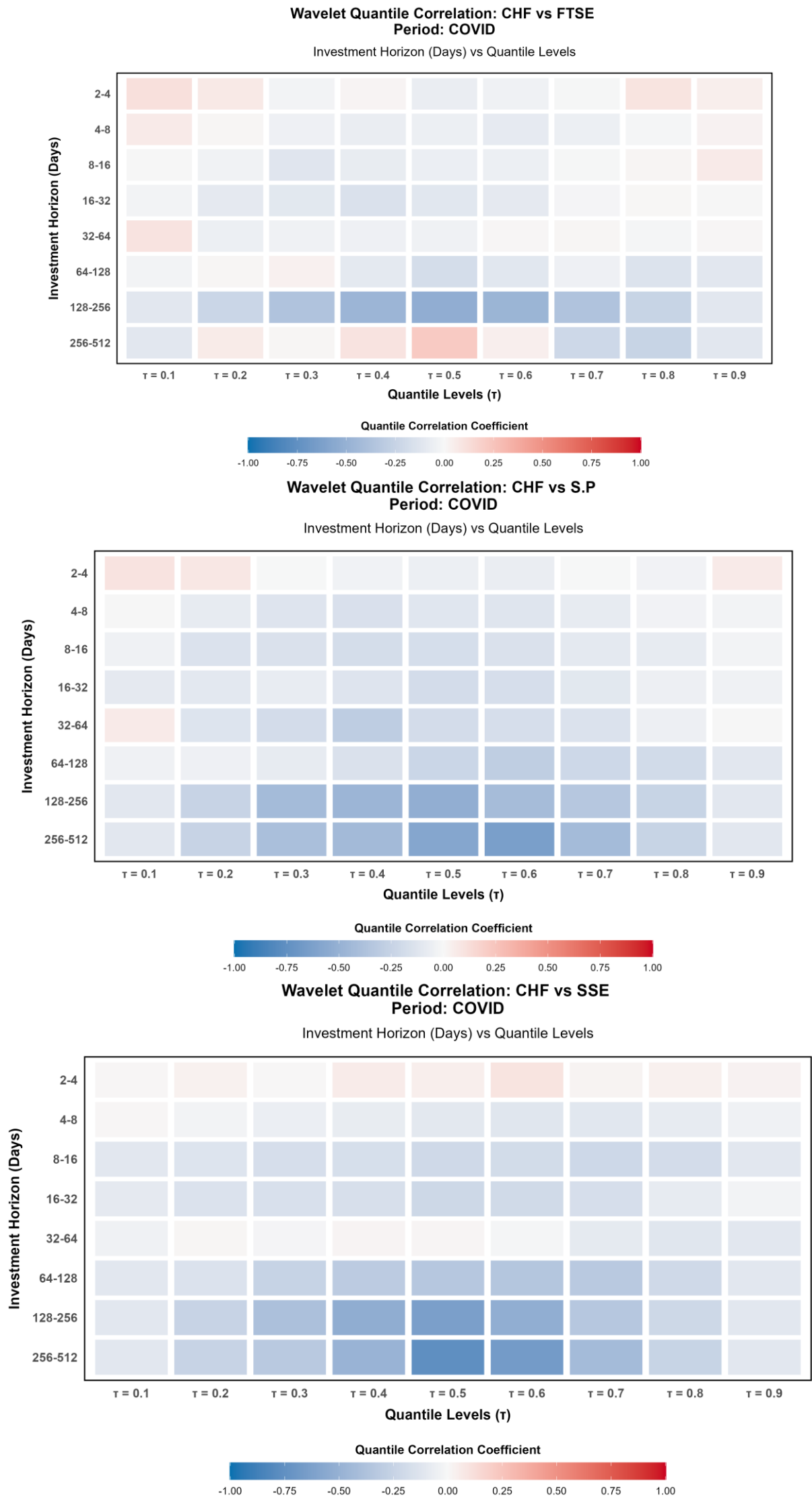
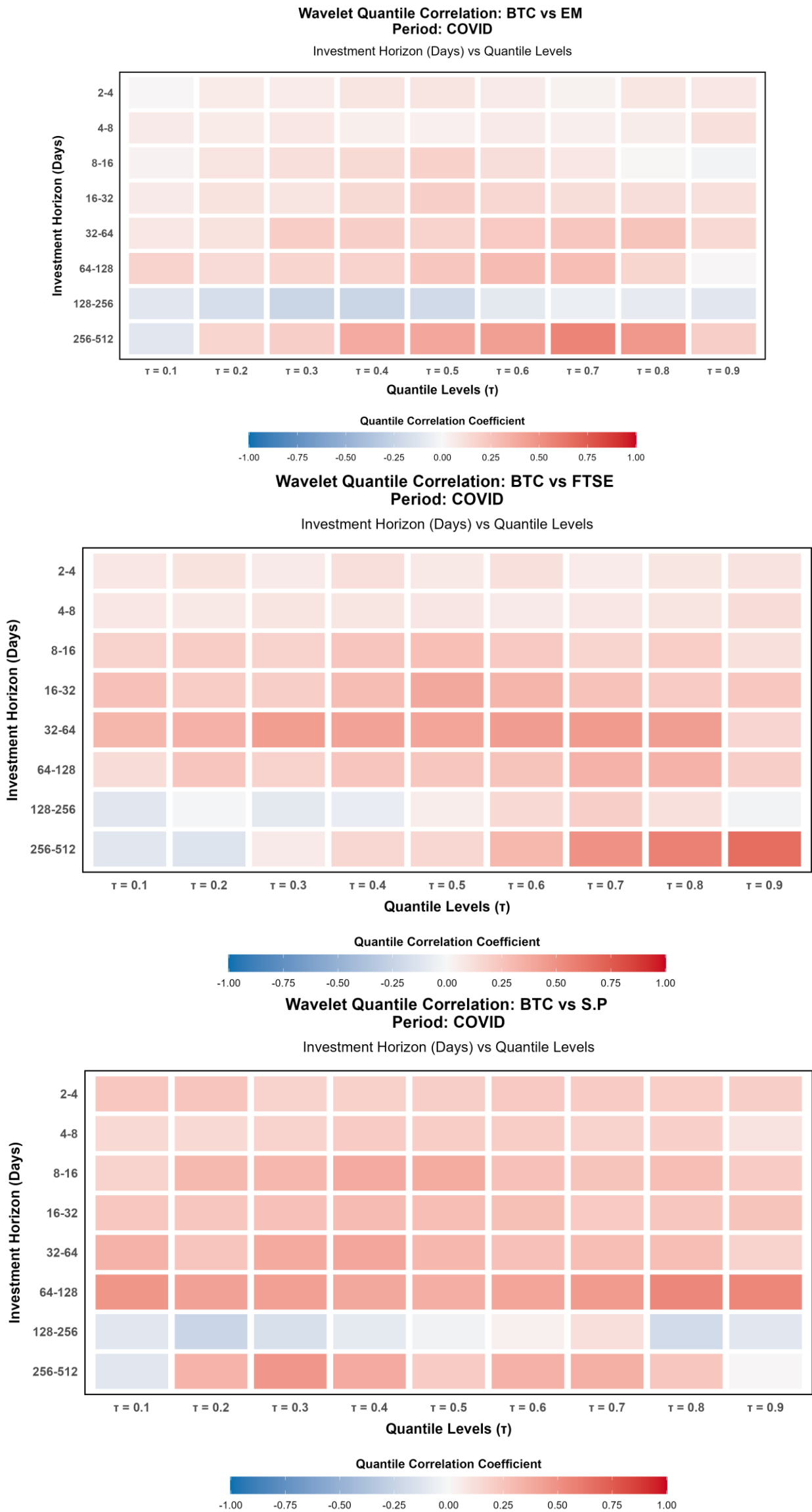


Figure 5. Wavelet Quantile Correlation between Swiss Franc and equities during the COVID- 19 period.



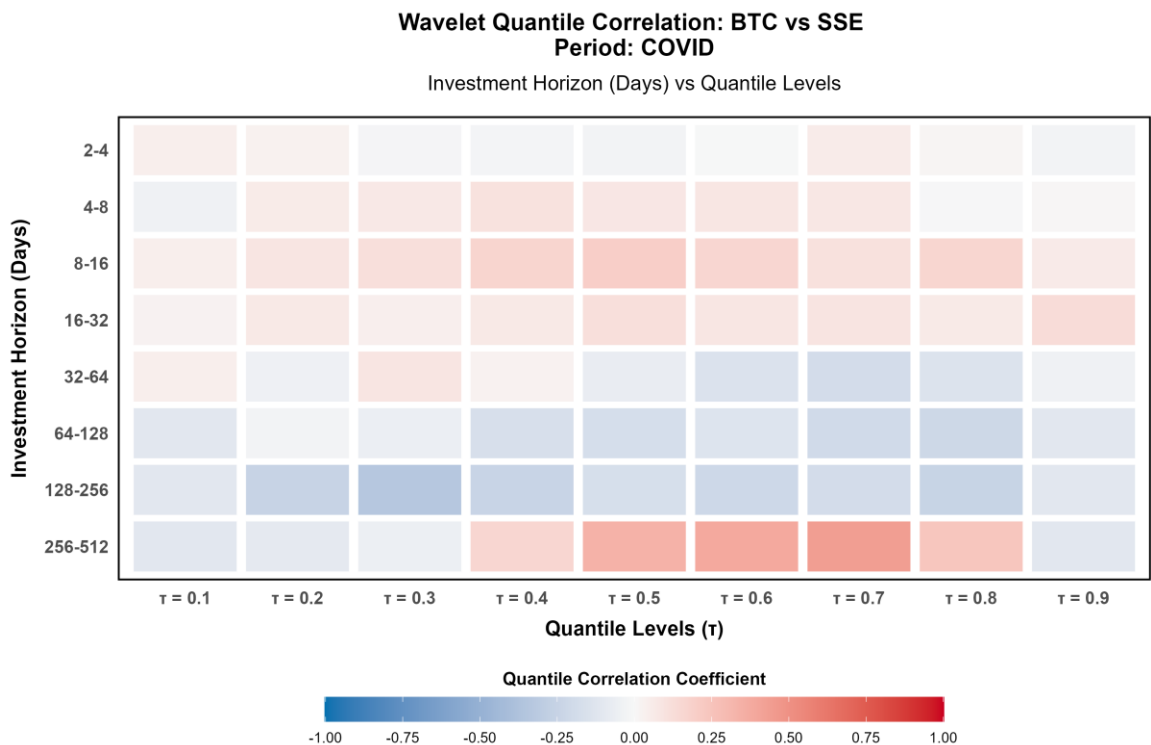


Figure 6. Wavelet Quantile Correlation between Bitcoin and equities during the COVID- 19 period.

4.2.1.2. WQC in Russia-Ukraine

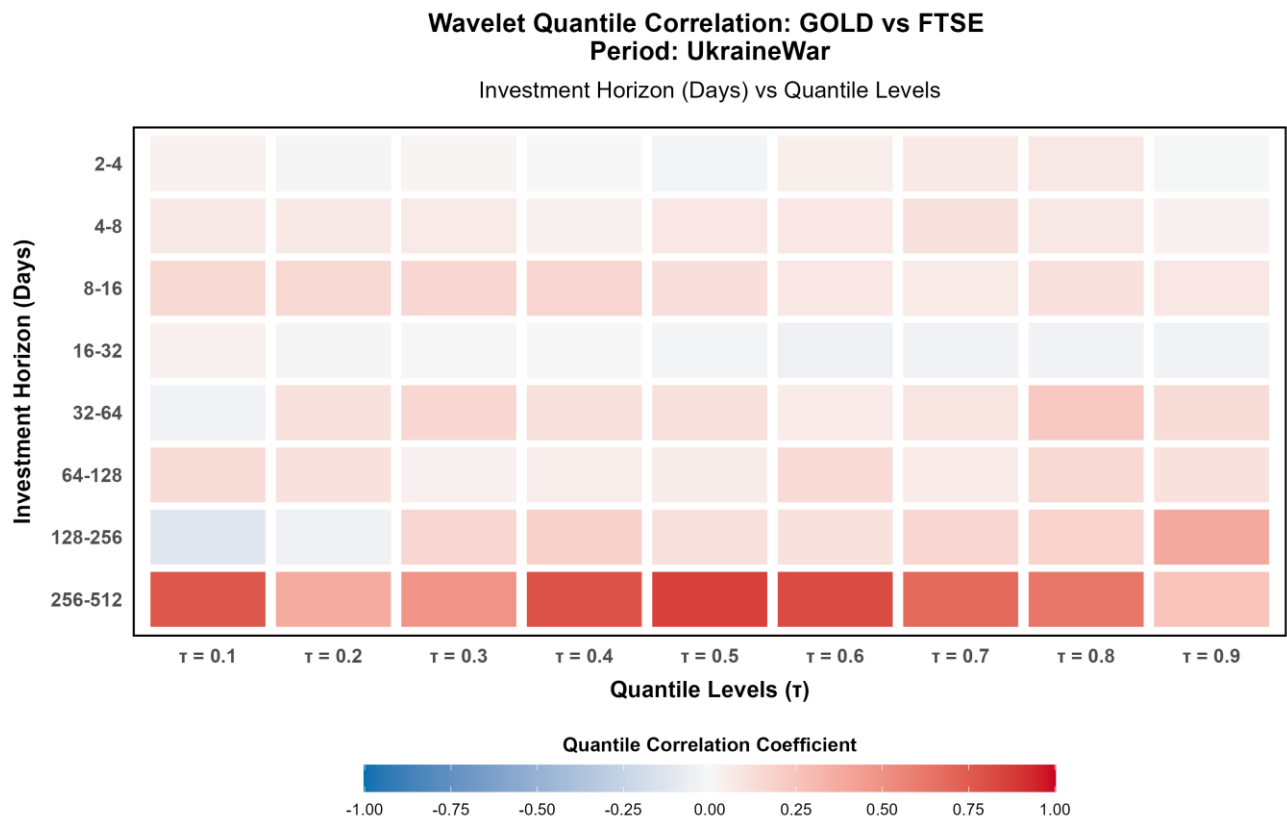
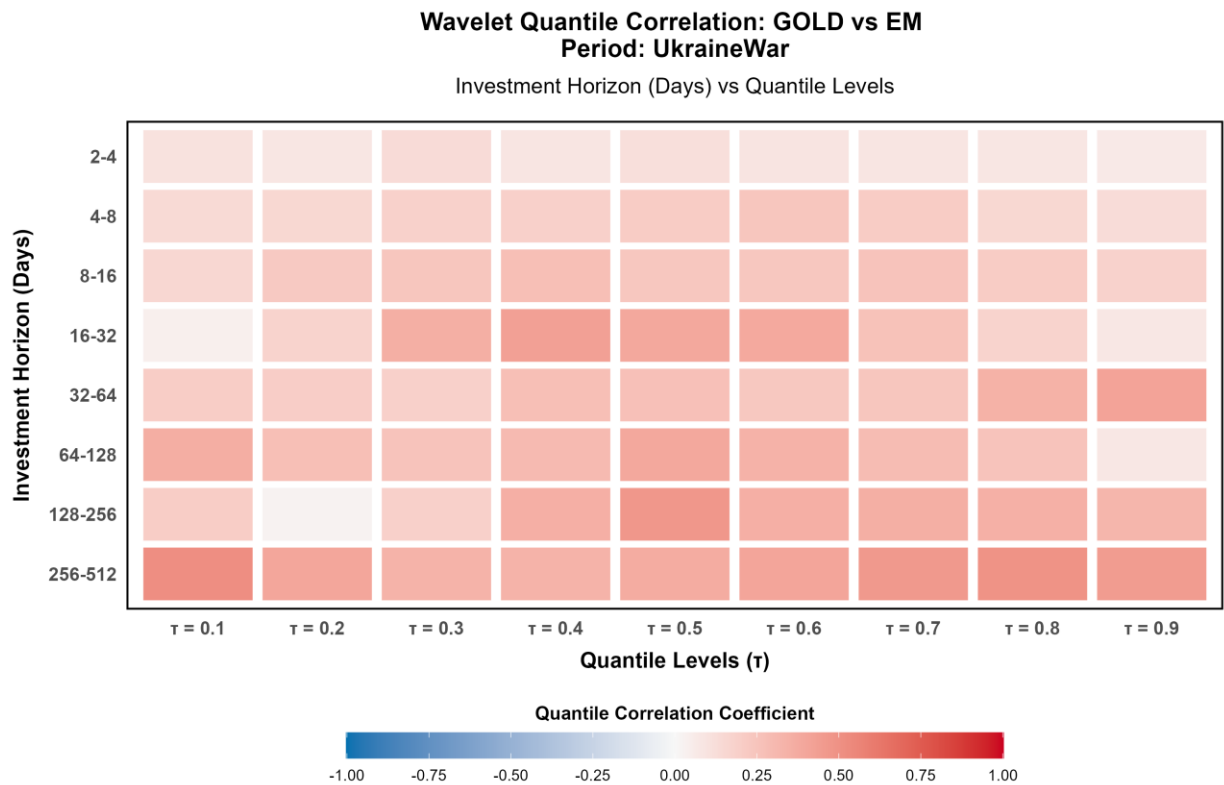
In the ongoing geopolitical crisis, Gold failed to exhibit consistent safe haven properties across the sampled markets. Its lower-quantile correlations weakened relative to the COVID-19 period, indicating a reduced ability to provide downside protection during extreme market stress. This deterioration aligns with the inflationary environment, where rising bond yields increased the opportunity cost of holding non-yielding assets such as gold. Consequently, its traditional store-of-value role appears partially weakened. Empirically, Gold only demonstrated safe haven behavior for the Shanghai Composite Index in China, and strictly in the long-term horizon (Figure 7), highlighting its market-specific and horizon-dependent effectiveness with no meaningful short- or medium-term benefits.

U.S. Treasuries also showed a decline in safe haven effectiveness compared to the pandemic period, supporting the notion of a structural shift in their role. This is consistent with Zhang (2025), who identified a regime change following the Federal Reserve’s April 2022 rate hikes. The resulting changes in yield dynamics weakened their typical inverse relationship with equities, a shift further confirmed by the Bai-Perron structural break test. As shown in Figure 8, Treasuries failed to act as a safe haven in the US, emerging, and Chinese markets, but retained limited effectiveness in the UK at short (2–4 days) and long-term (128–256 days) horizons.

The Swiss Franc (Figure 9) displayed a mixed but relatively resilient profile. It acted as a weak safe haven in the short and medium terms but strengthened in the long term for the S&P 500. It remained weak in the UK and China, yet served as a consistent safe haven for emerging markets across all horizons, reinforcing its role as a global risk-off currency.

Bitcoin (Figure 10) did not function as a safe haven in any sampled market. Its positive association with equities indicates that it behaved more like a speculative asset than a defensive instrument, offering diversification benefits at best rather than reliable protection during periods of stress.

These findings resonate with recent empirical research examining safe haven assets during crises. Akhtaruzzaman et al. (2021) documented that during crises, gold lost its safe haven status for most equity markets except China, consistent with the finding that gold only protected the Shanghai Composite and only in the long term. Będowska-Sójka, Demir, and Zaremba (2022) examined the Russia-Ukraine conflict and similarly found that gold's hedging properties were highly market-specific and time-varying, failing to provide consistent protection across developed markets. The result that US Treasuries only served as a haven for the UK in specific frequency bands aligns with Cheema, Faff, and Szulczyk (2022), who found that US Treasury bonds exhibited asymmetric safe haven properties during the pandemic, providing protection only in certain markets and horizons, and who documented that the relationship between stocks and bonds is regime-dependent and not reliably negative during crises. The Swiss Franc's performance as a haven for the S&P 500 supports the findings of Feder-Sempach et al. (2024). The finding that Bitcoin failed as a refuge due to positive equity correlations during geopolitical crises is in line with those who found that Bitcoin behaved more like a speculative asset than a safe haven during crises, contrary to earlier claims of its diversification benefits.



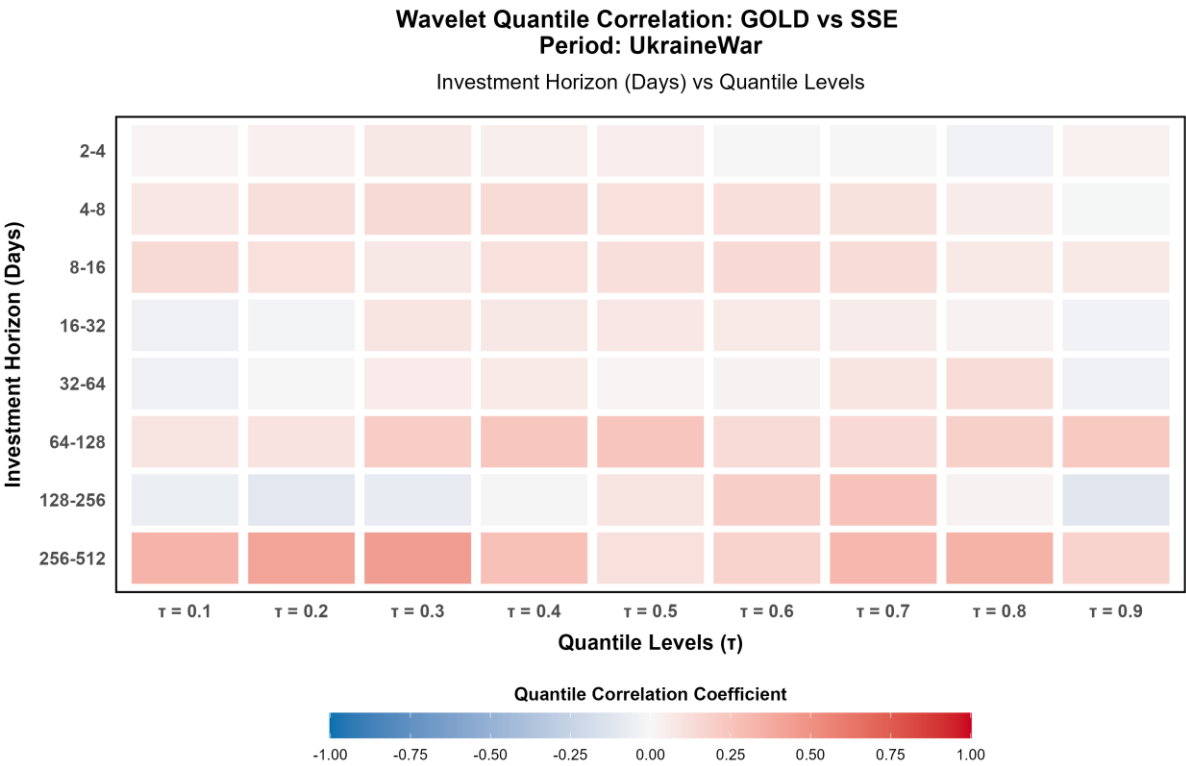
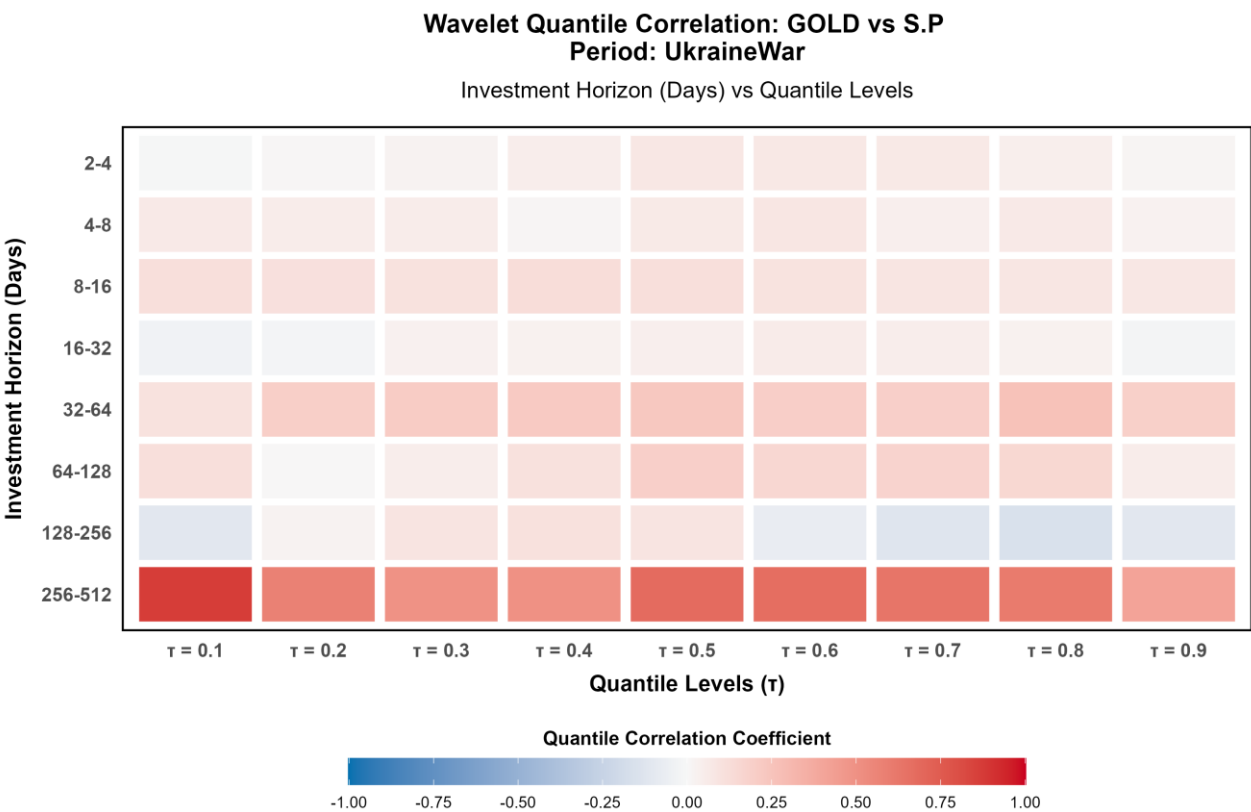
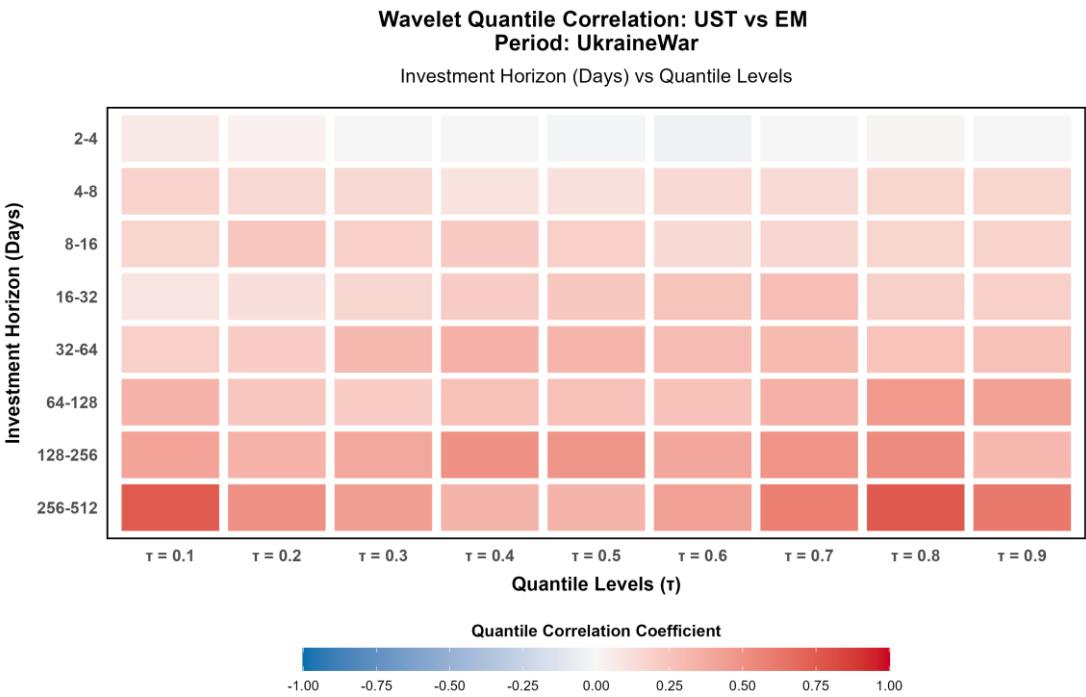
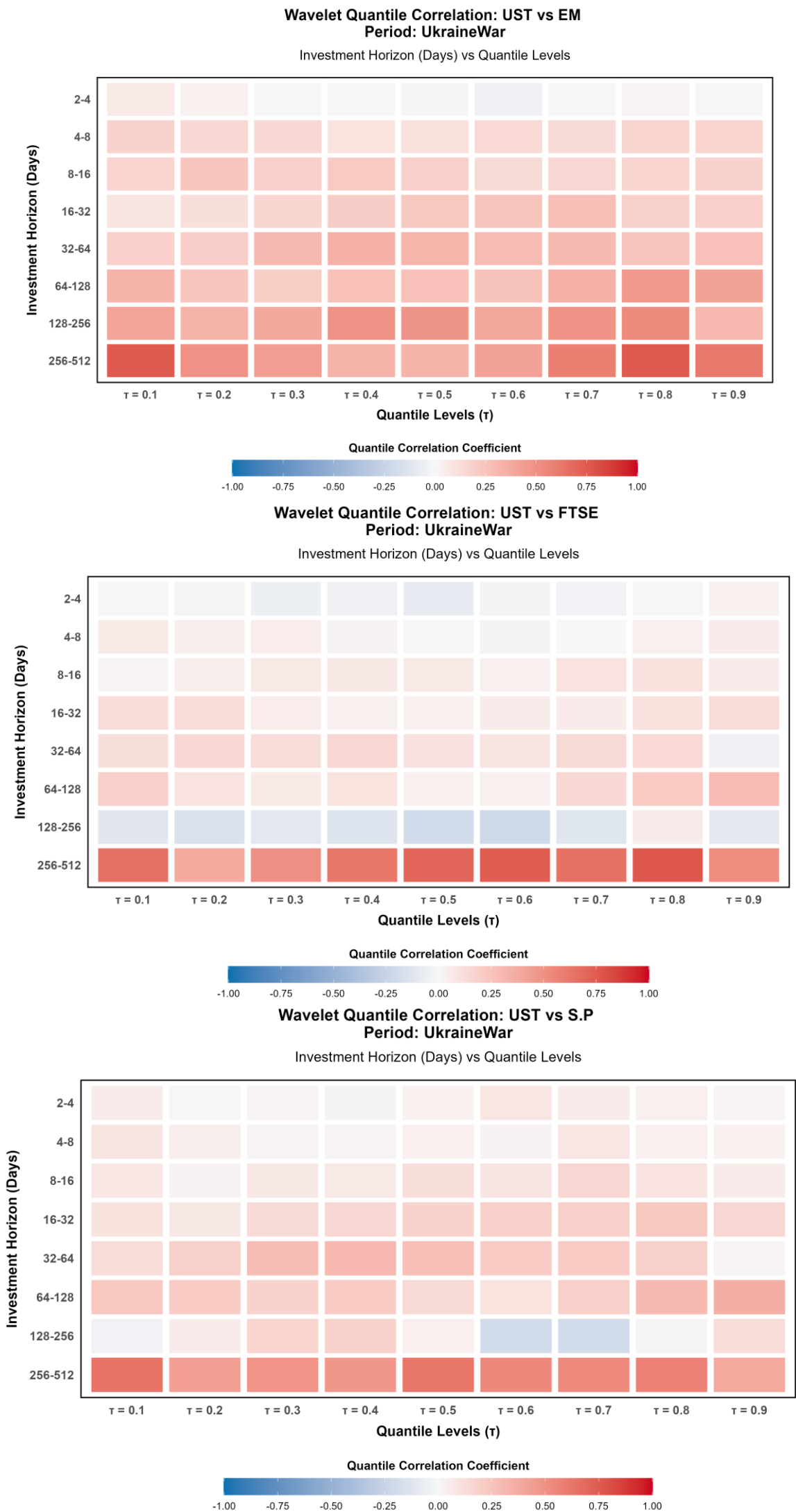


Figure 7. Wavelet Quantile Correlation between Gold and equities during the Russia-Ukraine war period.





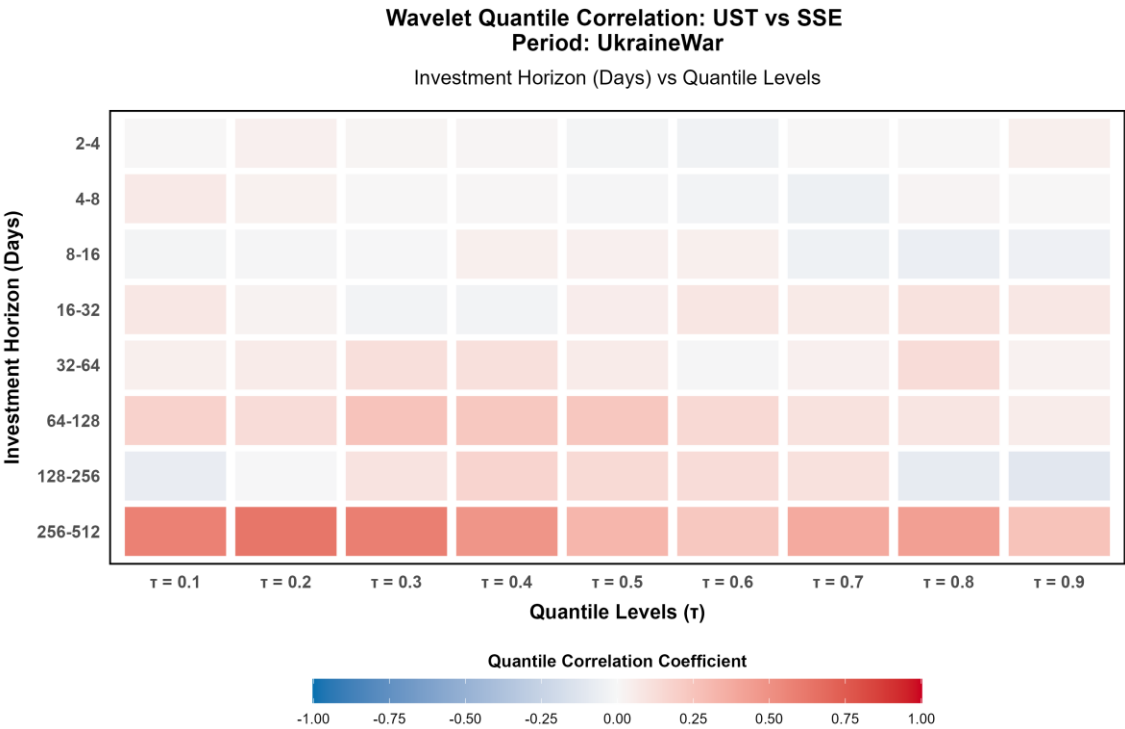
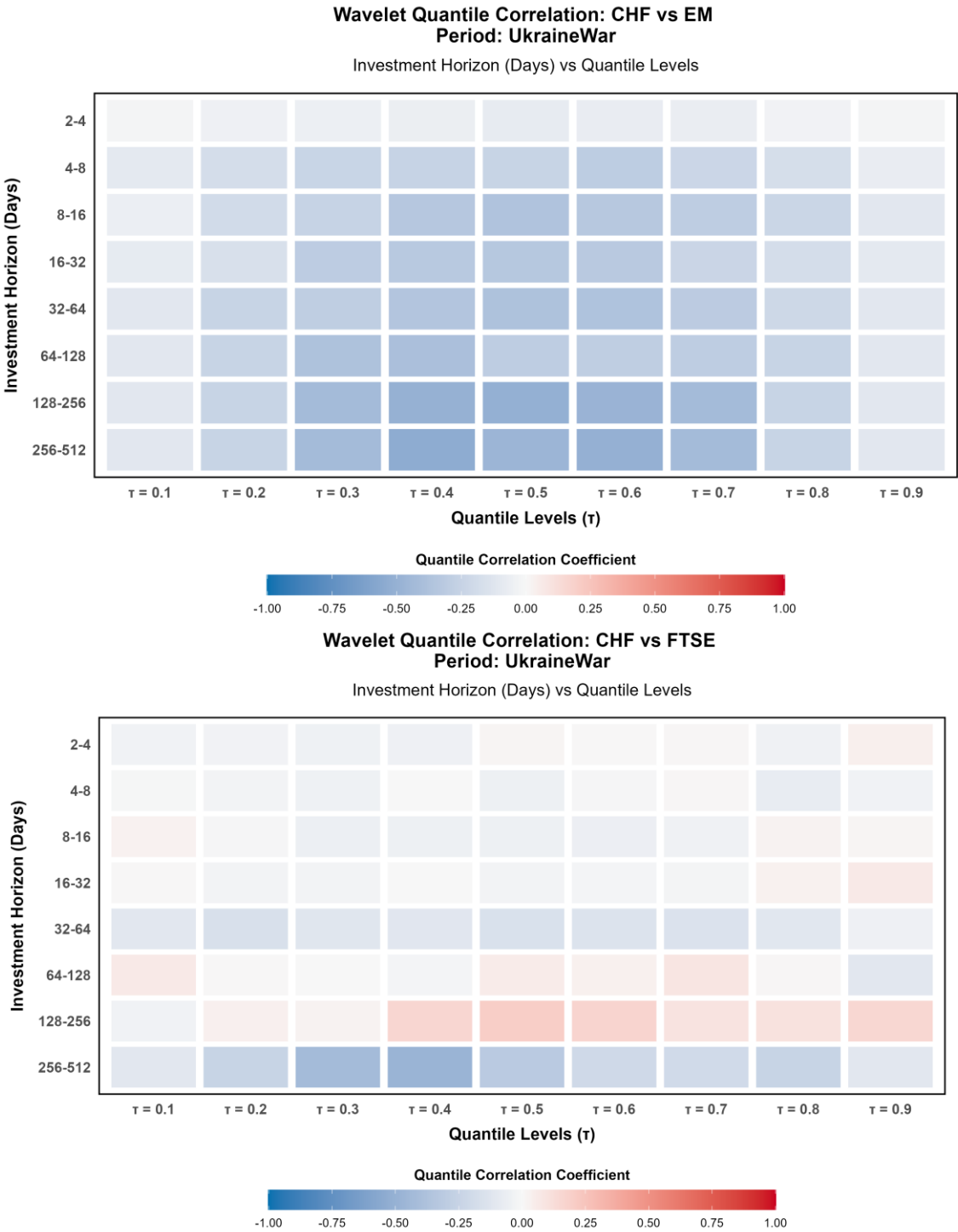


Figure 8. Wavelet Quantile Correlation between US Treasury and equities during the Russia-Ukraine war period.



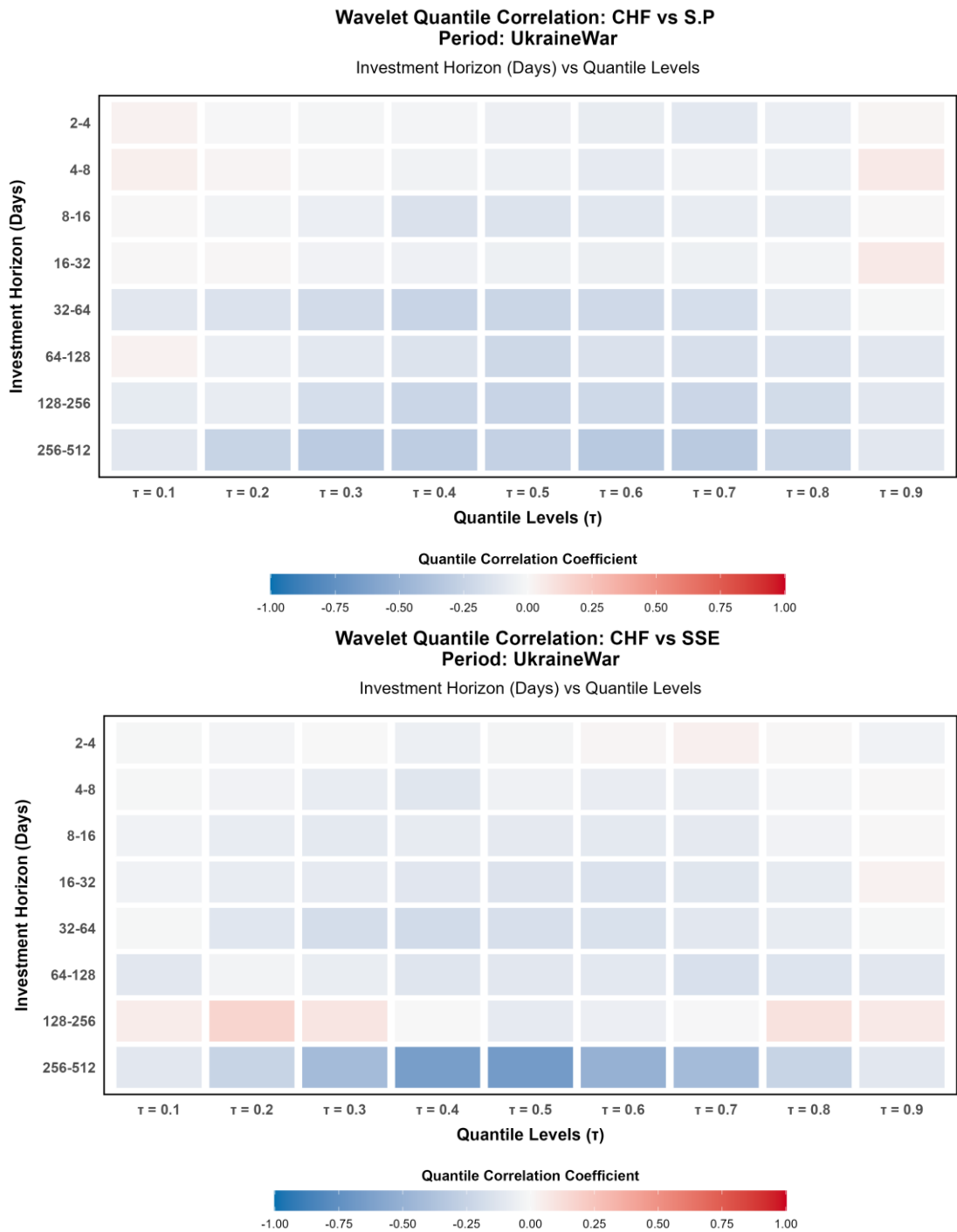
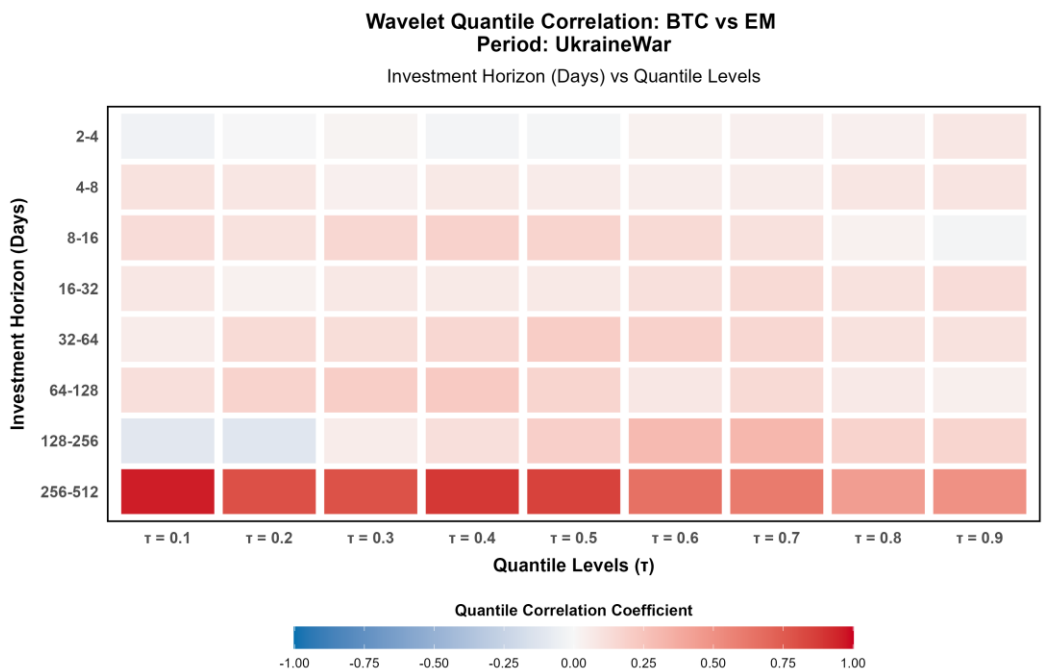


Figure 9. Wavelet Quantile Correlation between Swiss Franc and equities during the Russia-Ukraine war period.



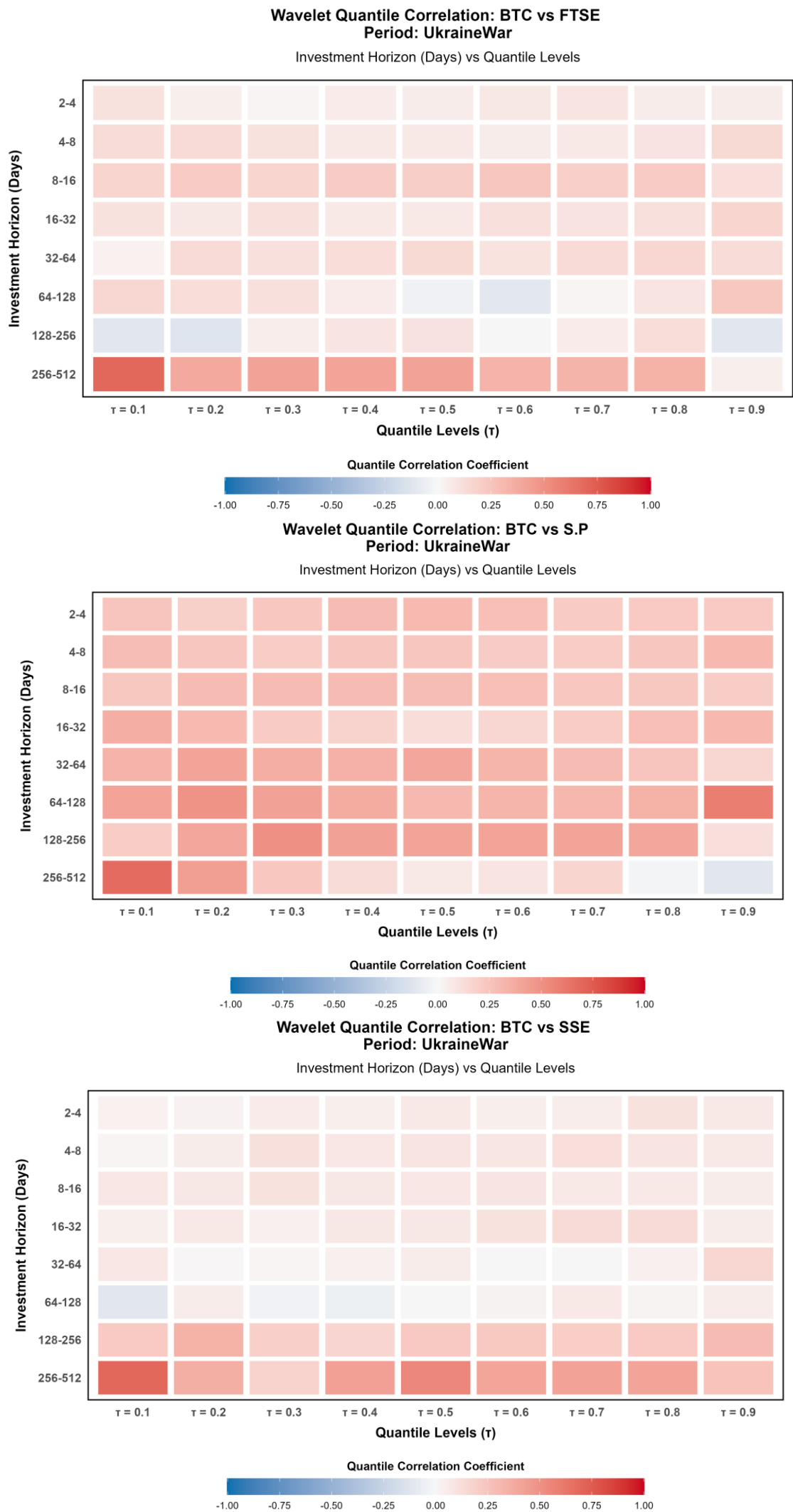


Figure 10. Wavelet Quantile Correlation between Bitcoin and equities during the Russia-Ukraine war period.

4.2.2. Connectedness Analysis

4.2.2.1. COVID

The connectedness matrix in Table 5 identifies a clear hierarchy of influence, with the S&P 500 and FTSE equity indices serving as the dominant net transmitters of shocks, posting positive net values of 20.97 and 13.20,

respectively. This confirms their role as primary drivers of volatility within the global financial system, meaning disturbances in these markets tend to propagate outward to other assets. In contrast, the Shanghai Composite (SSE), Swiss Franc (CHF), and Gold are the largest net receivers, with negative net values of -9.08, -9.75, and -6.34, indicating they are primarily shock absorbers that react to turmoil originating elsewhere rather than causing it. Bitcoin sits in a unique position as a near-neutral net receiver (-0.88), suggesting it operates with a degree of independence despite its high idiosyncratic volatility. US Treasuries (UST) also function as a marginal net receiver (-1.02), reinforcing their status as a relatively stable asset that is influenced by, but does not drive, broader market movements.

It is important to emphasize that the connectedness results should not be interpreted as direct evidence for or against safe-haven status. The TVP-VAR connectedness measures capture statistical interdependence and forecast-error variance attributable to each variable, not directional causal transmission. Factors exogenous to the model, including global monetary policy cycles, liquidity conditions, and central bank interventions, may simultaneously affect multiple assets, generating elevated co-movement that could be misattributed to direct shock transmission. The connectedness results are therefore interpreted as complementary to, not as the basis for, the safe-haven classification derived from WQC.

The S&P 500, as seen in Figure 11, is the primary transmitter of shocks, sending 67.09% to others, while receiving 46.11%, reflecting its deep integration. The FTSE is similarly influential, transmitting 61.87% and receiving the joint-highest amount at 48.67%, making it the most interconnected asset. Emerging Markets (EM) transmit 41.55% and receive 48.67%, positioning them as major recipients of shocks from developed markets. US Treasuries (UST) transmit only 32.5% and receive 33.52%, which means it was a net receiver in the health crisis. Gold transmits a low 25.16% and receives 31.5%, acting as a shock absorber. The Swiss Franc (CHF) transmits 24.87% and receives 34.61%, making it a net receiver. Bitcoin (BTC) transmits 28.1% and receives 28.99%, indicating it is largely driven by its own dynamics. Finally, the Shanghai Composite (SSE) receives 33.74% and transmits 24.66%, making it a net receiver with limited influence on others.

Table 5. Average total connectedness in the COVID-19 period.

Series	GOLD	UST	CHF	BTC	S&P	FTSE	EM	SSE	FROM
GOLD	68.50	6.64	7.95	4.05	3.75	3.30	2.95	2.87	31.50
UST	3.81	66.48	6.90	1.78	5.59	8.32	3.98	3.14	33.52
CHF	7.91	8.50	65.39	1.69	6.38	4.60	4.45	1.08	34.61
BTC	2.99	0.99	1.03	71.01	12.74	7.59	2.01	1.64	28.99
S&P	1.98	3.41	1.14	9.98	53.89	19.36	6.51	3.74	46.11
FTSE	1.75	5.76	1.04	5.25	19.90	51.33	11.04	3.92	48.67
EM	3.98	4.50	5.12	3.04	11.41	12.34	51.33	8.28	48.67
SSE	2.74	2.69	1.69	2.31	7.32	6.36	10.63	66.26	33.74
TO	25.16	32.50	24.87	28.10	67.09	61.87	41.55	24.66	305.81
Inc.Own	93.66	98.98	90.25	99.12	120.97	113.20	92.88	90.92	cTCI/TCI
NET	-6.34	-1.02	-9.75	-0.88	20.97	13.20	-7.12	-9.08	43.69/38.23
NPT	1	3	3	5	7	6	1	2	

Note: TO and FROM denote directional spillovers transmitted and received, respectively; NET denotes net spillovers (TO – FROM); NPT denotes net pairwise transmission ranking; Inc.Own denotes connectedness including own effects; TCI denotes the Total Connectedness Index; and cTCI denotes the corrected Total Connectedness Index.

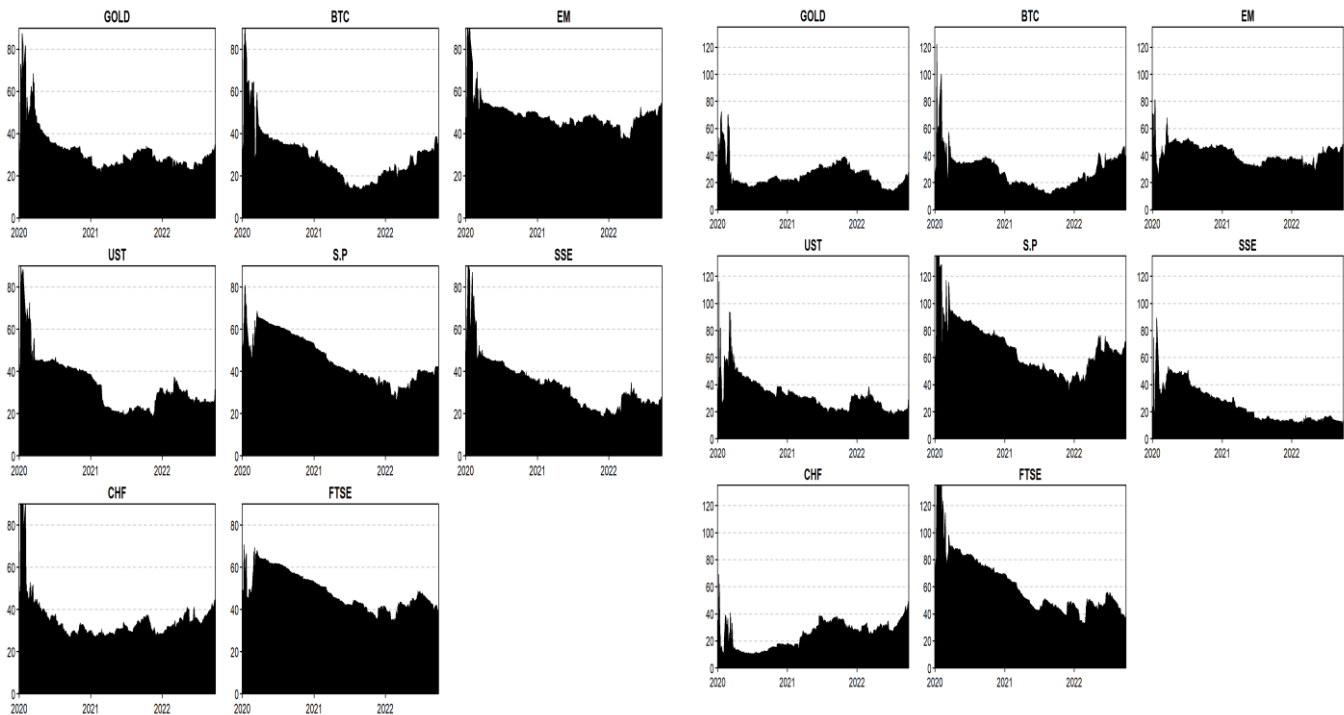


Figure 11. FROM & TO Connectedness during COVID-19 period.

4.2.2.2. Total Connectedness Analysis

The connectedness analysis in Figure 12 reveals a moderate level of integration among the assets, with a Total Connectedness Index (TCI) of 38.23%, indicating that while spillovers exist, a significant portion of asset movements remain idiosyncratic. The TCI indicates that, on average, approximately 38% of the 10-step-ahead forecast error variance of each variable can be attributed to innovations in the other variables in the system. This level of co-

movement is moderate, implying that a substantial portion of each asset’s return variation remains idiosyncratic and not explained by the shared dynamics of the system.

It should be noted that the TCI does not distinguish between contagion, defined as the transmission of financial distress across markets, and the reflection of common underlying fundamentals such as the global monetary policy cycle. During the COVID-19 period, both the pandemic shock and the Federal Reserve’s near-zero interest rate policy were exogenous shocks that simultaneously affected all assets in the system, which would inflate the measured co-movement independently of any direct cross-asset shock transmission. The results should accordingly be interpreted as descriptive of statistical interdependence in the system rather than as evidence of structural causal channels.

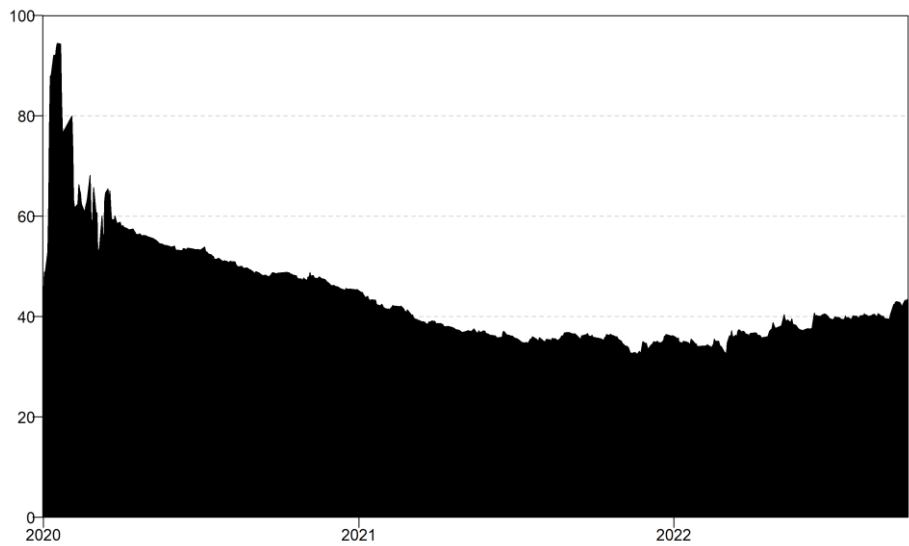


Figure 12. Total Connectedness Index During Covid-19 Period.

4.2.2.3. Net Pairwise Directional Connectedness

Figure 13 presents the Net Pairwise Directional Connectedness (NPDC) network where arrows indicate the direction of spillovers and edge thickness reflects the strength of shock transmission. The S&P 500 (S.P) emerges as the main net transmitter, sending strong spillovers to assets such as the Swiss Franc (CHF), Emerging Markets (EM), and the Shanghai Stock Exchange (SSE), indicating the dominant influence of the U.S. equity market. The FTSE also contributes to shock transmission, particularly toward CHF and SSE. In contrast, EM, Gold, and SSE mainly act as net receivers as several shocks converge toward them, with EM especially absorbing shocks from developed markets. U.S. Treasuries (UST) display mixed roles, transmitting and receiving shocks within the network. Overall, the results suggest that developed equity markets drive spillover transmission while emerging markets and some safe haven assets primarily absorb these shocks.

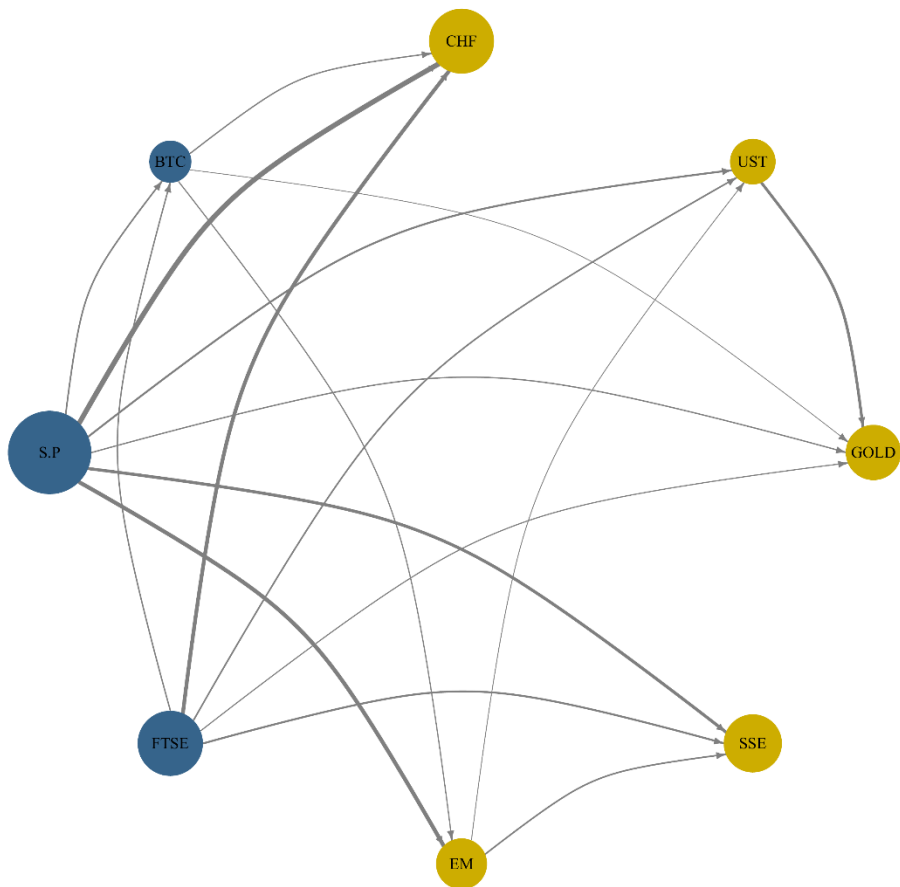


Figure 13. Time-Network plot During Covid-19 Period.

4.2.2.4. Russia-Ukraine

From Table 6, the Swiss Franc (CHF) emerges as the most significant transmitter of shocks, sending 51.07% to other assets, while receiving a substantial 40.82%, indicating its central role in propagating volatility within this system. The S&P 500 is another major transmitter at 50.30%, though it receives a relatively lower 35.34%, confirming its influence as a net driver of global markets, as evidenced by Figure 14. In contrast, Emerging Markets (EM) are the largest receivers, importing 44.68% from others while transmitting only 32.61%, positioning them as primary shock absorbers. The Shanghai Composite (SSE) is the most insulated asset, receiving the least (20.31%) and transmitting the least (14.23%), suggesting it operates with relative independence from the global system. Gold and US Treasuries (UST) show near-balanced profiles, receiving 32.32% and 33.59% while transmitting 30.97% and 32.80% respectively, acting as net recipients. Bitcoin (BTC) receives the least after SSE (26.28%) and transmits a modest 23.36%, reinforcing its idiosyncratic nature.

Table 6. Average total connectedness in the Russia-Ukraine war period.

Series	GOLD	UST	CHF	BTC	S&P	FTSE	EM	SSE	FROM
GOLD	67.68	8.09	11.04	1.68	2.99	2.78	4.64	1.11	32.32
UST	8.95	66.41	14.67	1.99	3.19	2.26	2.05	0.48	33.59
CHF	8.69	11.89	59.18	2.66	7.74	3.06	6.00	0.78	40.82
BTC	2.27	2.25	3.07	73.72	13.18	3.78	0.79	0.96	26.28
S&P	1.73	1.98	6.89	10.69	64.66	8.64	3.75	1.66	35.34
FTSE	1.70	1.78	2.79	3.16	13.00	68.43	6.21	2.93	31.57
EM	6.41	5.95	11.34	2.22	7.03	5.42	55.32	6.31	44.68
SSE	1.22	0.87	1.27	0.97	3.17	3.64	9.18	79.69	20.31
TO	30.97	32.8	51.07	23.36	50.3	29.57	32.61	14.23	264.91
Inc.Own	98.65	99.21	110.25	97.08	114.96	98.00	87.94	93.92	cTCI/TCI
NET	-1.35	-0.79	10.25	-2.92	14.96	-2	-12.06	-6.08	37.84/33.11
NPT	4	3	5	2	7	5	2	0	

Note: TO and FROM denote directional spillovers transmitted and received, respectively; NET denotes net spillovers (TO – FROM); NPT denotes net pairwise transmission ranking; Inc.Own denotes connectedness including own effects; TCI denotes the Total Connectedness Index; and cTCI denotes the corrected Total Connectedness Index.

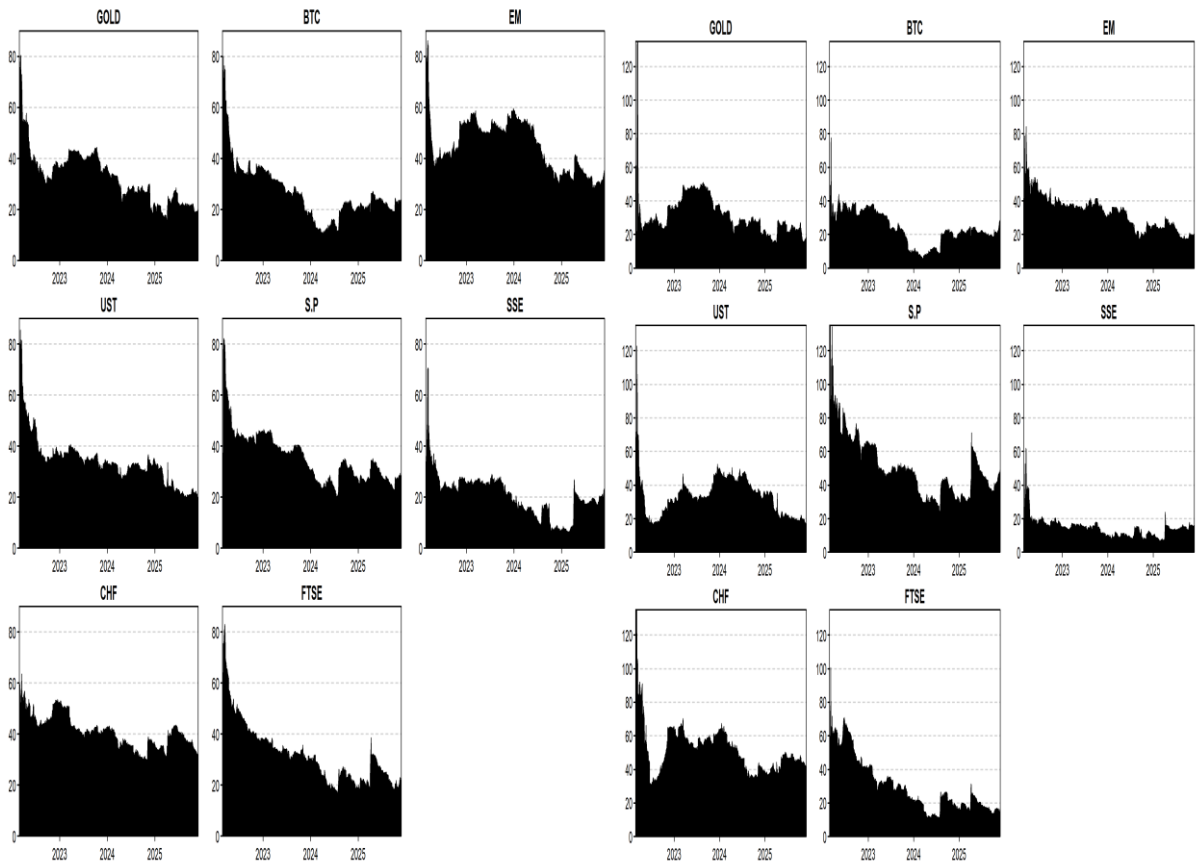


Figure 14. FROM & TO Connectedness during Russia-Ukraine war period.

4.2.2.5. Total Connectedness Index

The Total Connectedness Index (TCI) shown by Figure 15 stands at 33.11%, which is relatively moderate and slightly lower than that of the COVID period. This value suggests that while spillovers exist between assets, approximately two-thirds of the forecast error variance is explained by idiosyncratic shocks, indicating a moderately integrated but not highly interconnected financial system. The TCI is slightly lower than during COVID-19, suggesting that the Russia-Ukraine conflict generated somewhat less synchronized cross-asset co-movement than the pandemic, a plausible result given that the geopolitical conflict had more regionally concentrated direct effects, whereas the pandemic was a universal shock affecting all economies simultaneously.



Figure 15. Total Connectedness Index During Russia-Ukraine War Period.

4.2.2.6. Net Pairwise Directional Connectedness

The network plot in Figure 16 illustrates the Net Pairwise Directional Connectedness (NPDC) among the assets, where the direction of the arrows represents the direction of shock transmission and the thickness of the edges reflects the magnitude of spillovers between markets. The S&P 500 (S.P) clearly emerges as the dominant net transmitter, sending shocks to several assets including Bitcoin (BTC), FTSE, Emerging Markets (EM), U.S. Treasuries (UST), and Gold, indicating that disturbances in the U.S. equity market propagate widely across both equity and safe-haven assets. The Swiss Franc (CHF) also plays a transmitting role with spillovers directed toward assets such as UST and EM, suggesting that movements in this traditional safe-haven currency influence other markets during the sample period. In contrast, Emerging Markets (EM) act largely as a net receiver, with multiple arrows particularly from S.P and UST, indicating that it absorbs shocks from major global financial markets. Likewise, Gold, the Shanghai Stock Exchange (SSE), and FTSE display more incoming than outgoing links, implying that they function primarily as shock recipients rather than transmitters. Overall, the NPDC structure highlights that developed markets and key safe-haven currencies drive the transmission of shocks, while emerging and some regional equity markets predominantly absorb these spillovers, underscoring the dominant role of the U.S. market in global cross-asset risk transmission.

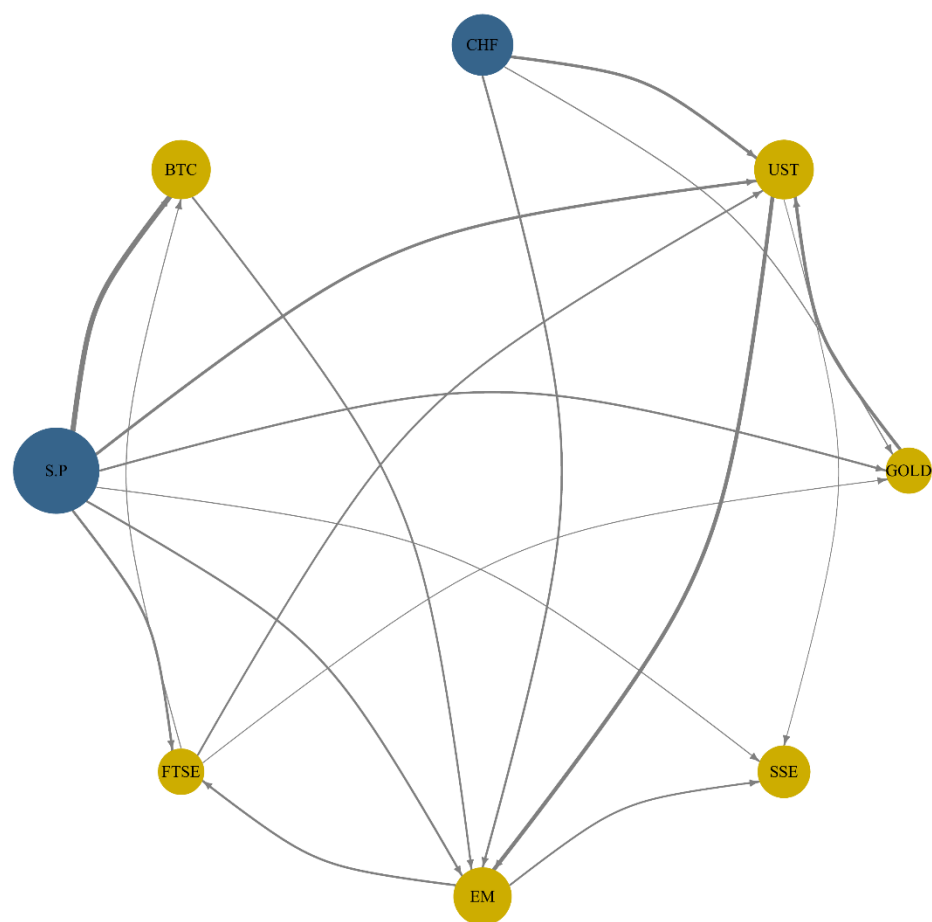


Figure 16. Time-Network plot during the Russia-Ukraine war period.

The connectedness results reported above align with, but also complicate, the accumulating empirical record on volatility transmission during systemic shocks, and two patterns merit closer scrutiny against recent literature: the identity of dominant transmitters and receivers, and the regime shift observed in the Swiss franc. The finding that the S&P 500 and FTSE 100 acted as the principal net transmitters during COVID-19, while gold, the Swiss franc, and the Shanghai Composite absorbed shocks, largely confirms earlier TVP-VAR evidence. Adekoya and Oliyide (2021), using a comparable TVP-VAR and causality-in-quantiles design on commodity and financial assets during the pandemic, similarly identified gold and the US dollar as consistent net receivers rather than transmitters of volatility, attributing this to the flight-to-quality behavior that pulls capital into store-of-value assets during equity sell-offs. The present result therefore extends this evidence to an African equity market context, showing that the receiver status of gold documented in developed and commodity markets also holds when the shock-generating markets are large developed equity indices rather than commodity-financial pairs. The near-neutral role of Bitcoin is broadly consistent with, but not identical to, findings elsewhere in the cryptocurrency-connectedness literature, where Bitcoin's systemic role has been shown to be markedly heterogeneous and regime-dependent rather than fixed, shifting between receiver and transmitter status depending on the sample window and the assets included in the network (Ha, 2023). This refines rather than contradicts prior evidence: Bitcoin's connectedness role appears to be genuinely unstable across studies, and the near-neutral finding here is one realization of that instability rather than an outlier.

The shift of the Swiss franc from net receiver during COVID-19 to the most significant net transmitter during the Russia-Ukraine war is the most theoretically interesting finding, and it extends rather than confirms existing evidence. Prior connectedness studies covering both crisis periods have documented exactly this kind of asset-role instability across shocks of different geographic and structural character. Rubbaniy, Khalid, Syriopoulos, and Polyzos (2024), applying TVP-VAR connectedness to global assets across both the COVID-19 pandemic and the Russia-Ukraine war, found that the systemic roles of energy and soft commodities changed materially between the two episodes, with portfolio hedge effectiveness proving stable for some assets and highly variable for others depending on which crisis was examined. Although their asset set differs from the present study, the underlying message is the same: connectedness roles are shock-specific rather than fixed asset characteristics, and a single crisis period is an unreliable basis for generalizing an asset's systemic position. The present finding therefore extends this literature by identifying the specific mechanism, geographic proximity to a regionally concentrated conflict, as a plausible driver of the Swiss franc's reversal, a channel that is consistent with, though not directly tested in, the broader connectedness-instability literature. Relatedly, the result that MSCI Emerging Markets was the largest net receiver during the Russia-Ukraine war corroborates evidence from the geopolitical risk literature specifically focused on emerging economies. Agyei (2023) examined the E7 emerging equity markets (Brazil, China, India, Indonesia, Mexico, Russia, and Turkey) during the same conflict using wavelet coherence and TVP-VAR connectedness, and found that these markets were consistently net receivers of geopolitical risk shocks rather than transmitters, a pattern the author interpreted as reflecting emerging markets' relatively shallower liquidity and weaker informational efficiency relative to developed markets. This is directly consistent with the present finding and reinforces the interpretation that emerging equity markets, including African markets by extension, tend to occupy a structurally subordinate position in global shock transmission networks during geopolitically driven crises. It is worth noting, however, that this pattern is not universal: El Khoury, Nasrallah, Hussainey, and Assaf (2023) studying FinTech, ESG, and MSCI indices during the same war, found that MSCI indices were net transmitters rather than receivers in their emerging-market subsample, and this divergence suggests that whether emerging equity benchmarks transmit or receive shocks may depend on the composition of the connectedness network and the specific comparator assets included, a qualification that should temper any claim of a universal emerging-market receiver status.

The moderate TCI of 38.23% during COVID-19 relative to 33.11% during the Russia-Ukraine war is consistent with the broader empirical distinction between systemically uniform and regionally concentrated shocks. This pattern echoes findings in the wider spillover literature, where studies directly comparing the two crisis periods have generally reported higher aggregate connectedness during the pandemic, reflecting its simultaneous, non-selective disruption of global demand and liquidity, compared with the more geographically bounded transmission channels activated by the Russia-Ukraine war (Rubbaniy et al., 2024). The present TCI differential therefore refines this literature by providing further asset-specific quantitative support for the view that shock scope, rather than shock magnitude alone, is a key determinant of aggregate network connectedness.

4.2.3. Comparison Across Crisis Regimes

Comparing the WQC and connectedness results across the two crisis regimes yields three substantive insights that the full-sample analysis would obscure. First, the supply-side, inflationary nature of the Russia-Ukraine shock systematically eroded the safe-haven effectiveness of both gold and U.S. Treasuries relative to the pandemic period. Rising real interest rates increased the opportunity cost of non-yielding assets like gold, while the positive stock-bond correlation that prevails in inflationary environments undermined Treasuries' diversification benefit, a regime shift explicitly documented for the post-April 2022 Treasury market by Zhang (2025) and consistent with this study's structural break findings.

Second, the Swiss franc was the only asset to maintain or strengthen its safe-haven profile across both crises, reinforcing its relative resilience during periods of heightened uncertainty. Its TVP-VAR connectedness position also changed notably across the two crises, shifting from a net receiver of shocks during COVID-19 (net value: -9.75) to a net transmitter during the Russia-Ukraine war (net value: +10.25). Within the TVP-VAR framework, this change indicates that the Swiss franc became relatively more influential in the transmission of return spillovers during the geopolitical crisis compared with the pandemic period. A possible explanation is that the geographically concentrated nature of the Russia-Ukraine conflict increased the sensitivity of European currency markets to movements in the Swiss franc. However, these results should be interpreted as evidence of dynamic connectedness rather than structural causality. More broadly, the findings suggest that the network role of a safe-haven asset may vary across crisis types, particularly between systemic global shocks and geographically concentrated geopolitical events.

Third, Bitcoin's positive equity co-movement and absence of safe-haven properties was consistent across both crises and all markets, providing strong evidence against the conditional safe-haven narrative for Bitcoin in the current market regime, and suggesting that its earlier classification as a diversifier (pre-2020) has not been restored following the pandemic-era financialization of crypto markets.

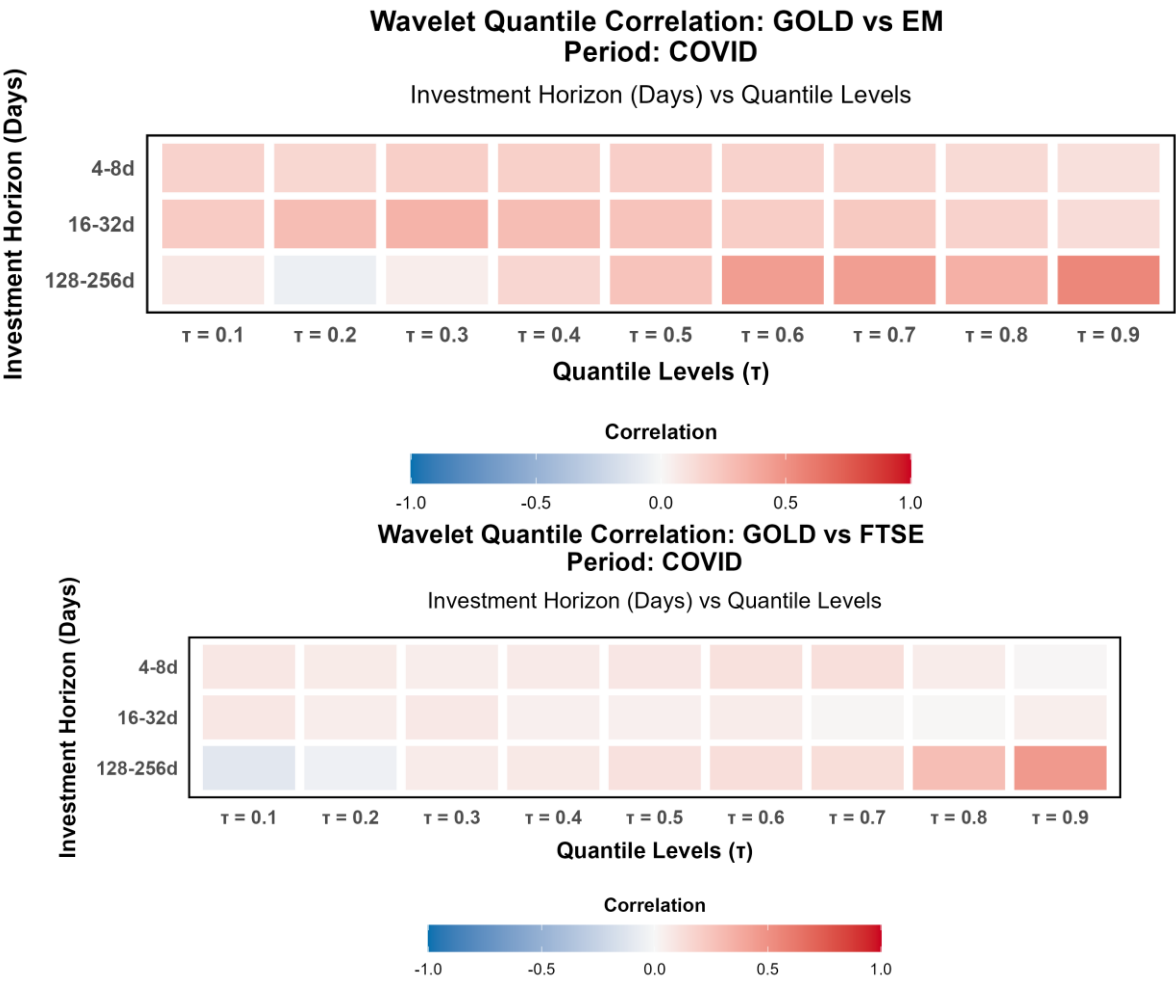
5. Robustness of Findings

The robustness of the main findings is assessed through three complementary exercises: an alternative wavelet family specification, alternative lag order specifications for the TVP-VAR, and non-overlapping crisis window checks.

5.1. Alternative Wavelet Family (Daubechies D4)

To verify that the WQC results are not specific to the LA8 wavelet specification, the analysis is replicated using the Daubechies D4 wavelet, which is a four-coefficient filter with higher frequency resolution but less smoothness than LA8. The D4 specification represents a meaningfully different trade-off between time and frequency localization. We followed Kumar and Padakandla (2022) to extract information at the scales of 4–8 days, 16–32 days, and 128–256 days to roughly capture the behavior across one trading week, one trading month, and one trading year. Across the majority of asset-market pairings and both crisis sub-samples, the qualitative results are preserved (Figures 17–24). Gold exhibits safe-haven properties for Chinese equities at specific frequency bands during COVID-19 (Figure 17); U.S. Treasuries satisfy the safe-haven criterion for UK equities (Figure 18); and the Swiss franc shows broader negative lower-tail correlations (Figure 19). However, an important qualification emerges: Bitcoin marginally satisfies the negative lower-tail correlation criterion at long-term horizons (128–256 days) during the COVID-19 period under the D4 specification, whereas it did not under the baseline LA8 specification (Figure 20).

This discrepancy reflects genuine sensitivity to the time-frequency localization trade-off: the D4 filter assigns more spectral weight to higher-frequency components, which can alter the estimated correlation structure at the longest decomposition levels. This result does not overturn the overall finding that Bitcoin fails as a safe haven; it applies only to one horizon band under one wavelet specification during one crisis, and is not replicated during the Russia–Ukraine period (Figures 21–24). This sensitivity has been incorporated into the conclusion section to ensure full transparency.



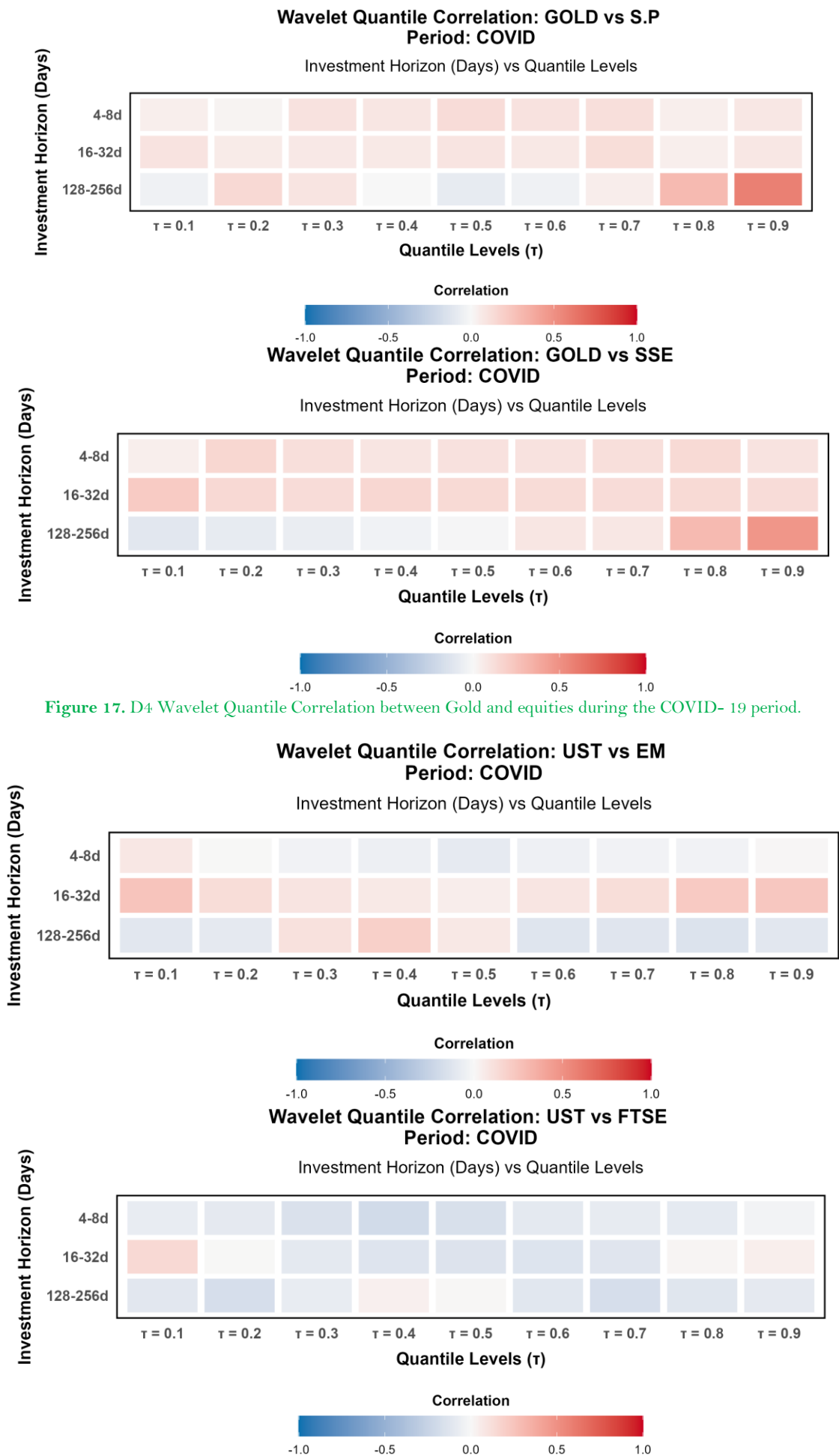


Figure 17. D4 Wavelet Quantile Correlation between Gold and equities during the COVID- 19 period.

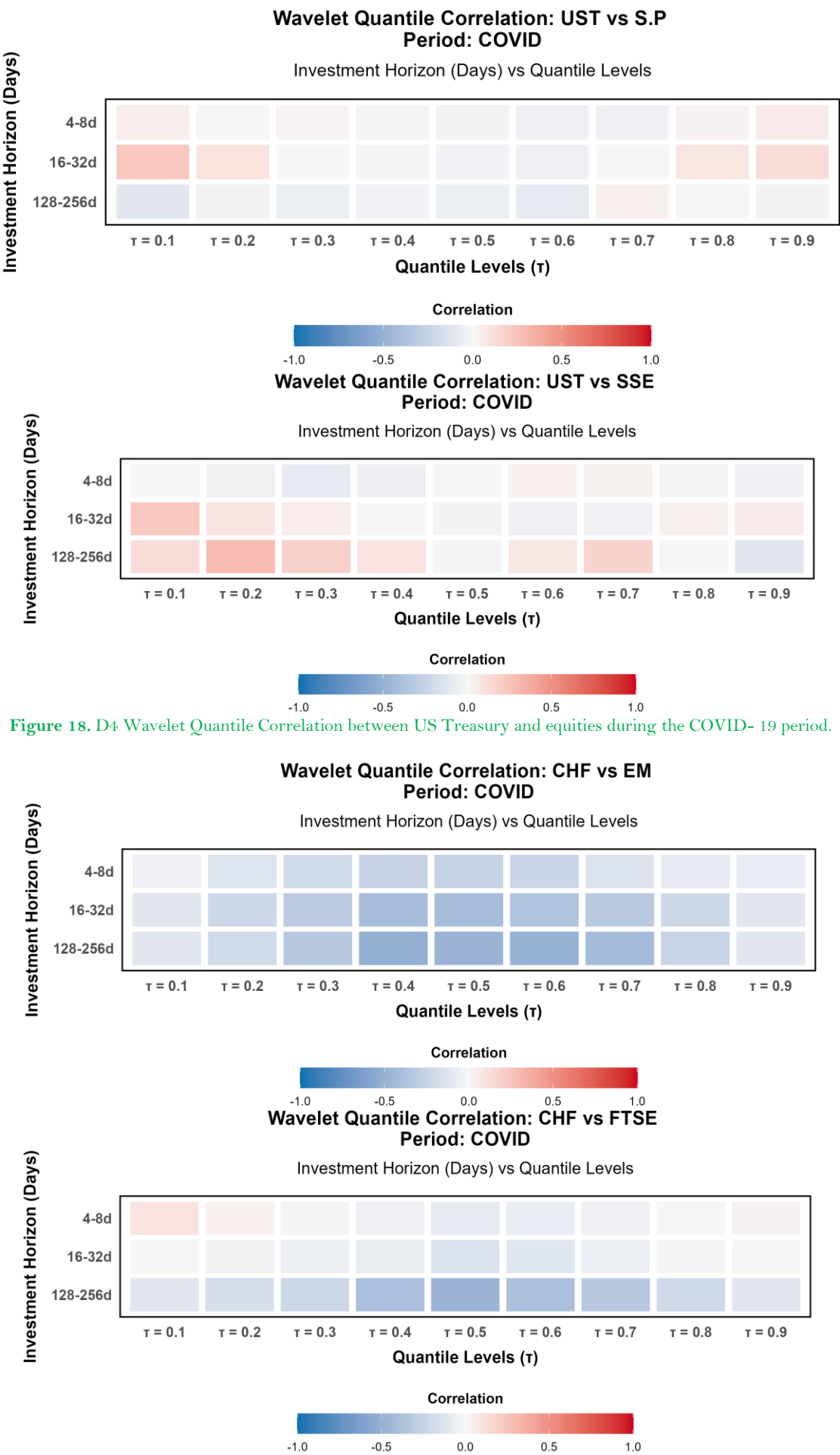


Figure 18. D4 Wavelet Quantile Correlation between US Treasury and equities during the COVID- 19 period.

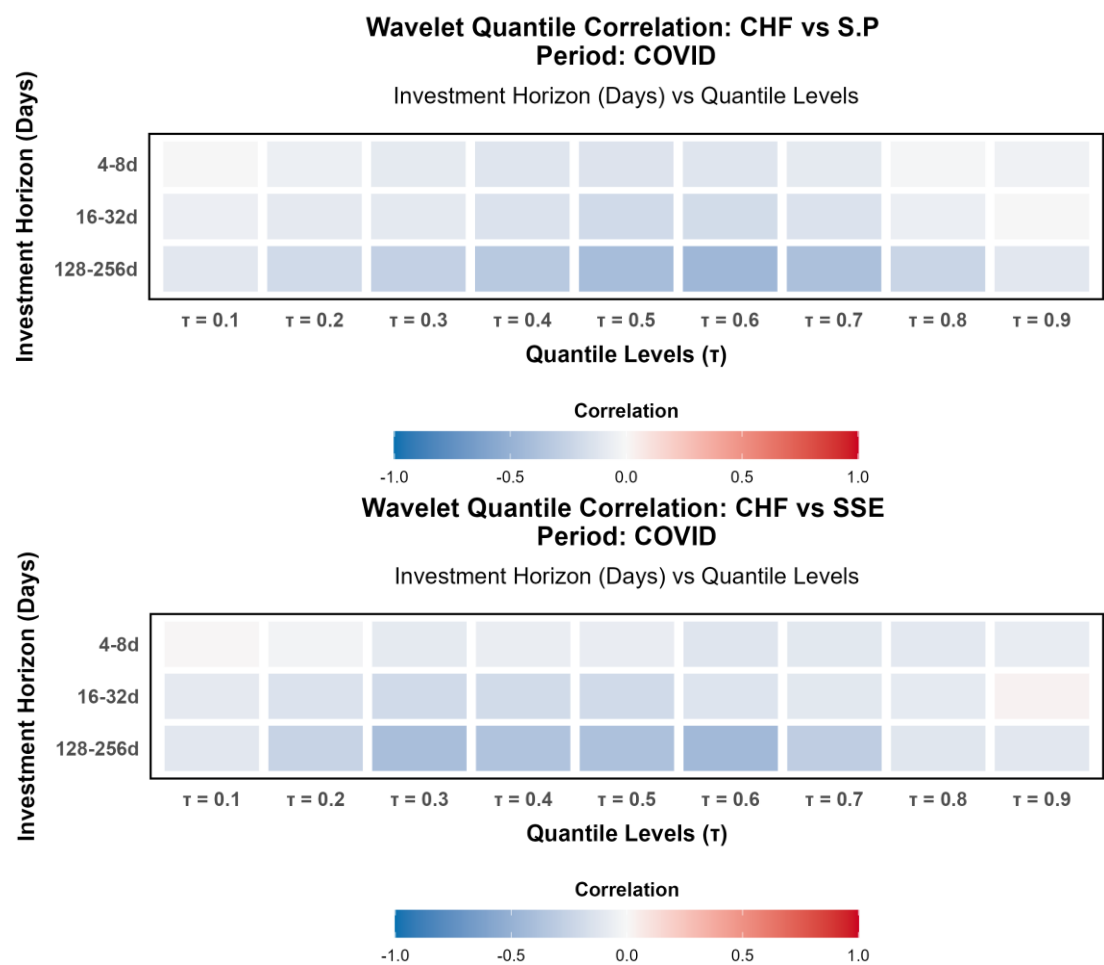
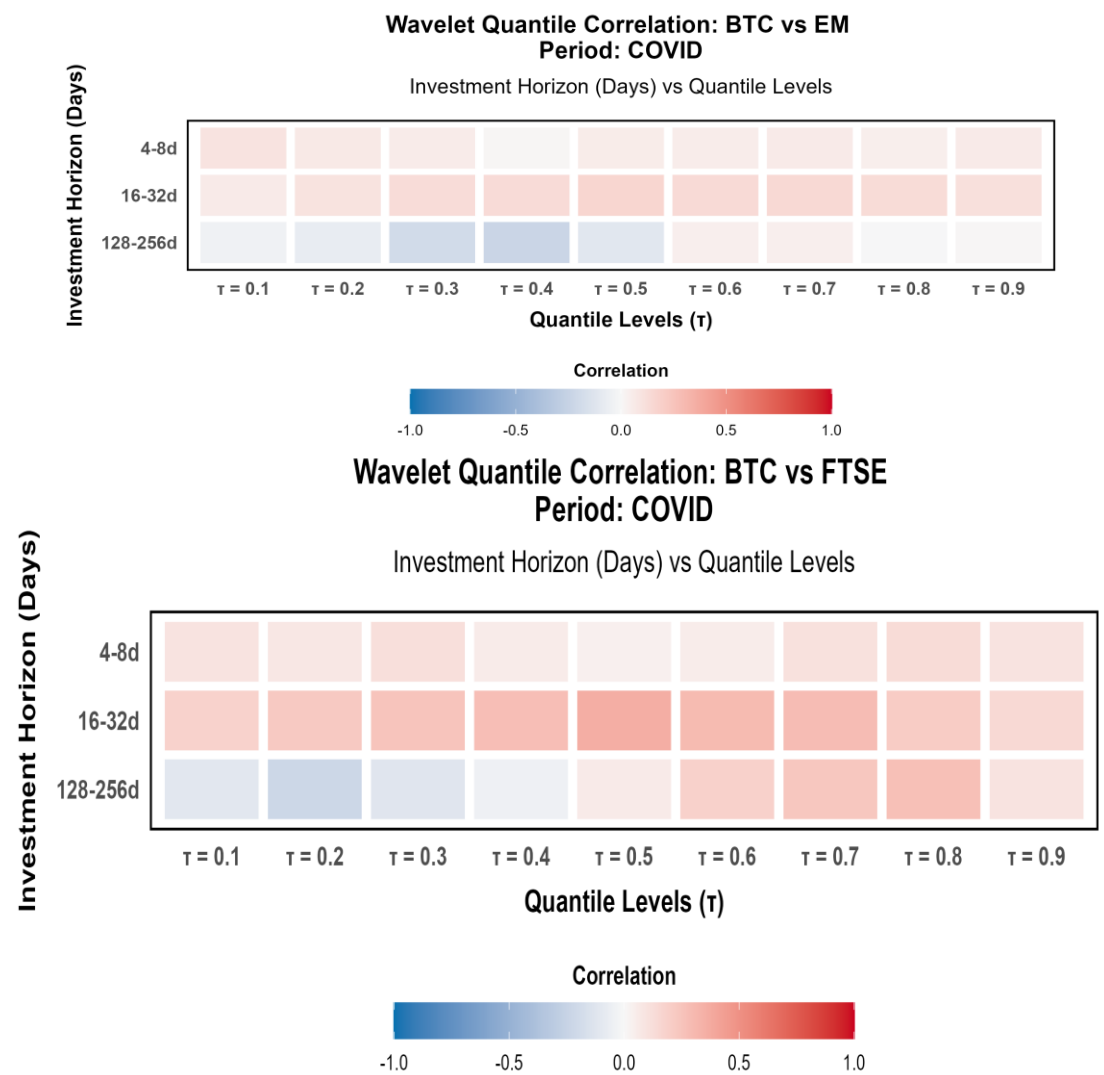
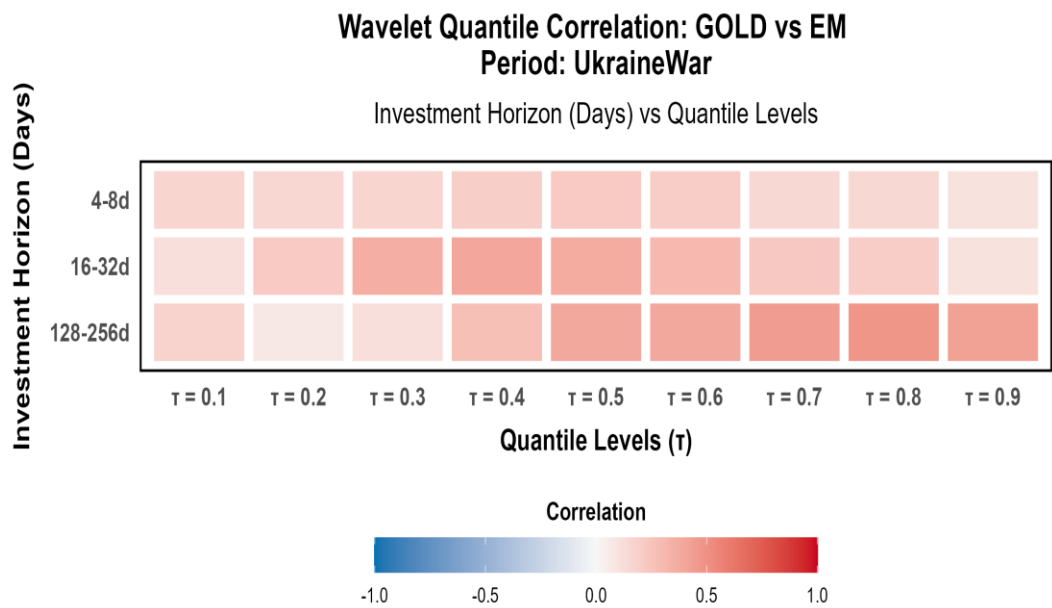
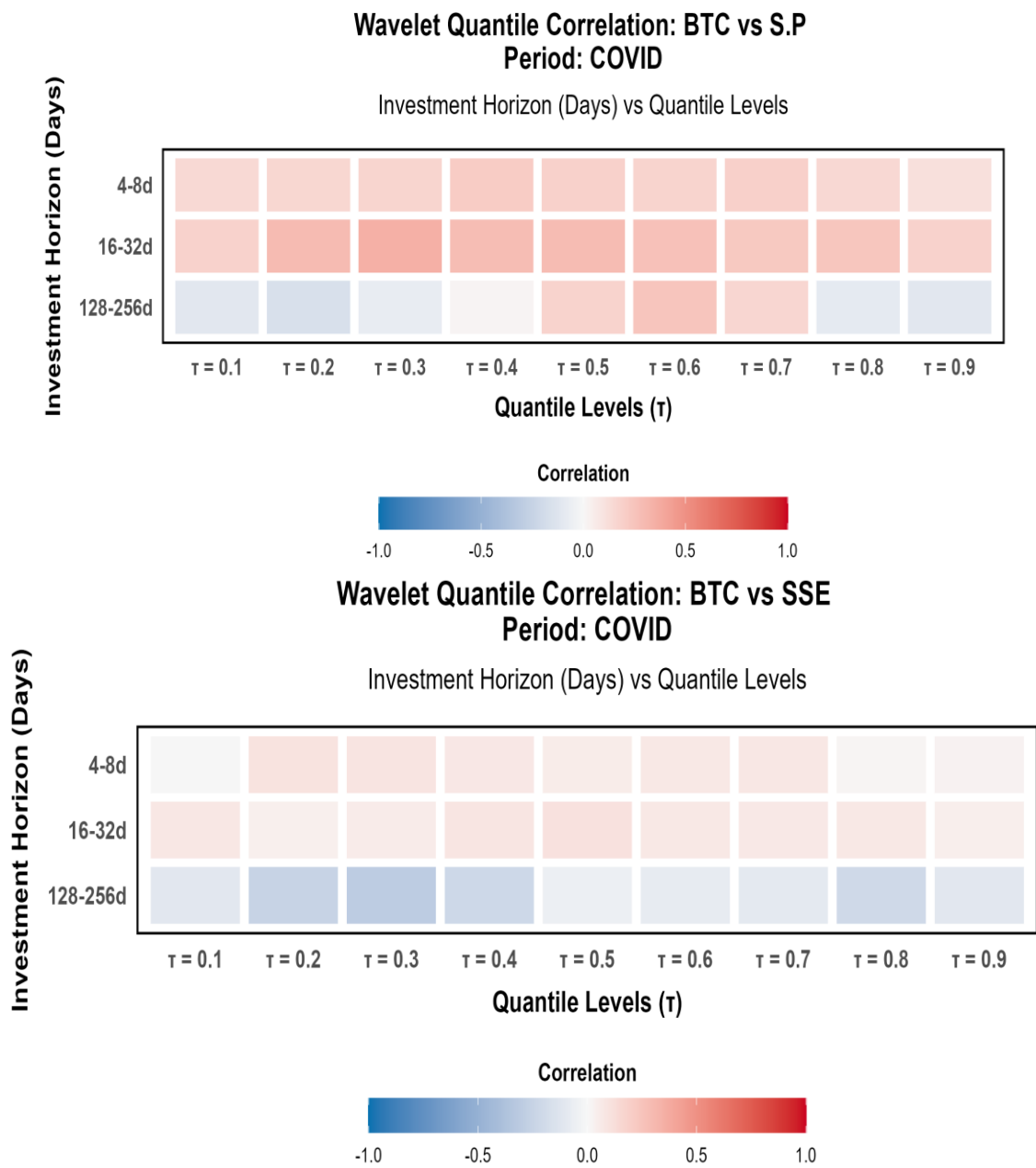
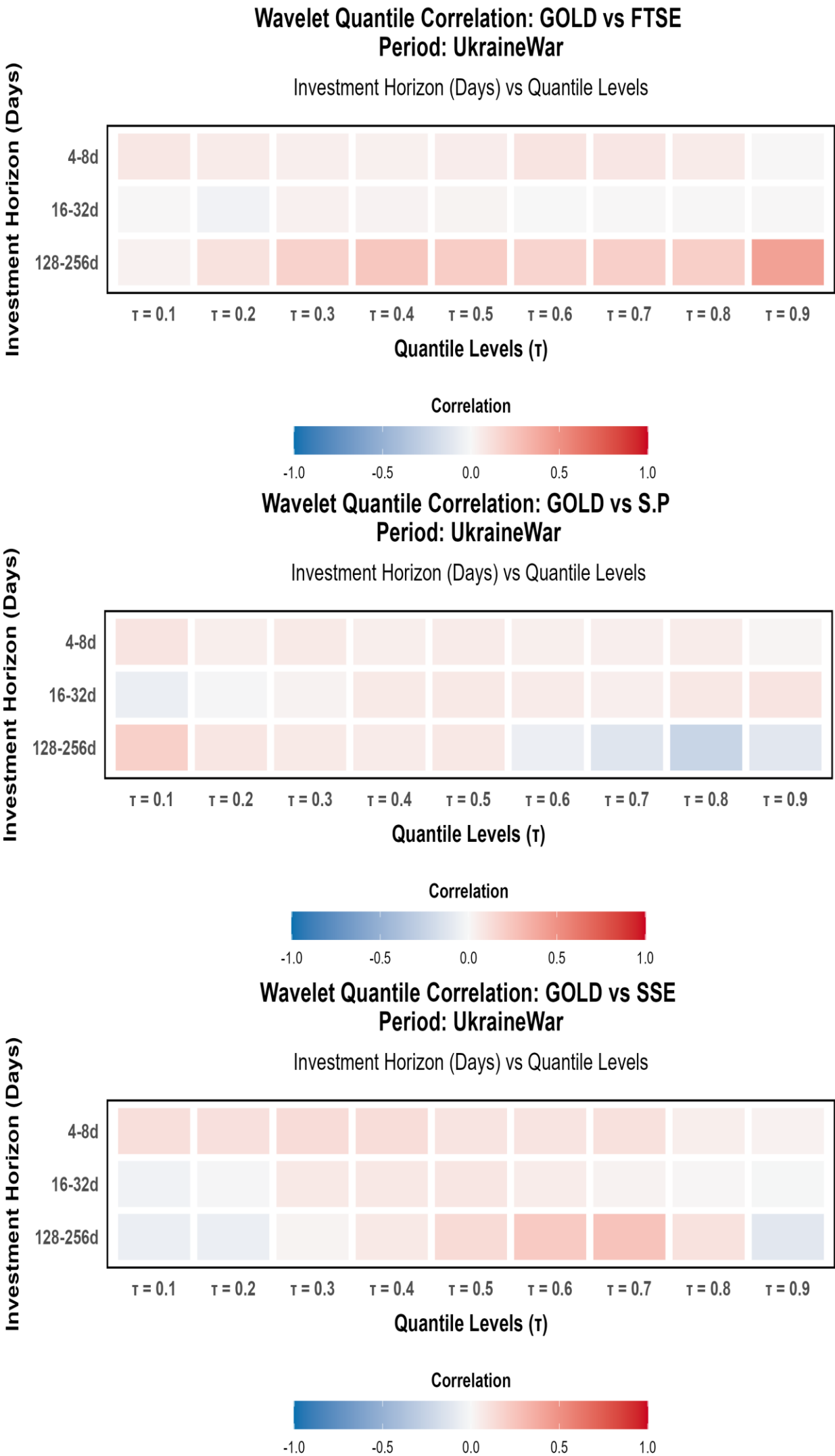
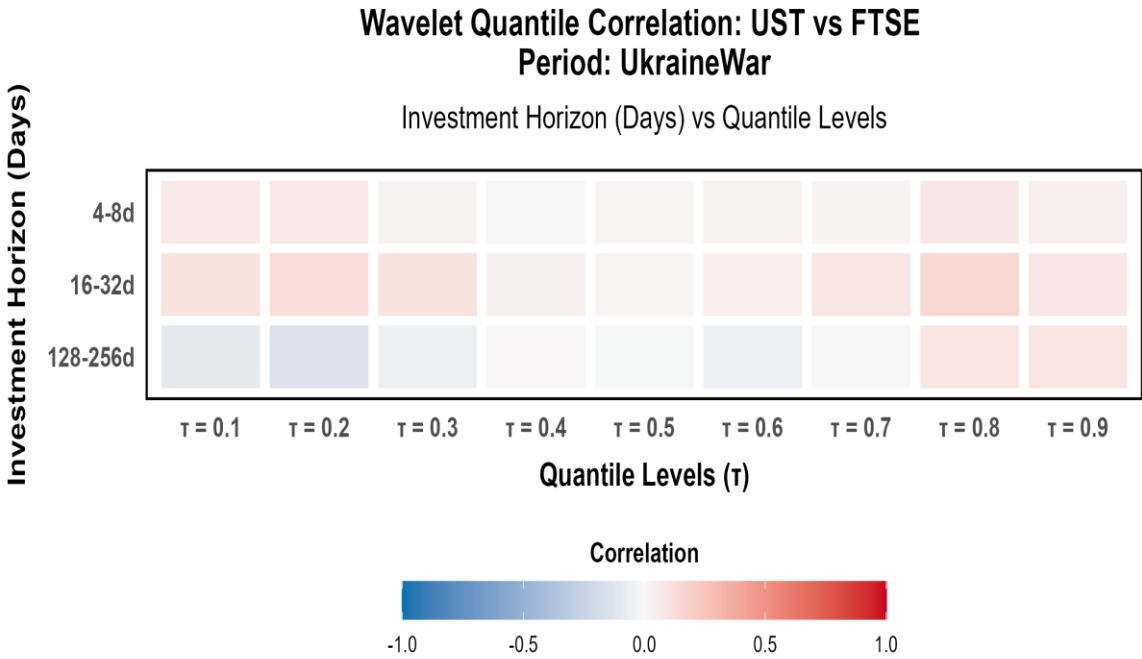
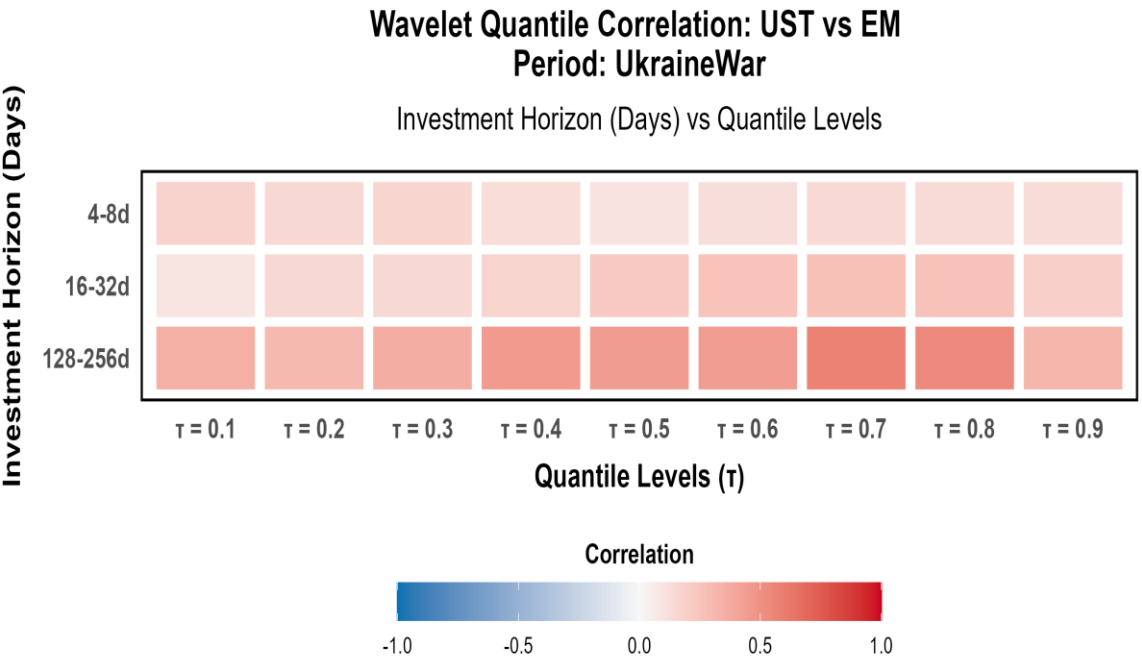


Figure 19. D4 Wavelet Quantile Correlation between Swiss Franc and equities during the COVID- 19 period.









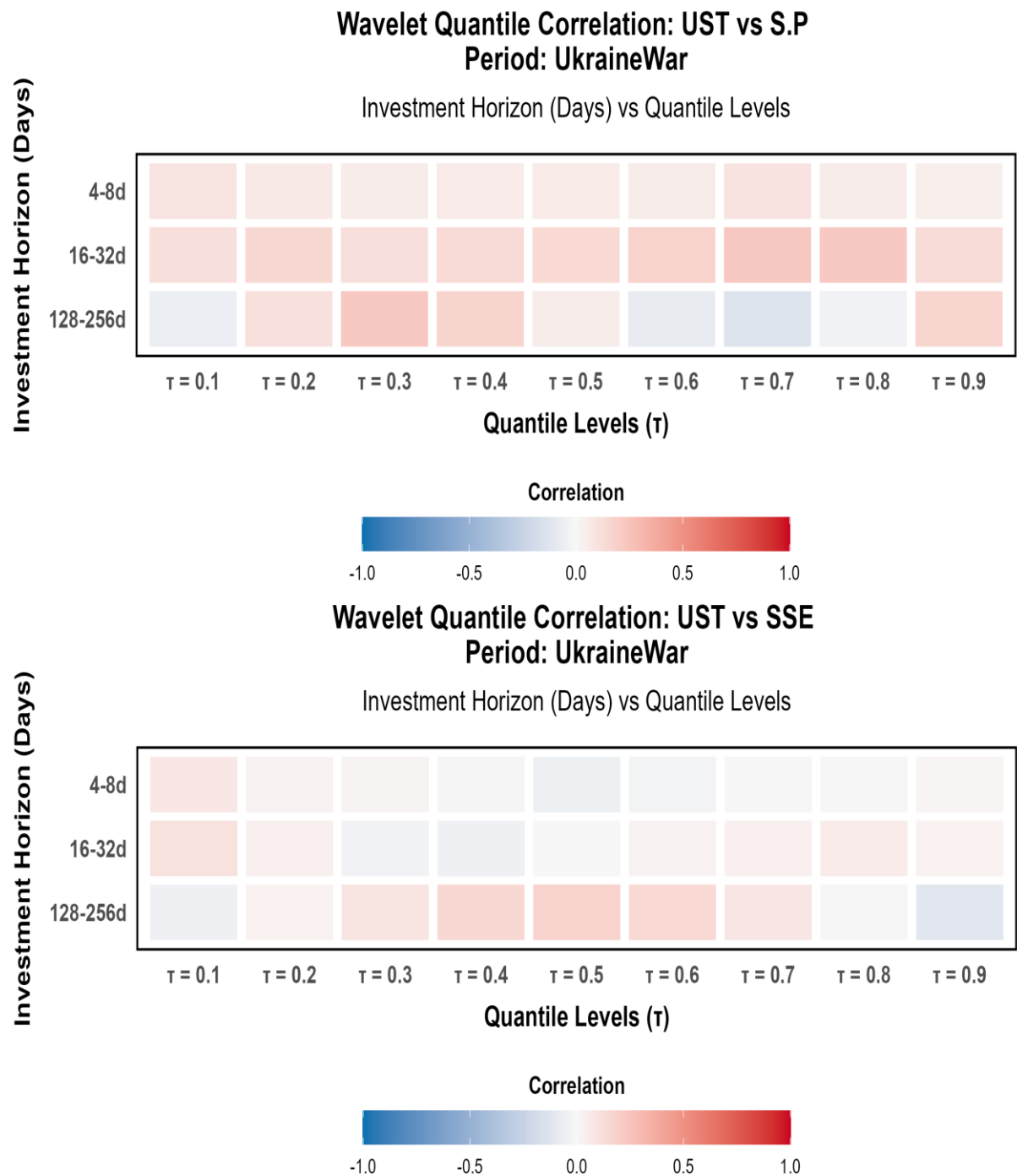


Figure 22. D4 Wavelet Quantile Correlation between US Treasury and equities during the Russia-Ukraine war period.

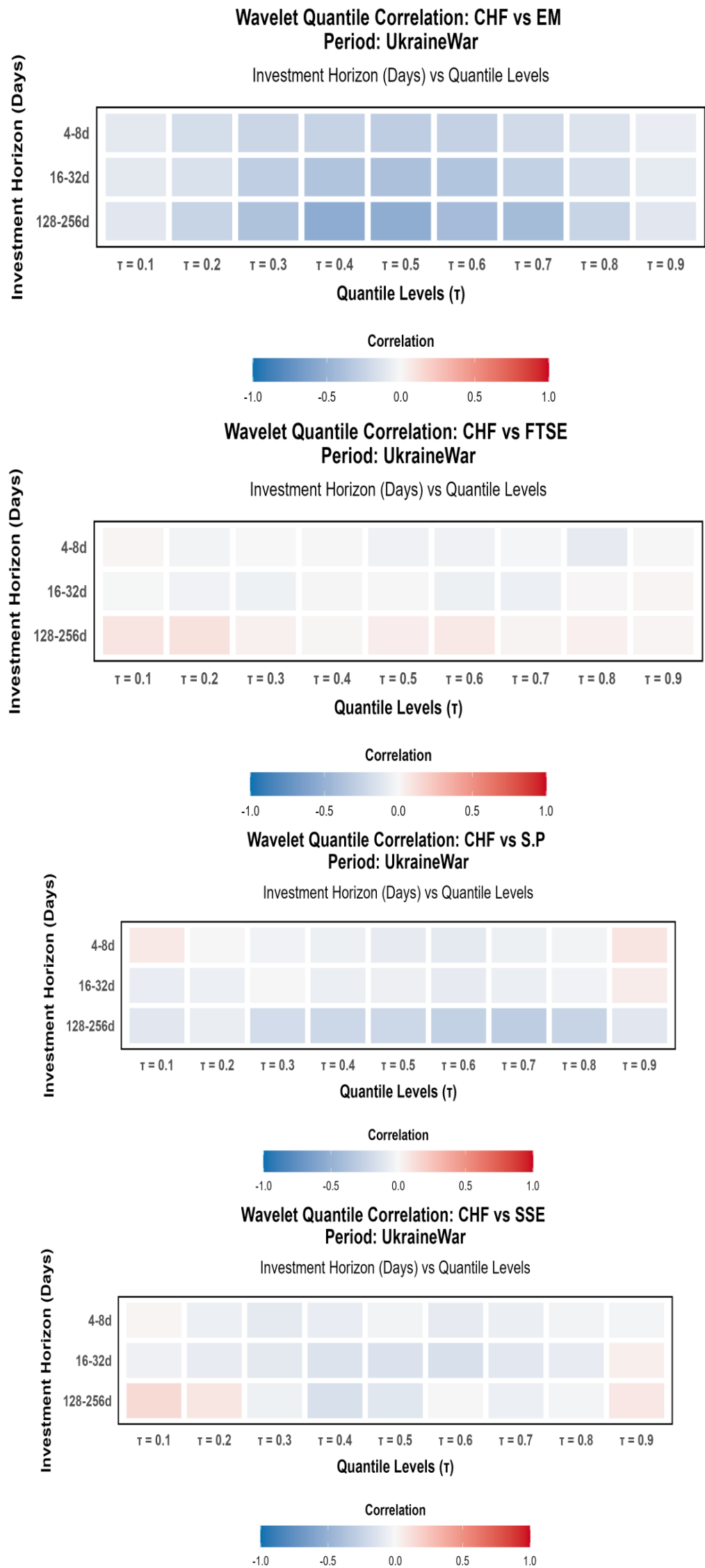


Figure 23. D4 Wavelet Quantile Correlation between Swiss Franc and equities during the Russia-Ukraine war period.

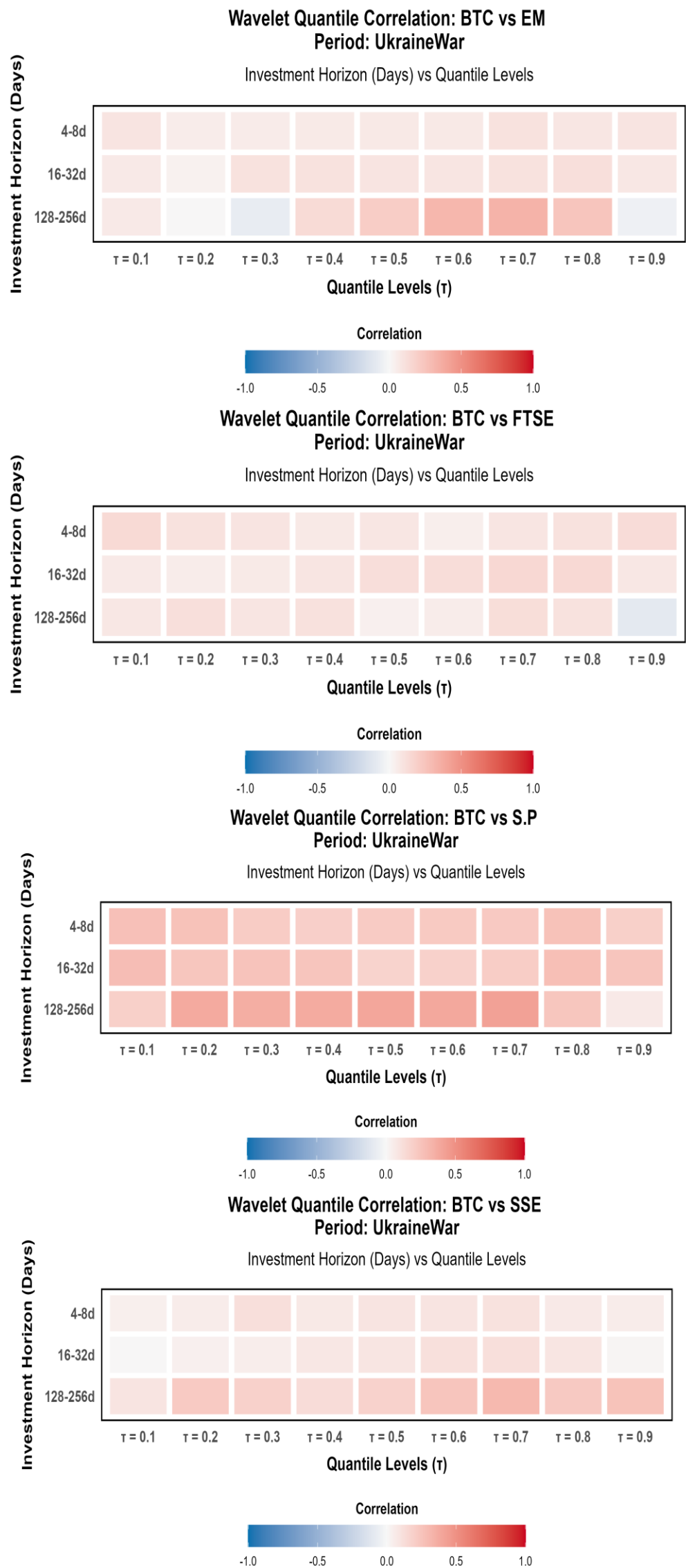


Figure 24. D4 Wavelet Quantile Correlation between Bitcoin and equities during the Russia-Ukraine war period.

5.2. Alternative Lag Order Specifications

Following Berkomah, Frimpong, Tweneboah, Woode, and Assifuah-Nunoo (2026), the connectedness analysis is re-estimated using alternative lag orders ($p = 2$ and $p = 3$) to assess robustness, rather than relying solely on the baseline TVP-VAR specification with $p = 1$ estimated over the full sample. The results remain qualitatively unchanged, indicating that the inferred safe-haven properties are not sensitive to lag selection or model specification. Table 7 reports the pairwise correlations between the baseline and alternative lag structures, while Table 8 presents a comparative analysis of asset-specific NET spillovers across the different lag specifications.

Table 7. Correlation between baseline ($p=1$) and alternative lag specifications.

	p=1 (Baseline)	p=2	p=3
p=1 (Baseline)	1	0.9612	0.8419
p=2	0.9612	1	0.9306
p=3	0.8419	0.9306	1

The pairwise correlations of connectedness measures across lag specifications further confirm the robustness of the results. The correlation between the baseline model ($p = 1$) and $p = 2$ is extremely high (0.9612), indicating near-identical spillover structures. Similarly, the correlation between $p = 2$ and $p = 3$ remains strong (0.9306), suggesting that increasing lag length does not materially alter the system dynamics. Although the correlation between $p = 1$ and $p = 3$ is slightly lower (0.8419), it still indicates substantial consistency, with only minor variations attributable to the inclusion of longer-horizon spillovers. Overall, these results demonstrate that the connectedness estimates are stable and not driven by lag specification.

Table 8. Asset-specific transmission shares (net).

Asset	NET_p1	NET_p2 (p1)	NET_p3 (p1)
GOLD	0.3	-0.41 (0.3)	0.06 (0.3)
US Treasury	0.66	0.68 (0.66)	2.5 (0.66)
CHF	1.56	1.06 (1.56)	-2.18 (1.56)
BTC	-0.42	-1.23 (-0.42)	-3.74 (-0.42)
S&P 500	14.59	14.07 (14.59)	15.68 (14.59)
FTSE 100	1.03	3.47 (1.03)	3.64 (1.03)
MSCI EM	-8.76	-9.38 (-8.76)	-8.78 (-8.76)
SSE	-8.95	-8.26 (-8.95)	-7.18 (-8.95)

The connectedness results are broadly robust to alternative lag specifications ($p = 2$ and $p = 3$), as both the magnitude patterns and directional roles of assets remain largely unchanged. The S&P 500 consistently emerges as the dominant net transmitter, while MSCI Emerging Markets and the Shanghai Composite persist as net receivers across all specifications. The FTSE 100 also retains its role as a secondary transmitter, whereas Bitcoin remains a net receiver, with its negative net position intensifying at higher lag orders.

Minor sensitivity is observed for gold and the Swiss franc. Gold exhibits near-zero net connectedness with occasional sign reversals, reinforcing its role as a weakly connected diversifier rather than a systematic transmitter or receiver of shocks. In contrast, the Swiss franc exhibits some lag sensitivity, shifting from net transmitter at lower lags to net receiver at $p = 3$, suggesting that its safe-haven characteristics may vary across transmission horizons. This sensitivity implies that the CHF’s network role is more dynamic than that of other assets and is sensitive to the choice of transmission horizon. This nuance strengthens rather than weakens the core finding about regime-dependence. Overall, the stability in both rankings and net spillover directions of most assets indicates that the connectedness structure is not heavily driven by lag selection, thereby confirming the robustness of the empirical findings.

5.3. Non-Overlapping Crisis Windows

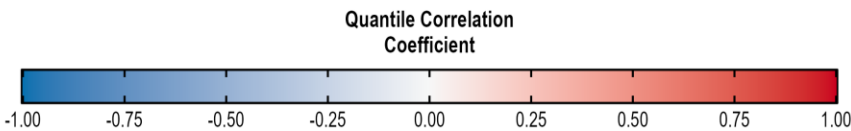
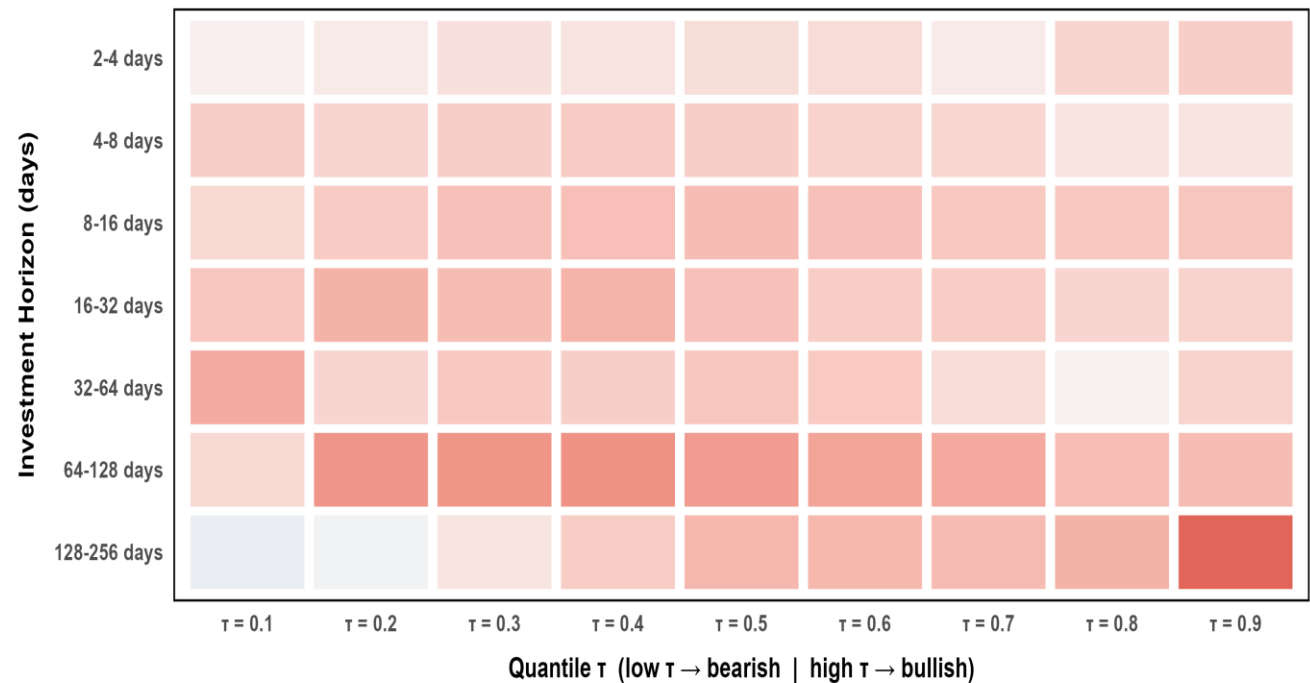
To address the potential concern that the overlapping sub-period design may weaken the distinction between crisis regimes, the main WQC analysis is replicated using strictly non-overlapping windows. Under this alternative specification, the COVID-19 crisis period is defined from December 31, 2019, to February 23, 2022, while the Russia–Ukraine war period begins on February 24, 2022, corresponding to the official commencement of the military conflict. This alternative partitioning ensures a clear temporal separation between the two crisis episodes and provides a more stringent robustness assessment of the estimated dependence structure.

Results under this alternative specification (Figures 25–32) are qualitatively consistent with the baseline findings. The direction, intensity, and time–frequency patterns of dependence between safe-haven assets and equity markets are largely preserved across quantiles and investment horizons. In particular, assets identified as weak or inconsistent safe havens under the baseline specification continue to exhibit similar behavior, while assets displaying stronger diversification or hedging properties maintain their relative performance under the revised crisis demarcations. This consistency indicates that the principal findings are not driven by the overlapping structure of the original sub-period design.

Overall, the robustness analysis confirms that the wavelet quantile dependence results are robust to alternative crisis window definitions. The consistency of the findings across specifications strengthens confidence in the empirical conclusions that safe-haven effectiveness is crisis-dependent, horizon-sensitive, and heterogeneous across assets and markets.

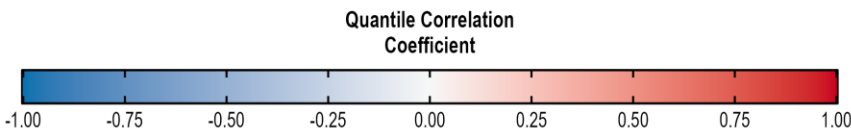
Wavelet Quantile Correlation: GOLD vs EM

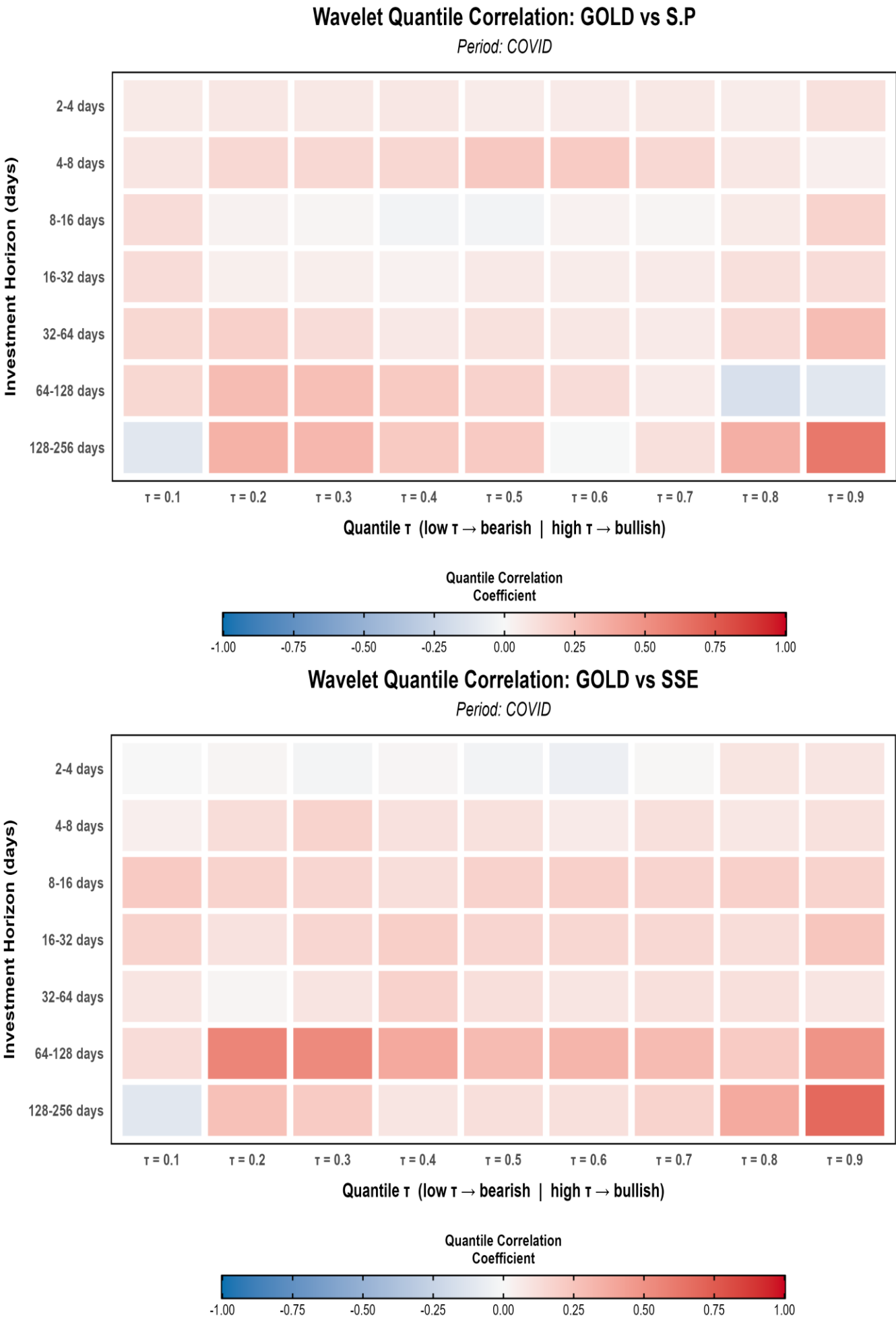
Period: COVID



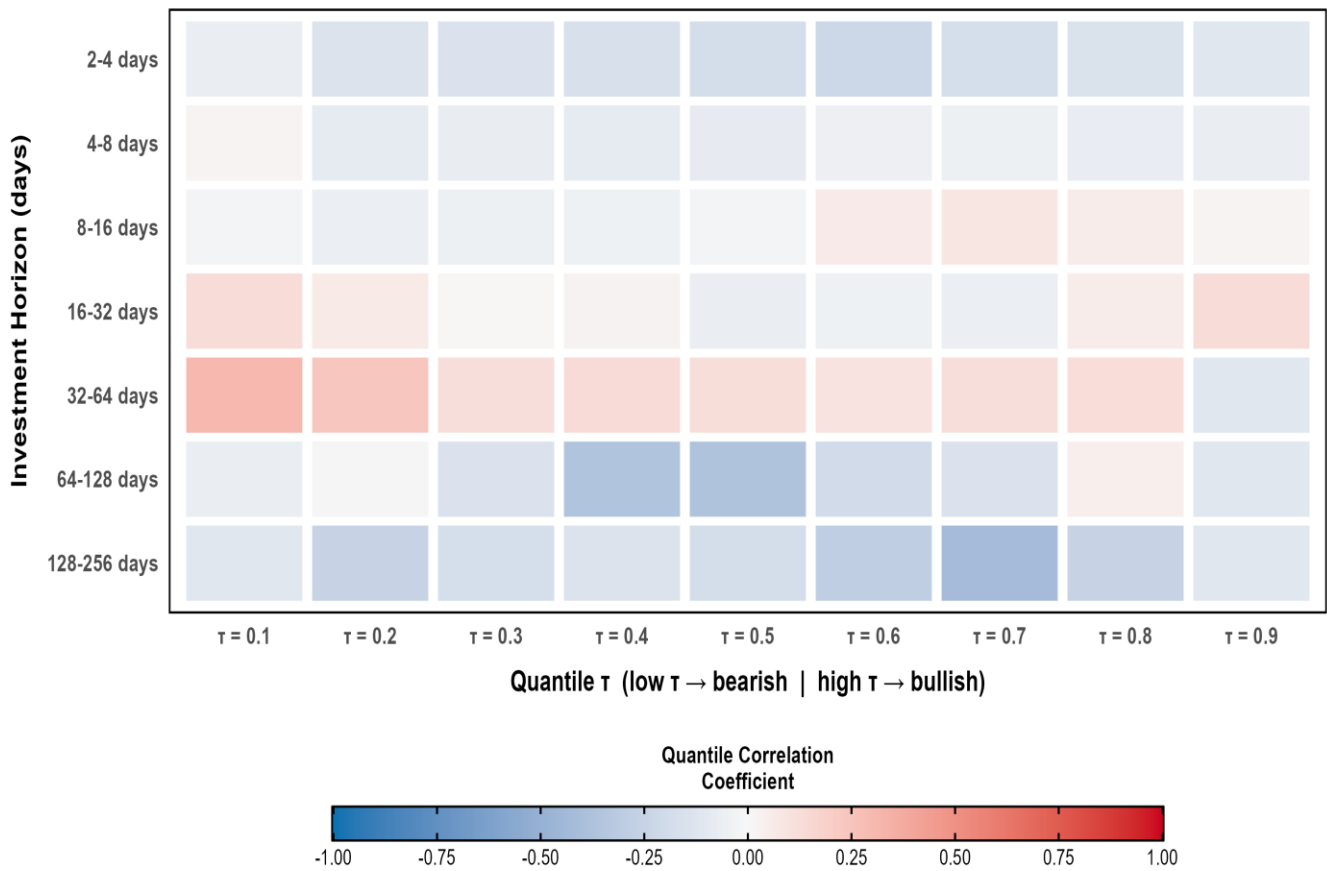
Wavelet Quantile Correlation: GOLD vs FTSE

Period: COVID

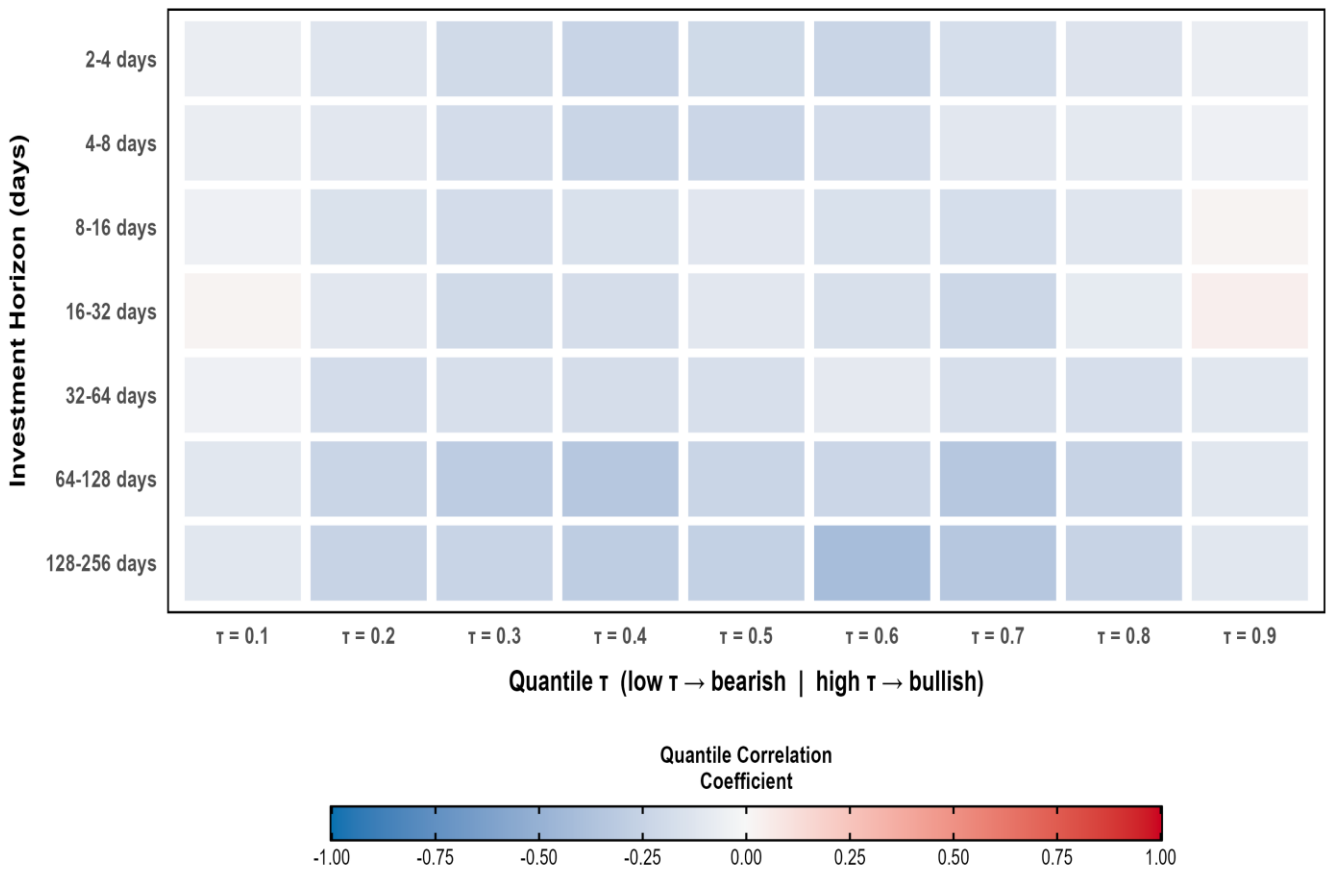




Wavelet Quantile Correlation: UST vs EM
Period: COVID



Wavelet Quantile Correlation: UST vs FTSE
Period: COVID



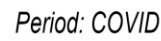
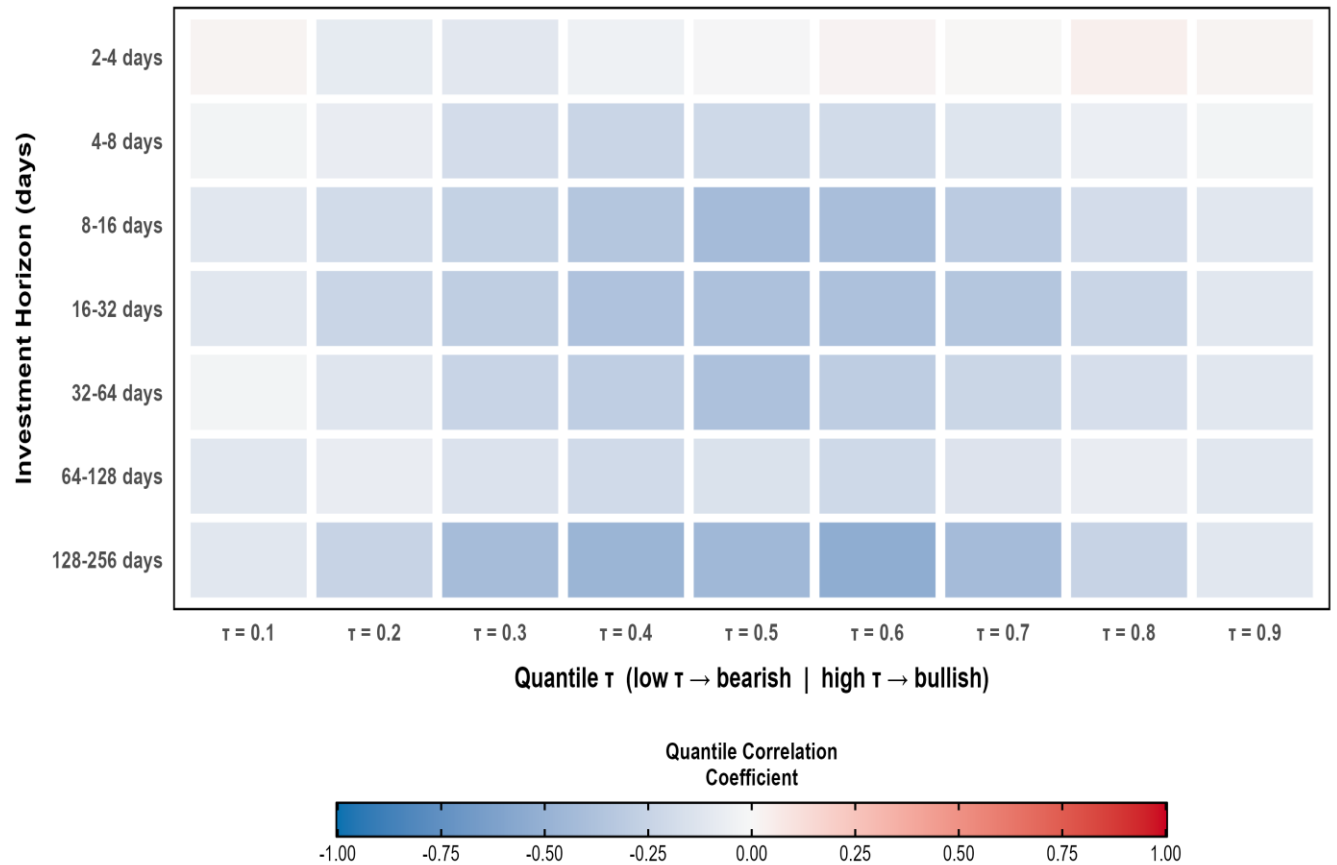


Figure 26. Wavelet Quantile Correlation between US Treasury and Equities during the COVID-19 Period: Strictly Non-Overlapping Windows.

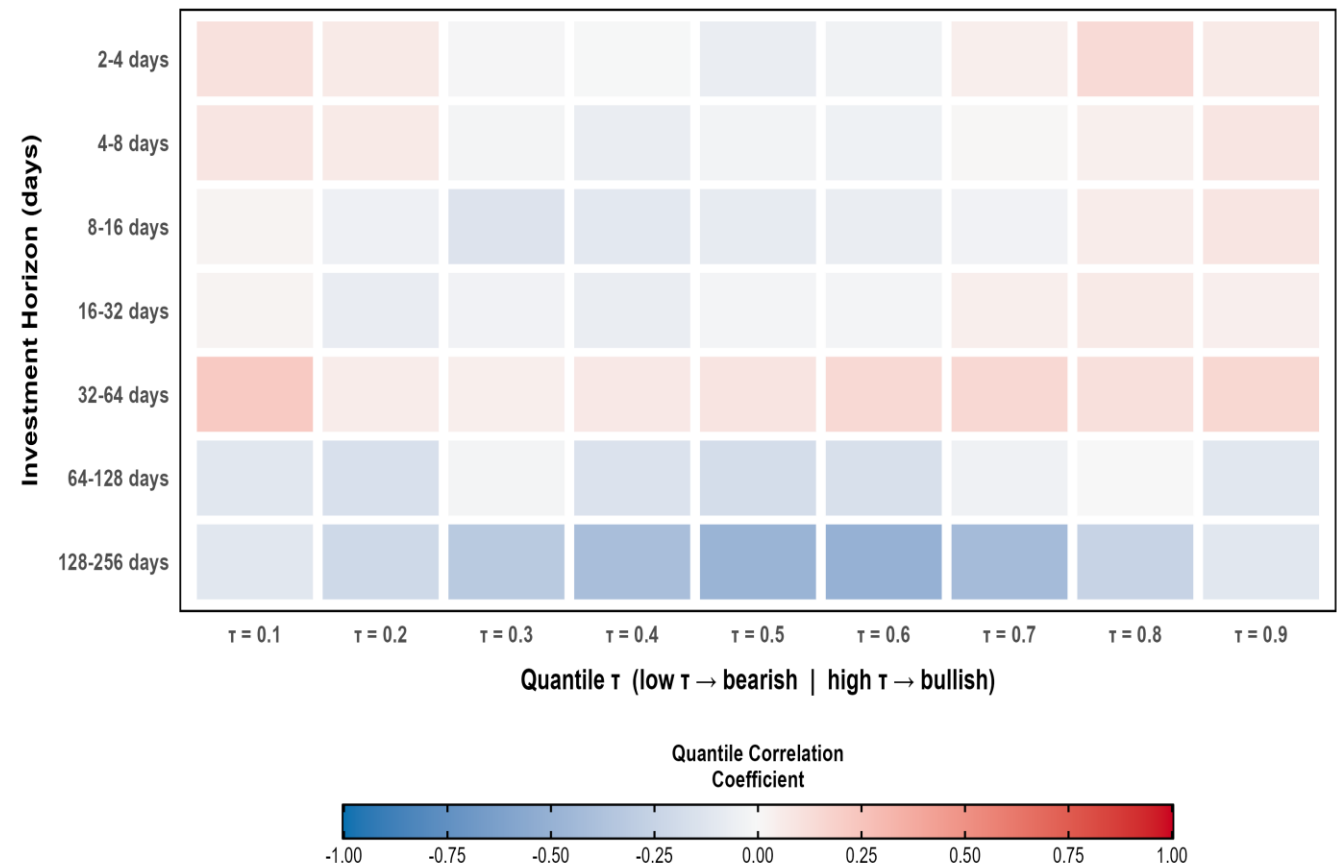
Wavelet Quantile Correlation: CHF vs EM

Period: COVID



Wavelet Quantile Correlation: CHF vs FTSE

Period: COVID



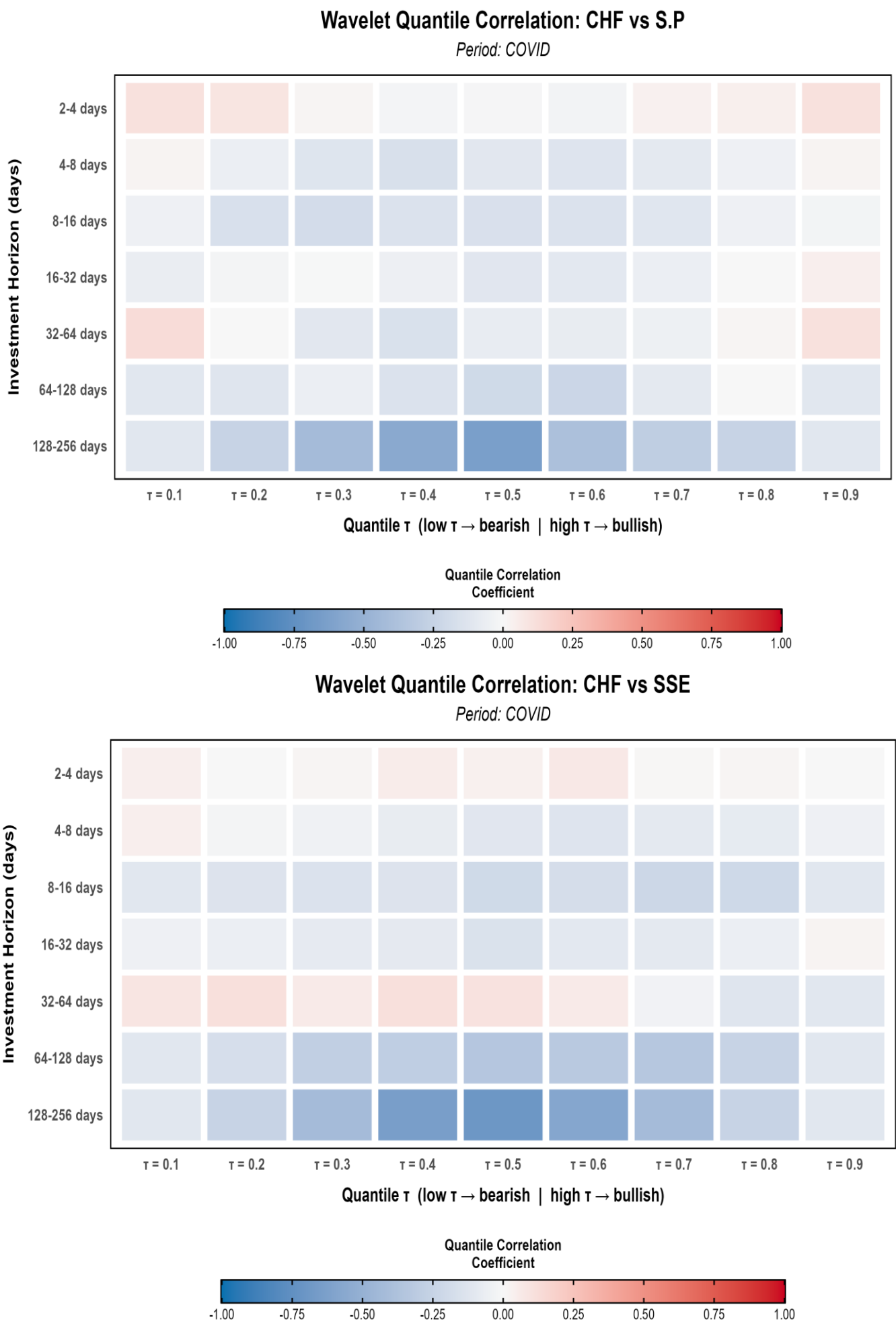
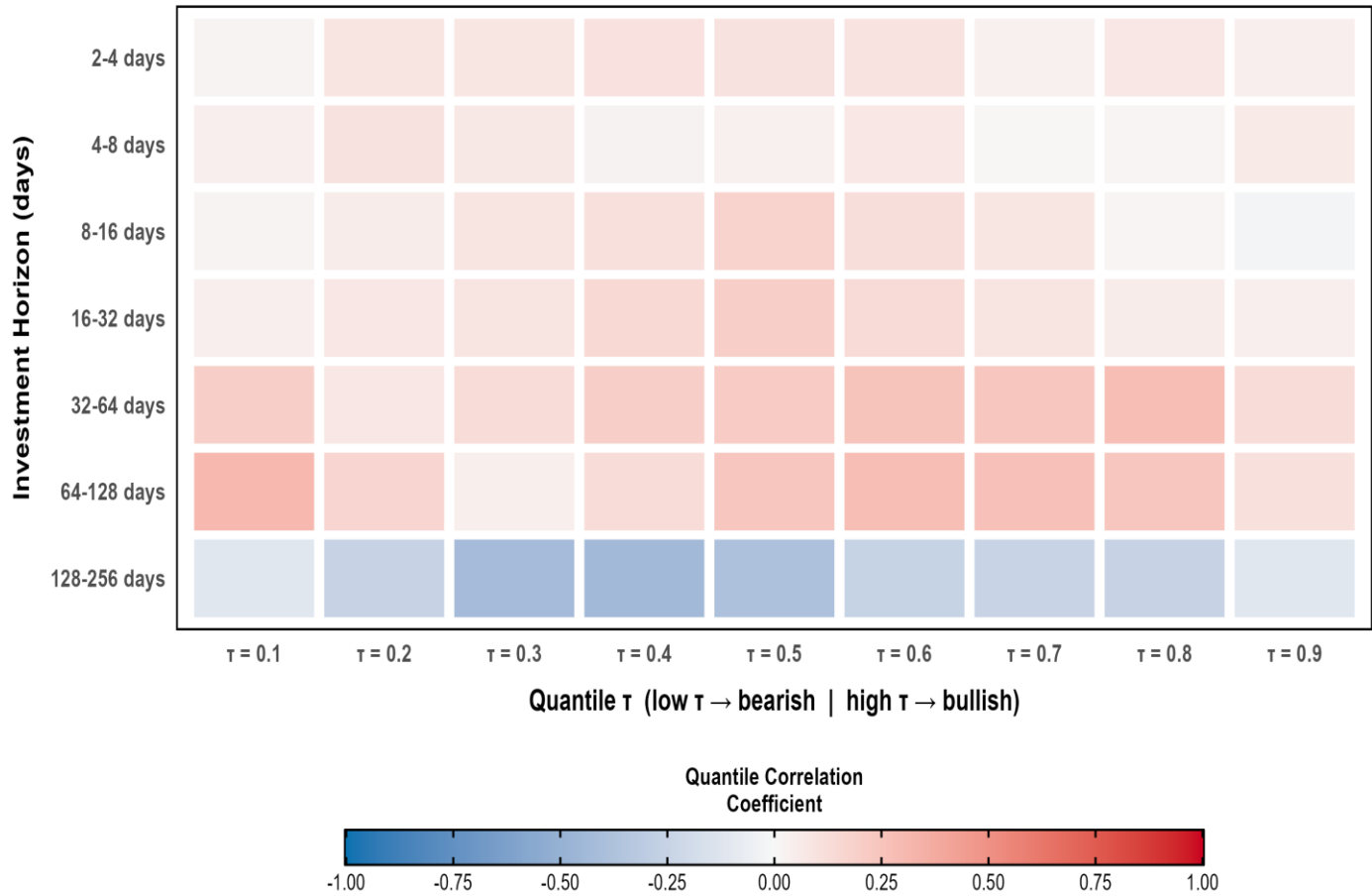


Figure 27. Wavelet Quantile Correlation between Swiss Franc and Equities during the COVID-19 Period: Strictly Non-Overlapping Windows.

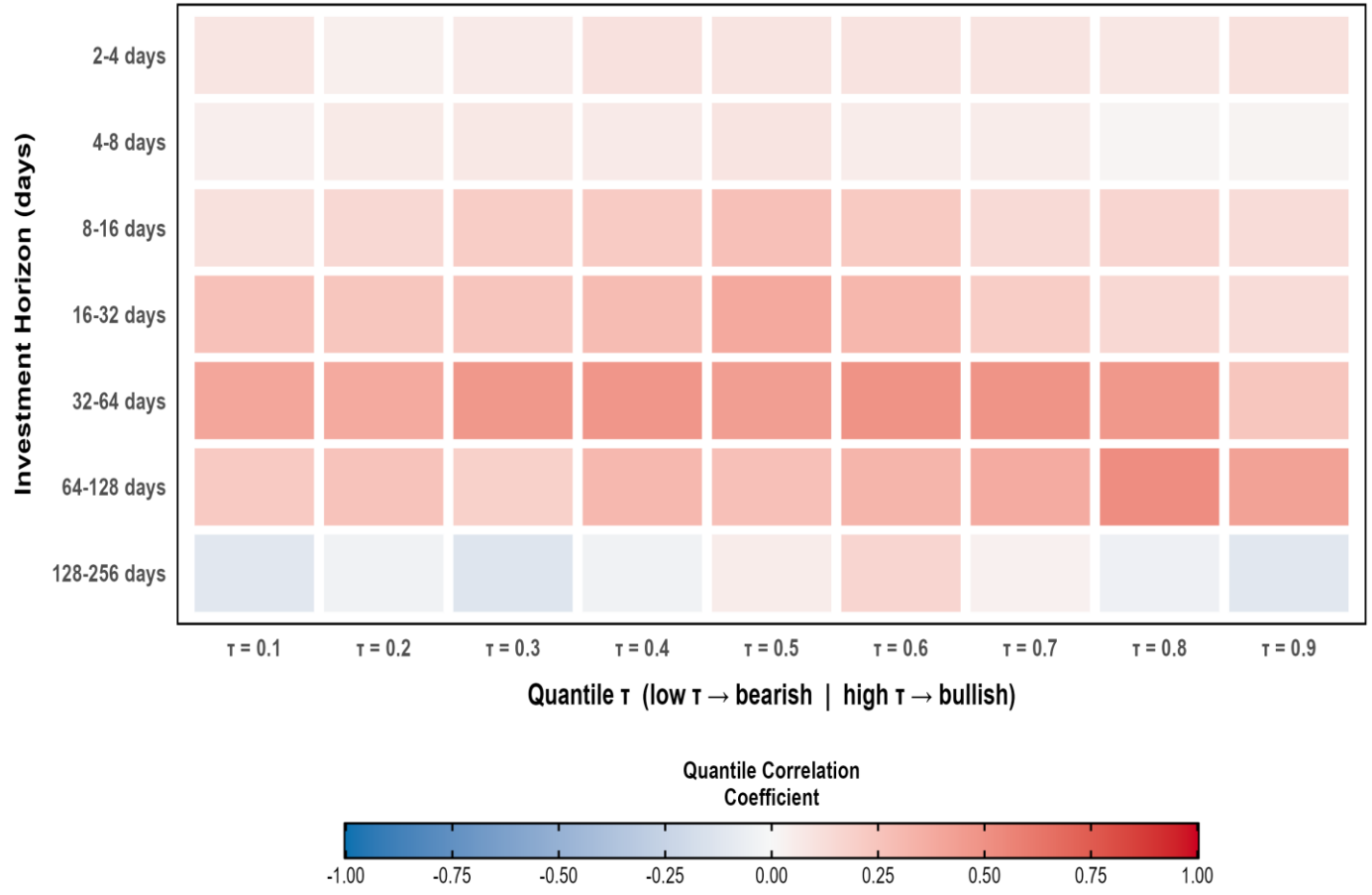
Wavelet Quantile Correlation: BTC vs EM

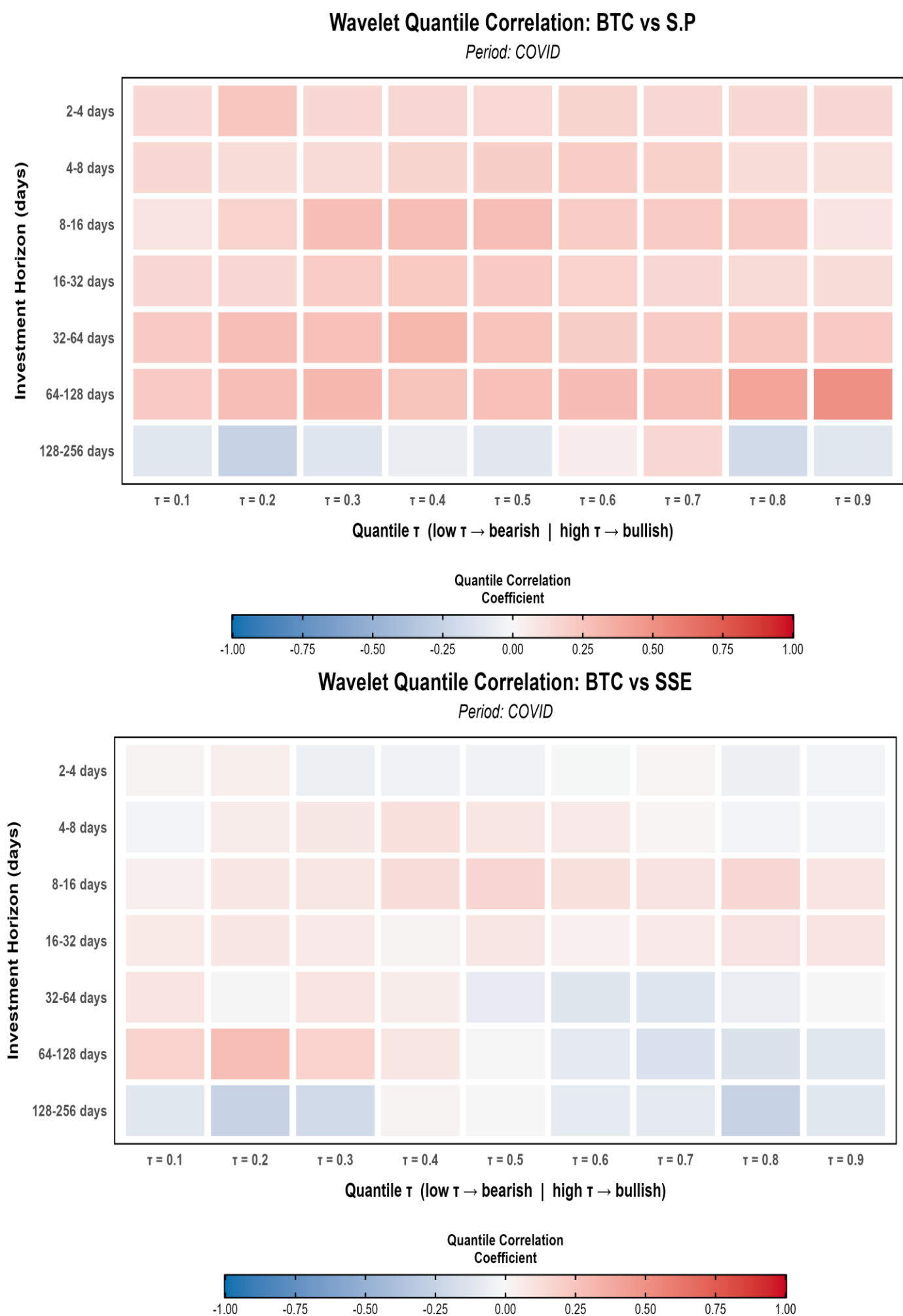
Period: COVID



Wavelet Quantile Correlation: BTC vs FTSE

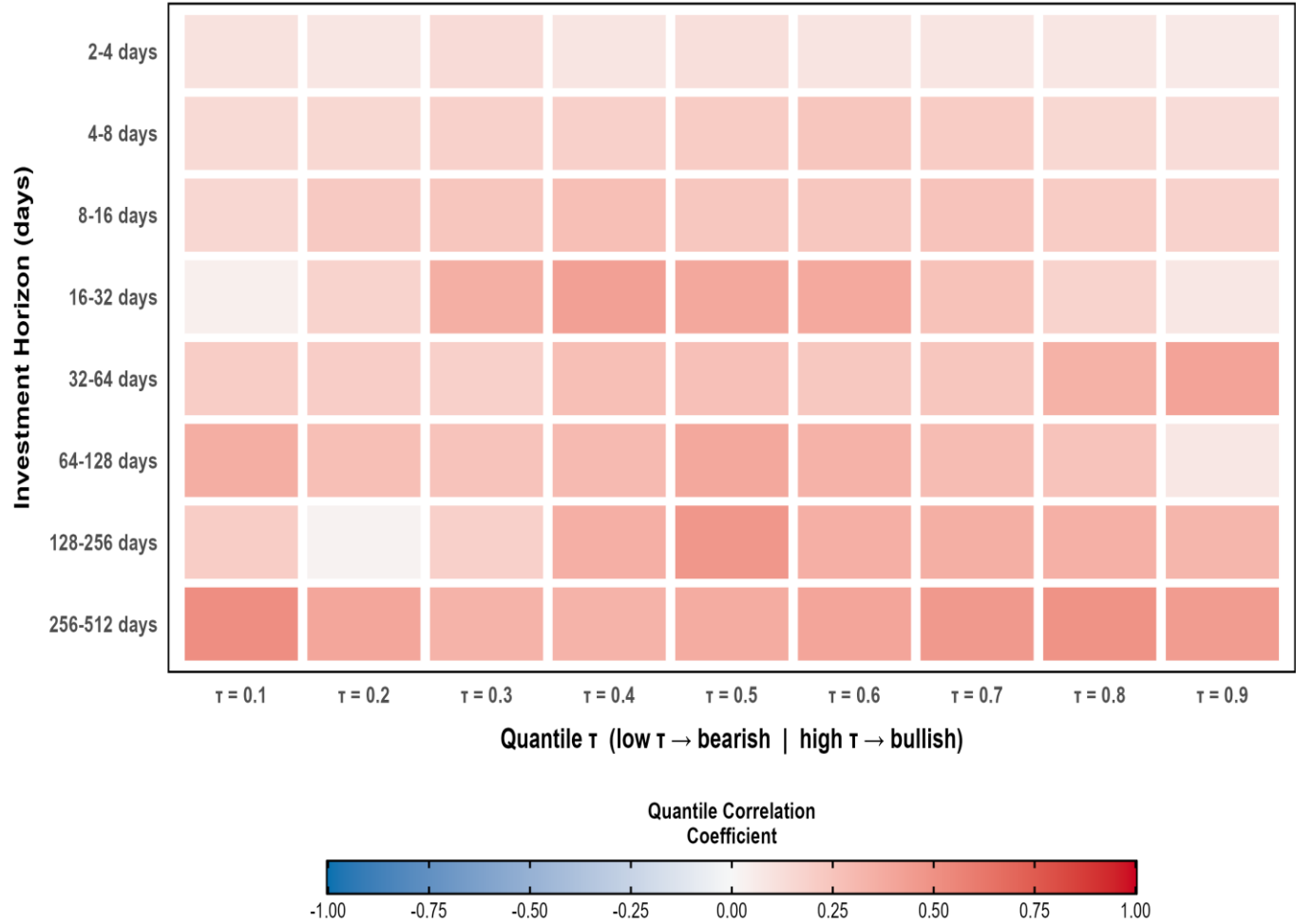
Period: COVID





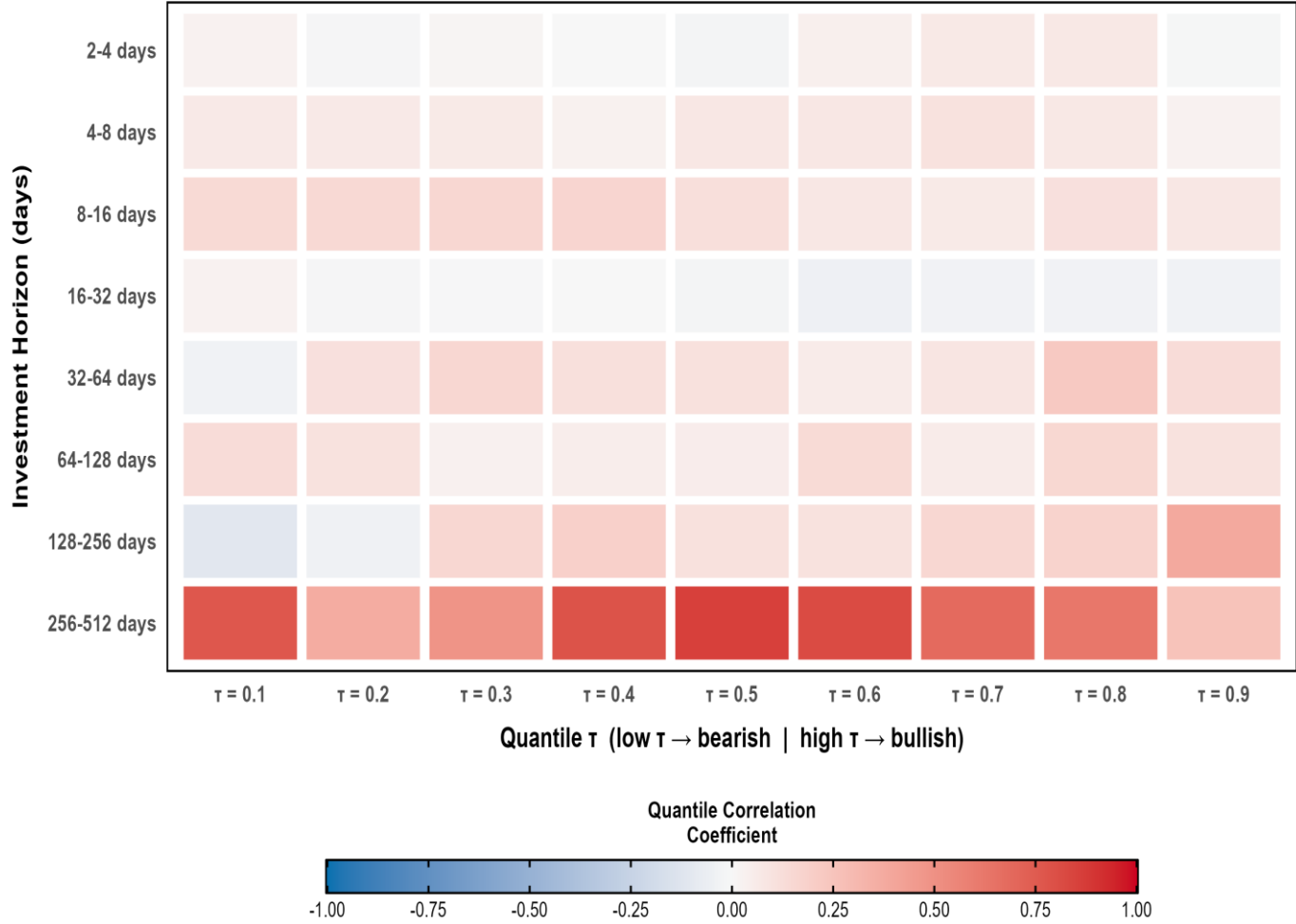
Wavelet Quantile Correlation: GOLD vs EM

Period: UkraineWar

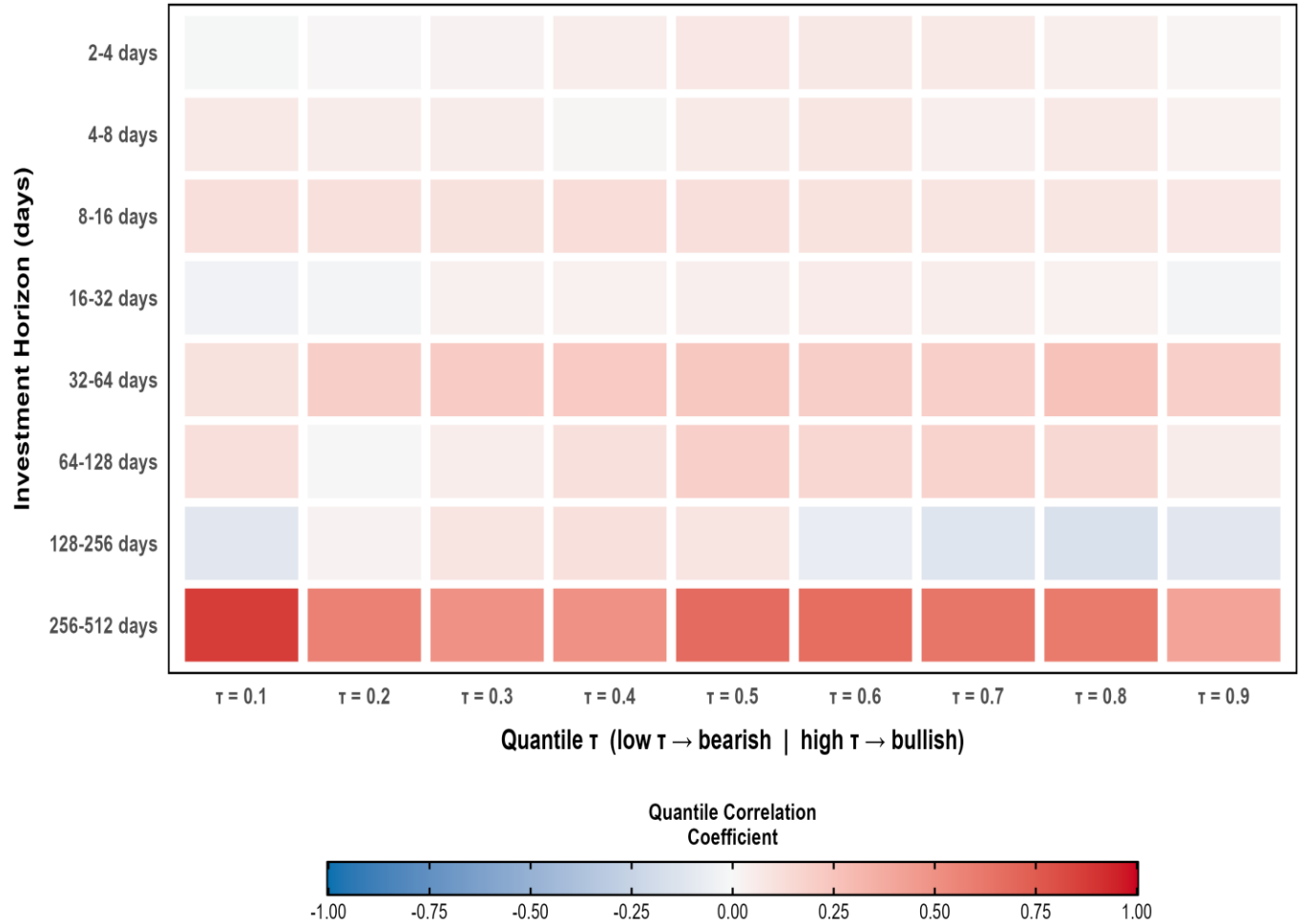


Wavelet Quantile Correlation: GOLD vs FTSE

Period: UkraineWar



Wavelet Quantile Correlation: GOLD vs S.P
Period: UkraineWar



Wavelet Quantile Correlation: GOLD vs SSE
Period: UkraineWar

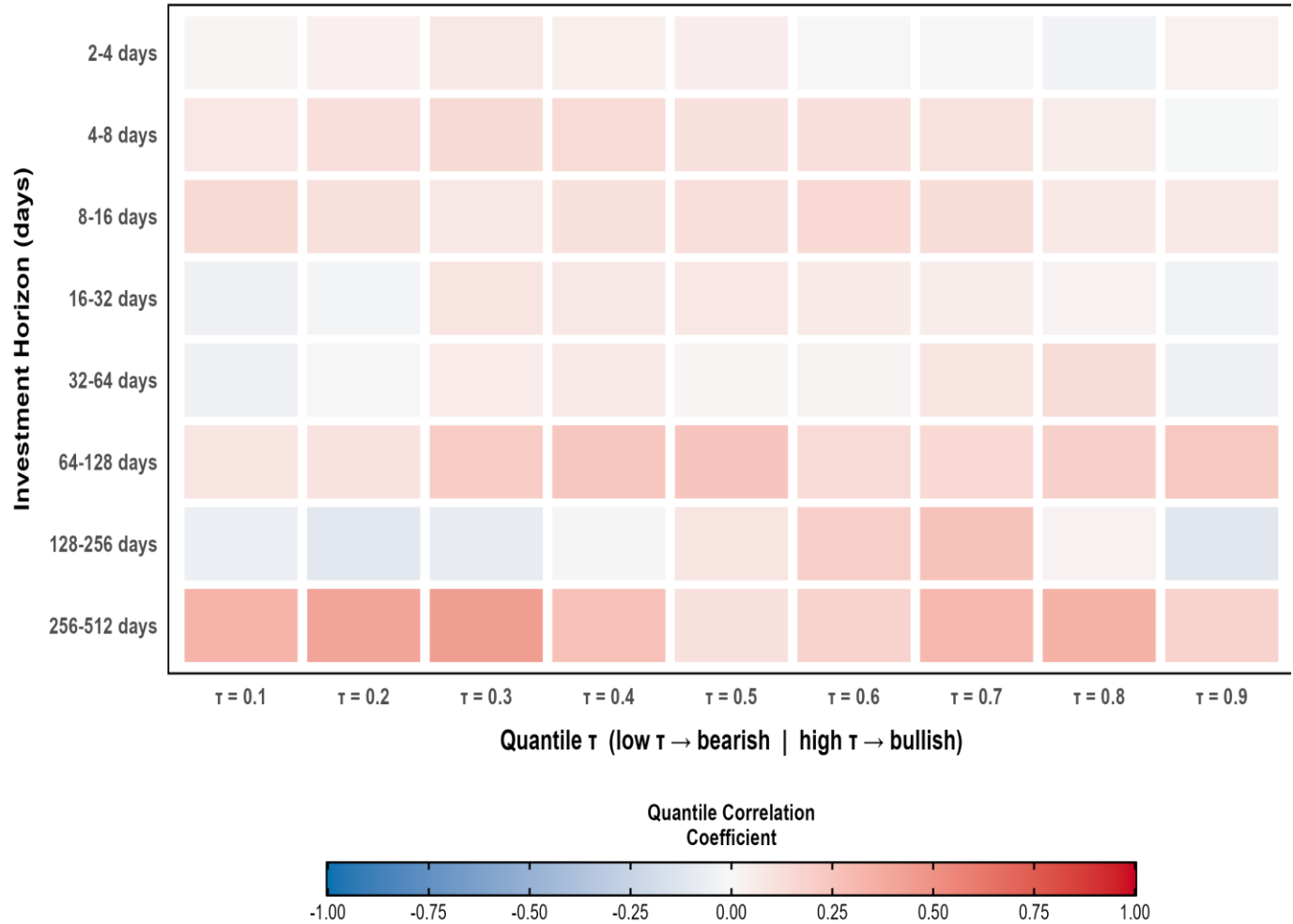
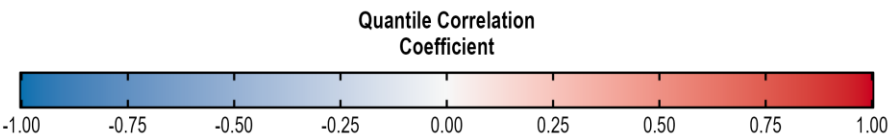
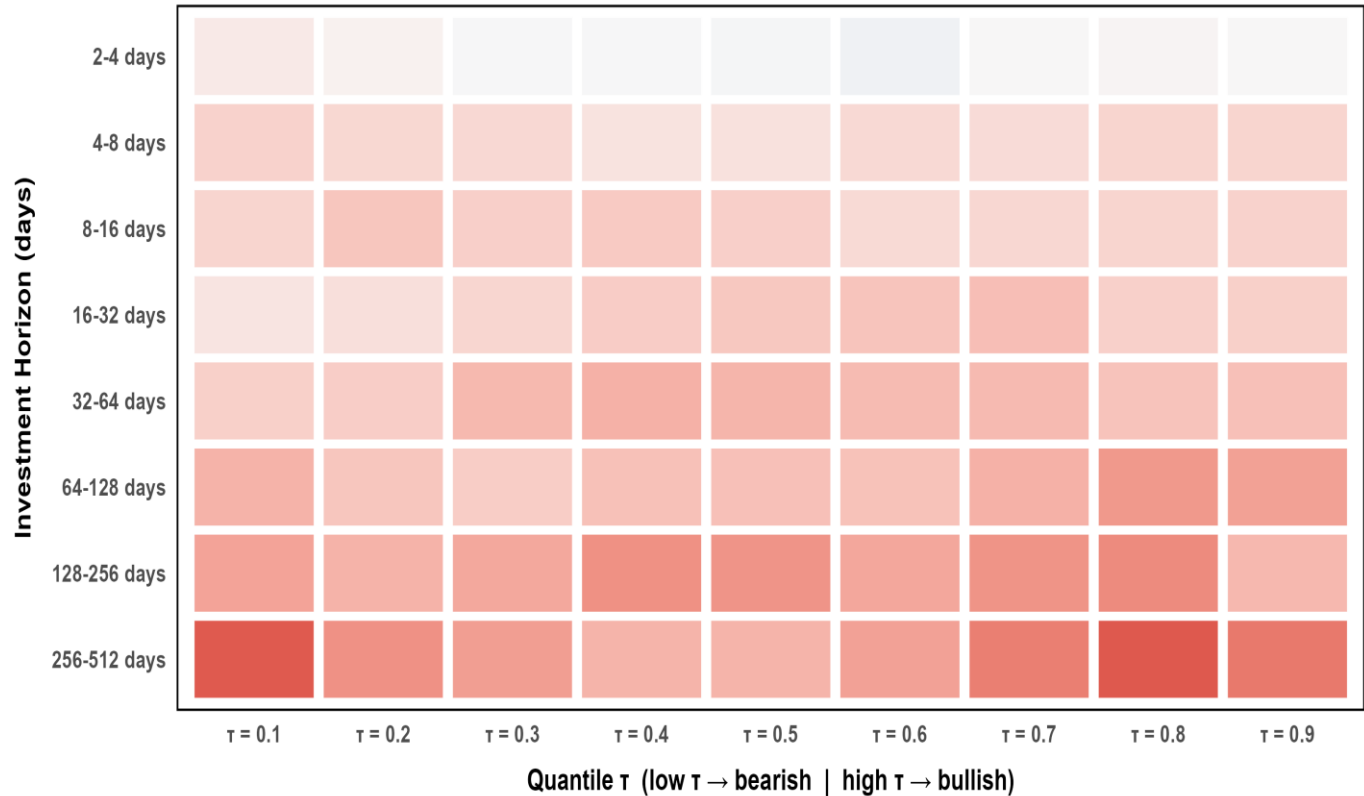


Figure 29. Wavelet Quantile Correlation between Gold and Equities during the Russia-Ukraine War Period: Strictly Non-Overlapping Windows.

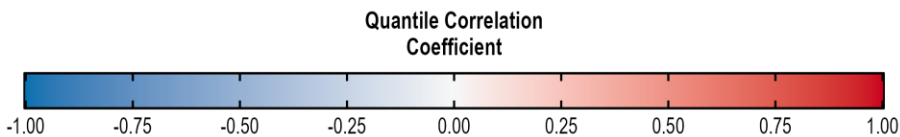
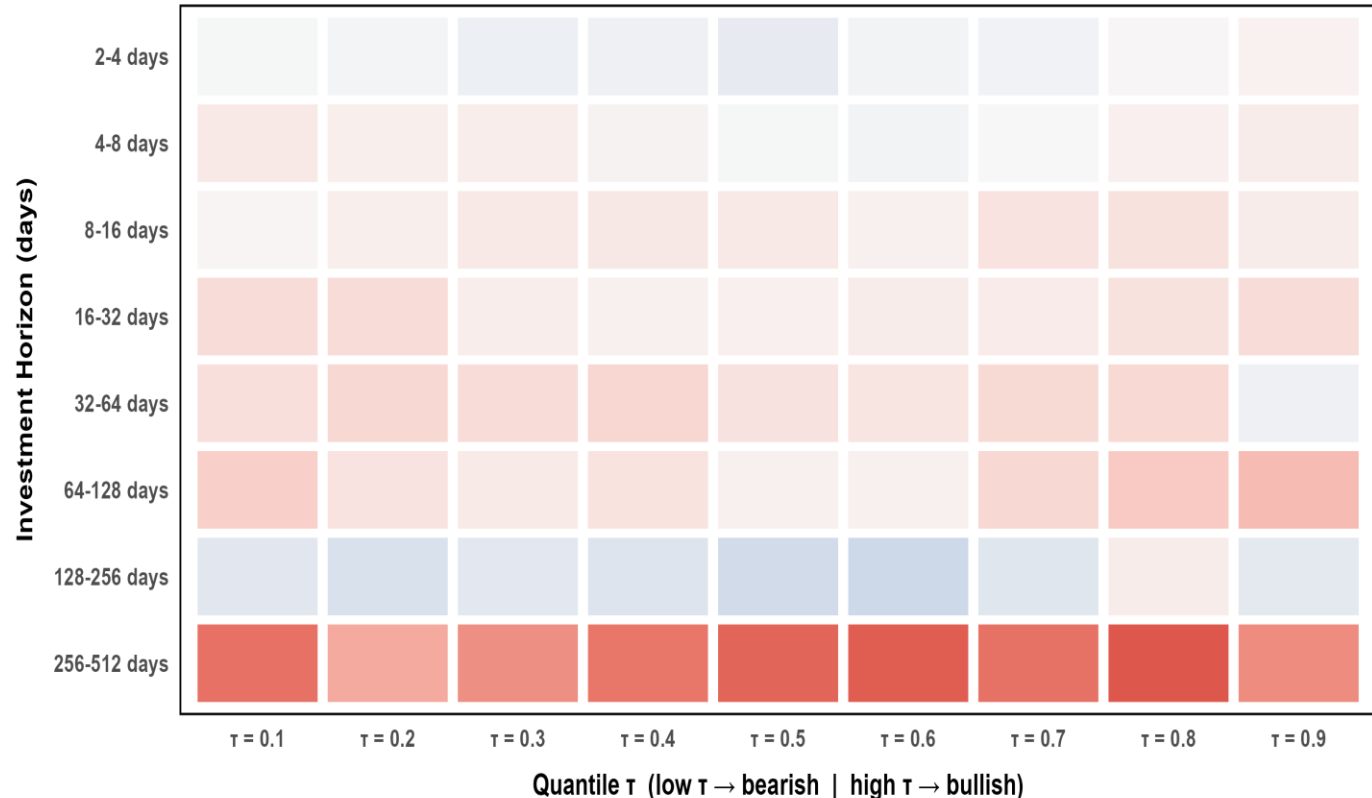
Wavelet Quantile Correlation: UST vs EM

Period: UkraineWar



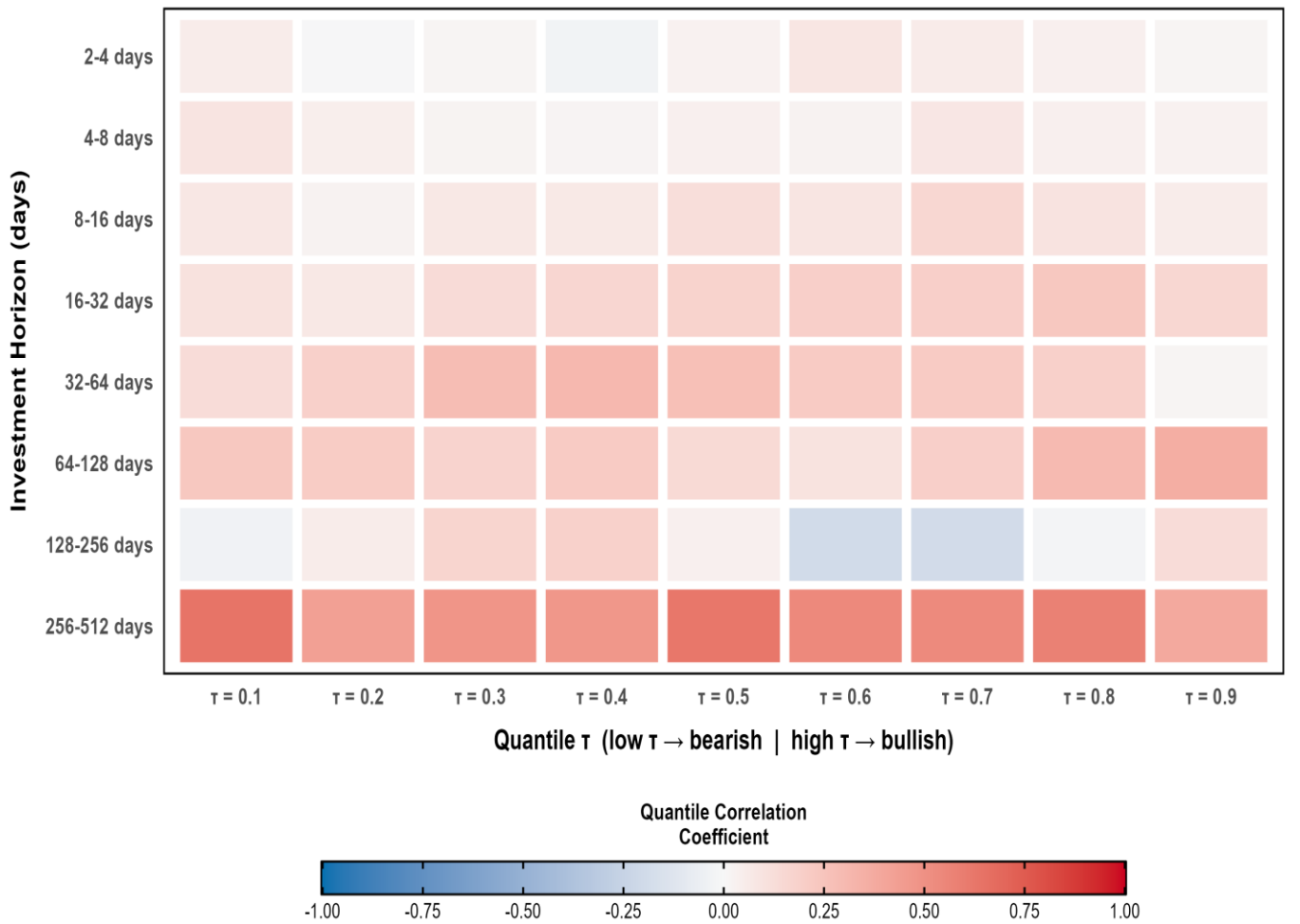
Wavelet Quantile Correlation: UST vs FTSE

Period: UkraineWar



Wavelet Quantile Correlation: UST vs S.P

Period: UkraineWar



Wavelet Quantile Correlation: UST vs SSE

Period: UkraineWar

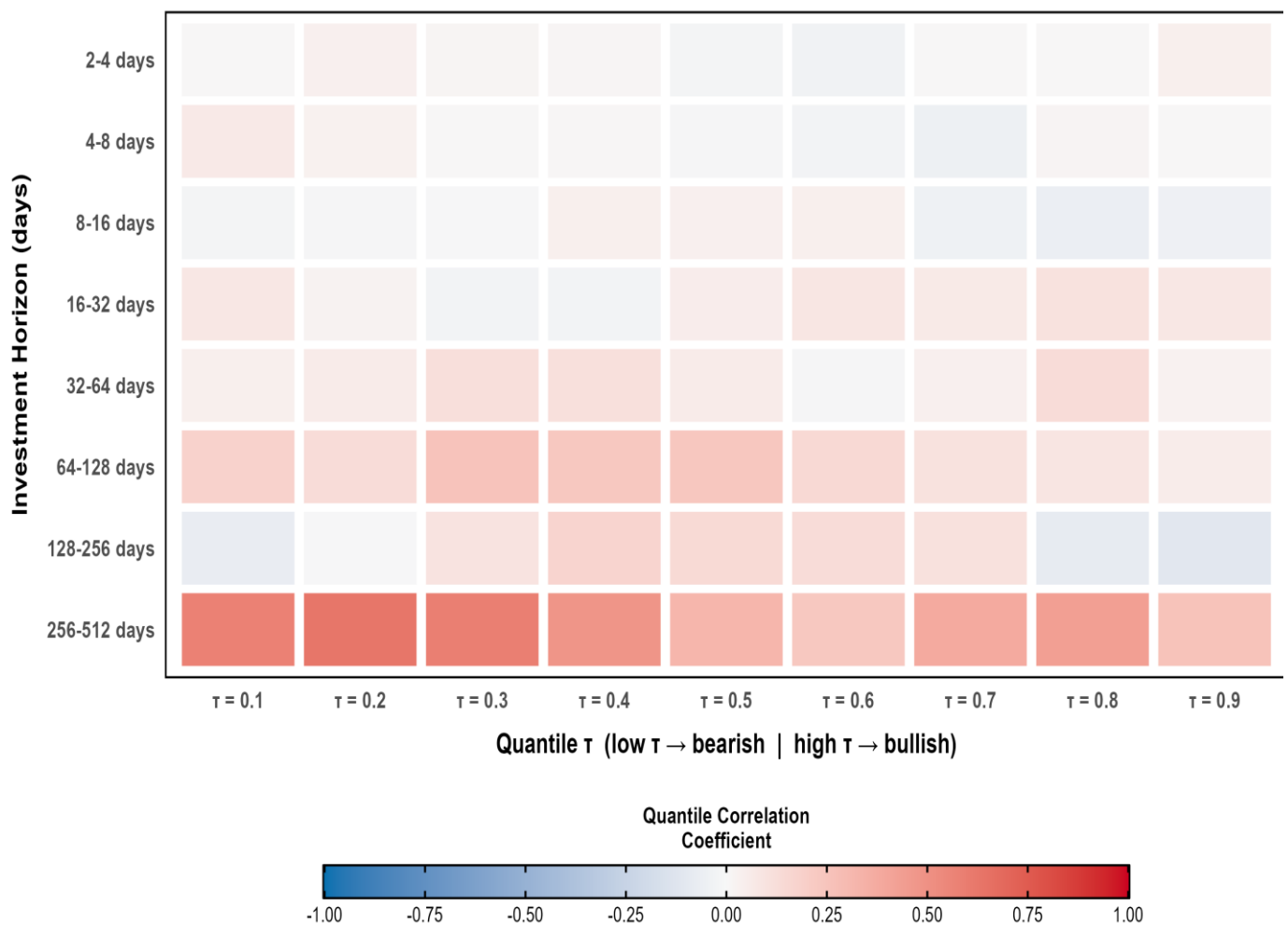
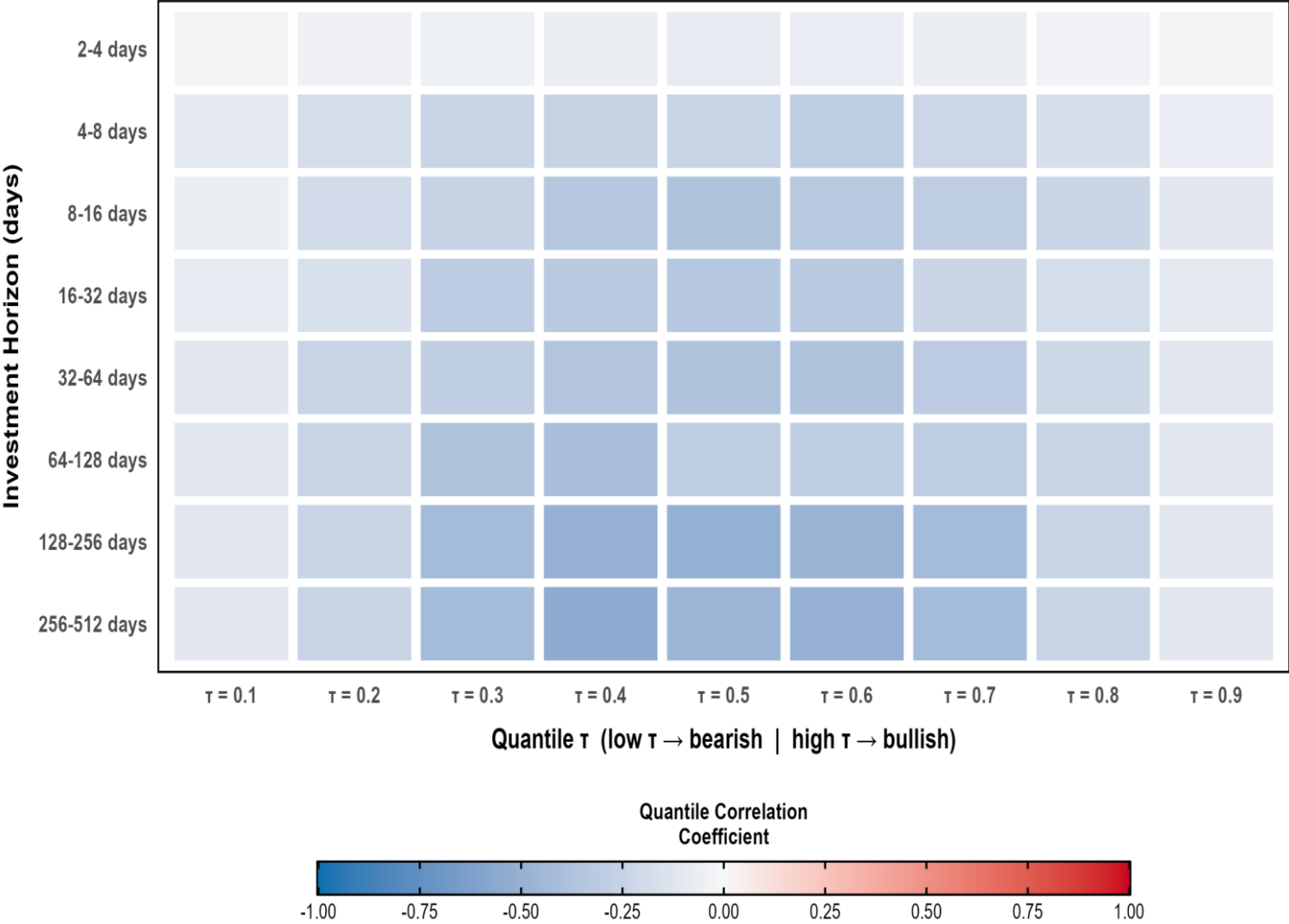


Figure 30. Wavelet Quantile Correlation between US Treasury and Equities during the Russia–Ukraine War Period: Strictly Non-Overlapping Windows.

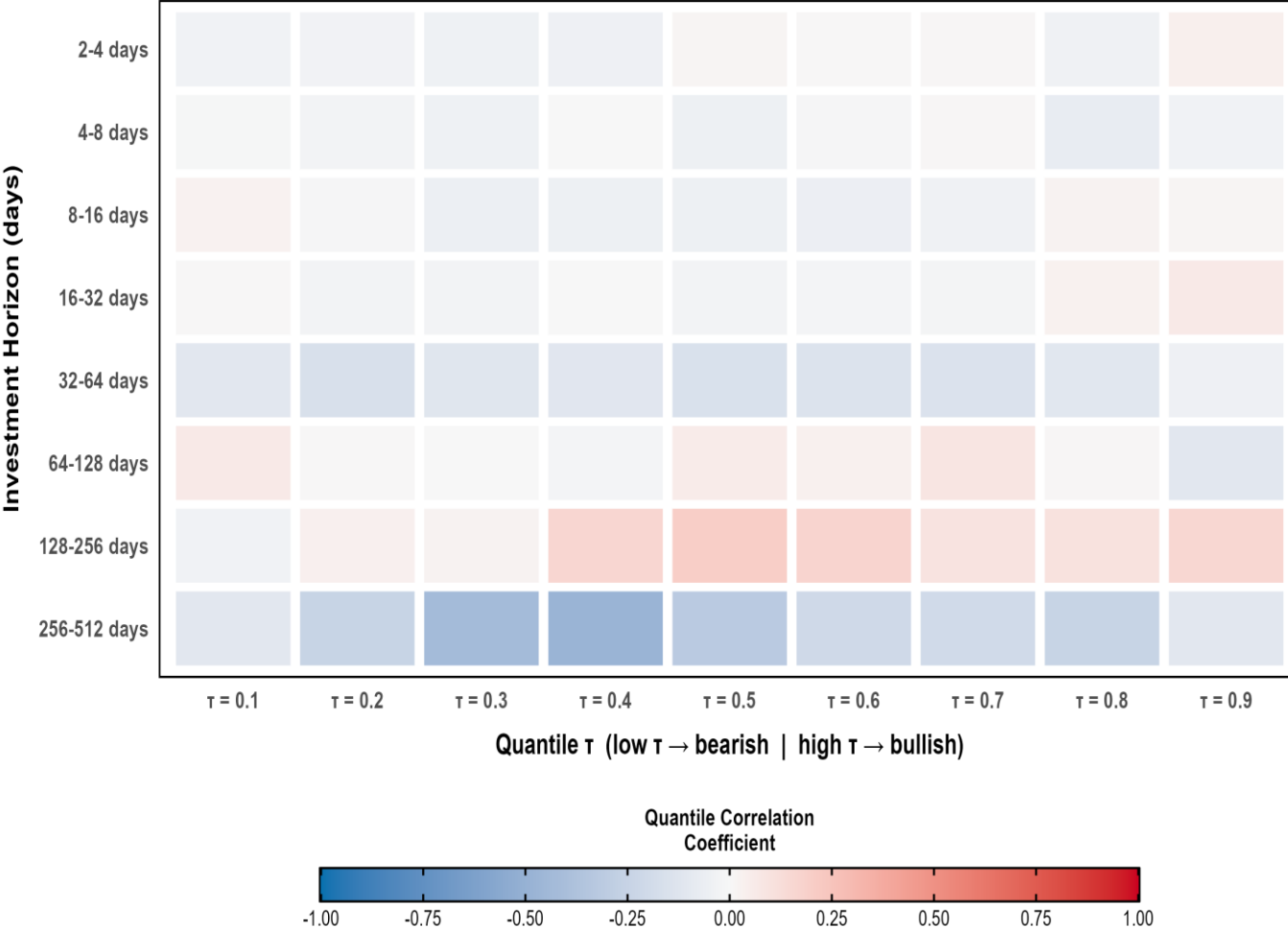
Wavelet Quantile Correlation: CHF vs EM

Period: UkraineWar



Wavelet Quantile Correlation: CHF vs FTSE

Period: UkraineWar



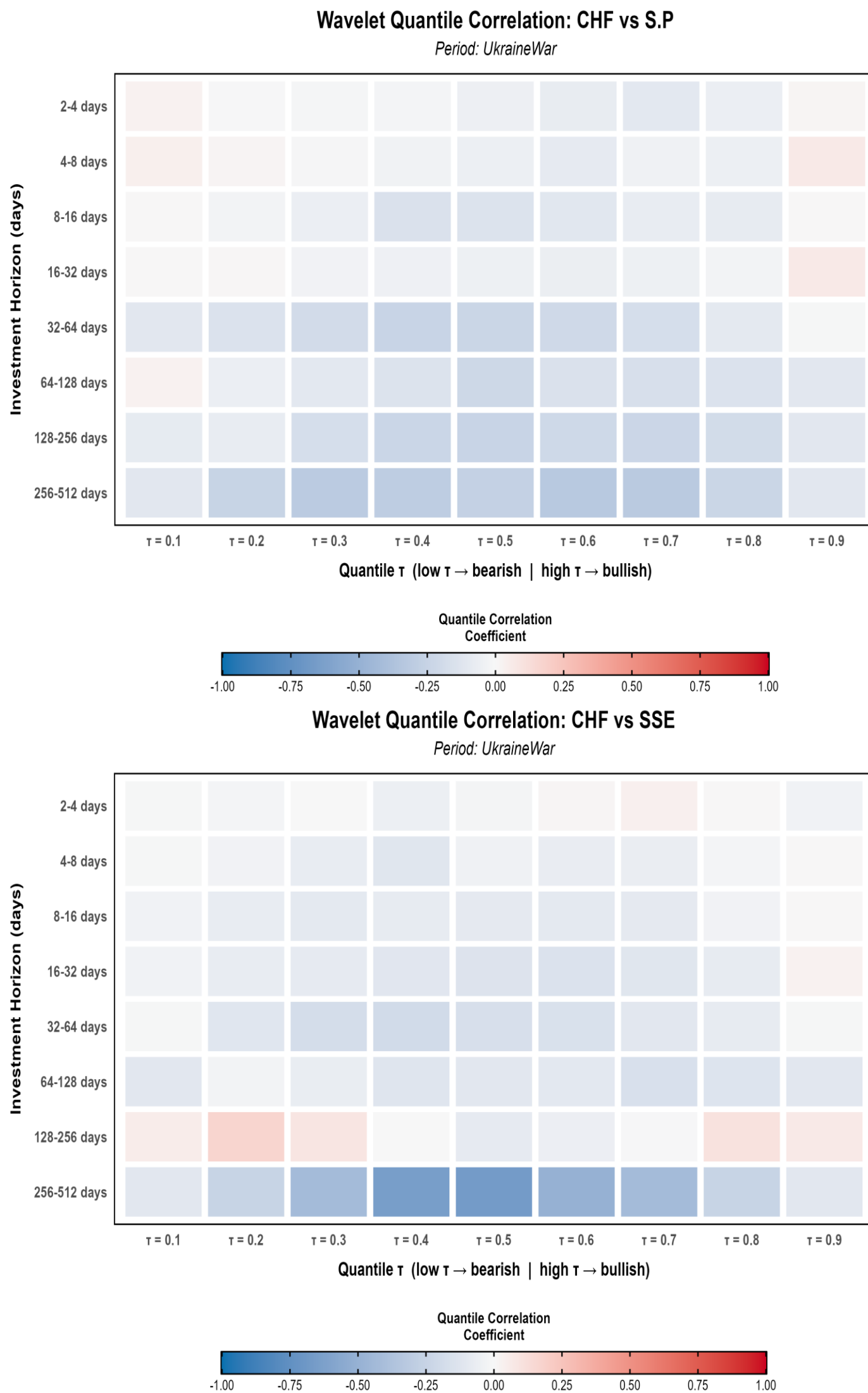
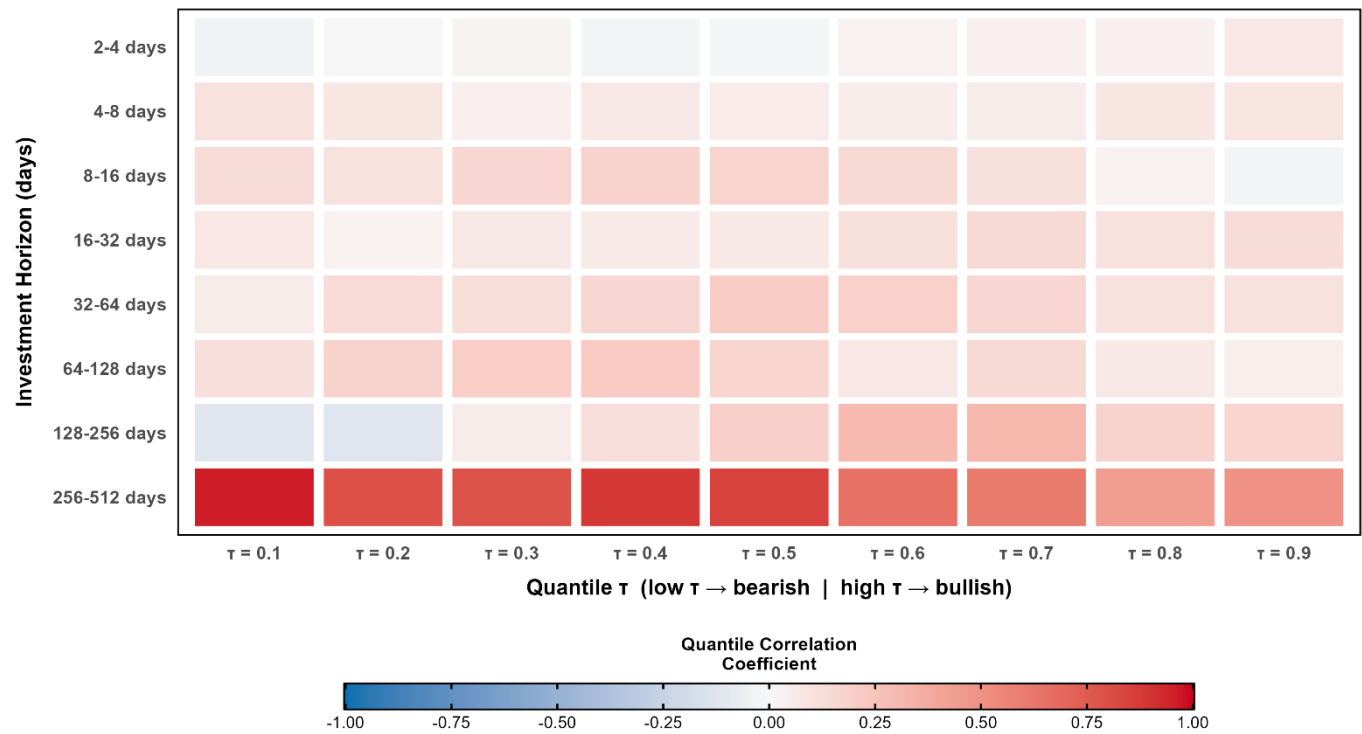


Figure 31. Wavelet Quantile Correlation between Swiss Franc and Equities during the Russia–Ukraine War Period: Strictly Non-Overlapping Windows.

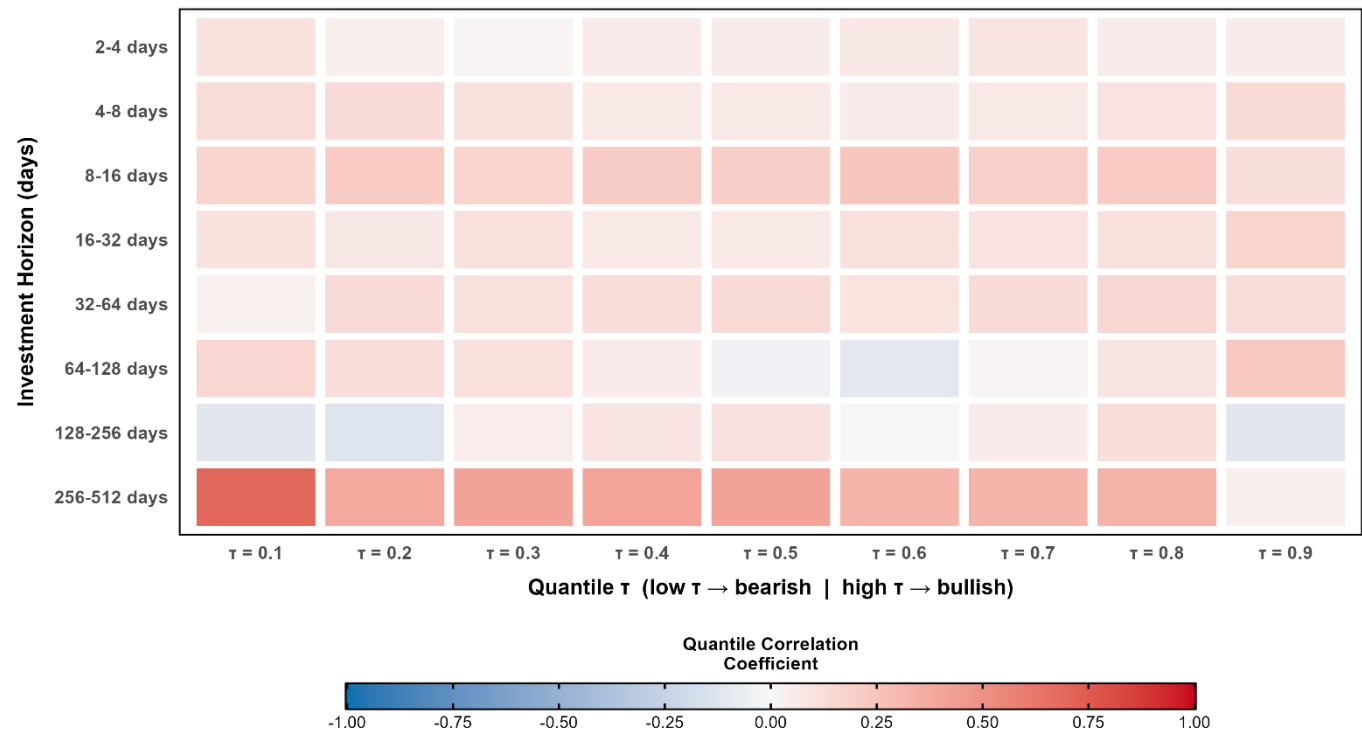
Wavelet Quantile Correlation: BTC vs EM

Period: UkraineWar



Wavelet Quantile Correlation: BTC vs FTSE

Period: UkraineWar



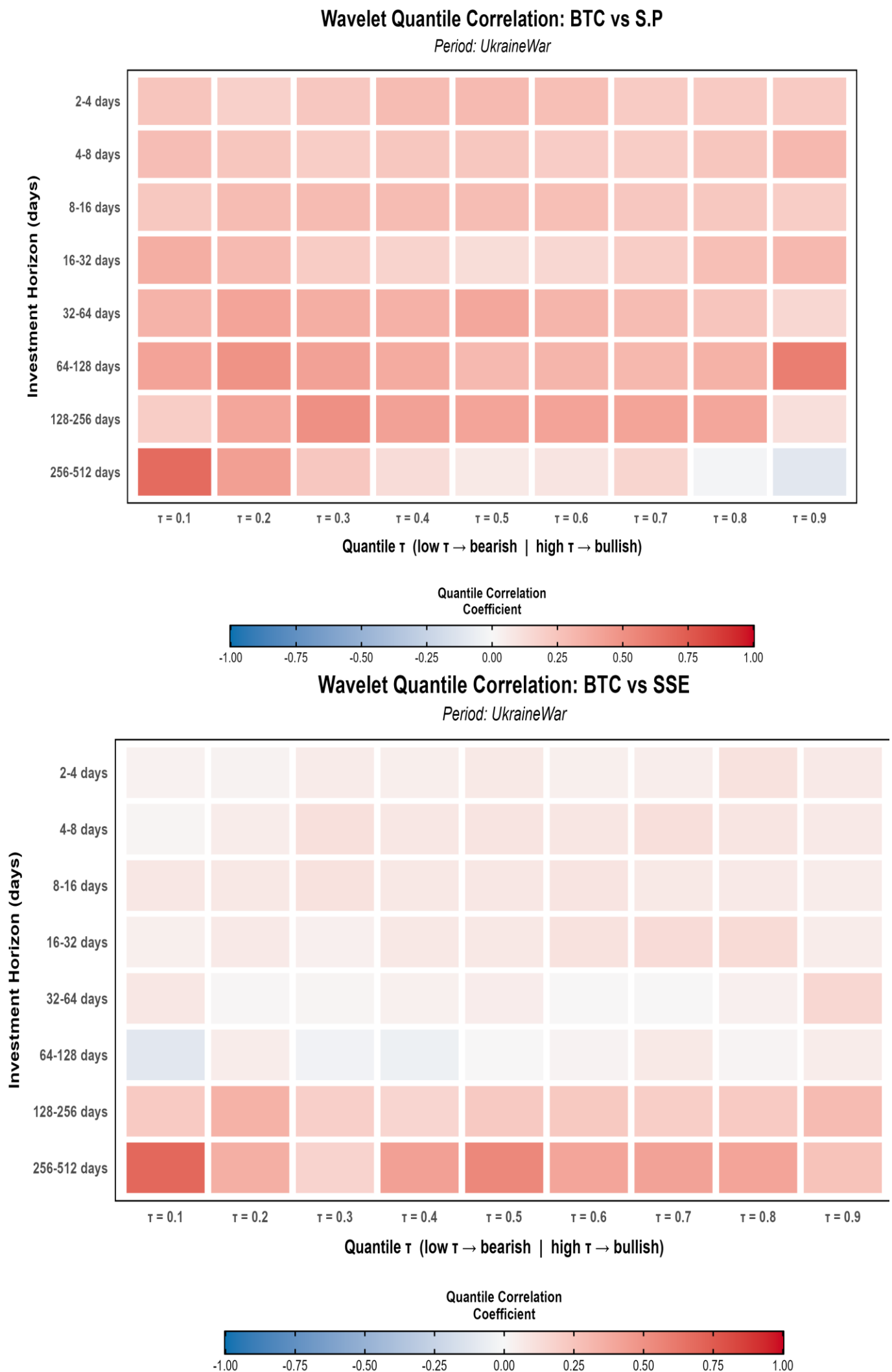


Figure 32. Wavelet Quantile Correlation between Bitcoin and Equities Russia-Ukraine war period: Strictly Non-Overlapping Windows.

6. Conclusions

This study examines the safe-haven properties and spillover dynamics of gold, U.S. Treasury securities, the Swiss franc, and Bitcoin relative to major global equity markets using a unified framework that integrates Wavelet Quantile Correlation and TVP-VAR connectedness analysis. By applying this framework across two structurally distinct crisis

regimes, namely the COVID-19 pandemic and the Russia-Ukraine war, the study provides evidence on whether safe-haven classification is crisis-type-specific, a question that prior single-crisis studies cannot address.

Gold does not qualify as a broad safe haven under either crisis regime for U.S., UK, or emerging market equities. A narrow exception applies to the Chinese equity market at the shortest (2-4 day) and longest (128-256 day) horizons during COVID-19, and at the longest horizon only during Russia-Ukraine. This market-specificity is consistent with Akhtaruzzaman et al. (2021), and the frequency-domain mechanism is a new contribution: the Chinese market's sequential isolation from the March 2020 global liquidity spiral preserved gold's protective properties at specific horizons that were disrupted in Western markets.

U.S. Treasuries qualify as a safe haven only for the UK equity market. This result is robust across both crisis periods and alternative specifications. For the U.S. domestic market, Treasuries failed under both the "dash-for-cash" dynamics of COVID-19 and the inflationary regime following April 2022. This finding refines and extends the existing literature (He et al., 2022; Zhang, 2025) by documenting the cross-market asymmetry in Treasury safe-haven failure.

The Swiss franc provides the most consistent safe-haven evidence, particularly for MSCI Emerging Markets across both crises. However, even CHF classification is conditional: protection weakened for the S&P 500 during Russia-Ukraine (long-horizon only) and was mixed for UK and Chinese markets. The CHF's connectedness network role inverted between crises, shifting from net receiver during COVID-19 to primary net transmitter during Russia-Ukraine, illustrating how geographically concentrated supply-side shocks can alter the information-transmission role of a traditional refuge currency without eliminating its crisis-period protective properties for specific markets.

Bitcoin does not satisfy the safe-haven criterion in any market under any robust specification during either crisis period. The sole qualification is a marginally negative WQC at the 128-256 day horizon during COVID-19 in the Chinese market under the D4 wavelet specification only. This result is specification-sensitive, not replicated under the baseline LA8 specification, and is not present during Russia-Ukraine. It does not alter the overall conclusion that Bitcoin fails as a safe haven under any reliable, replicable specification. Portfolio managers should evaluate cryptocurrency allocations based on their diversification properties during normal market conditions, not on the expectation of crisis-period protection.

The overarching conclusion is that safe-haven status is not an intrinsic asset property but a conditional, regime-dependent, and horizon-sensitive relationship. The crisis transmission channel (demand-side versus supply-side inflationary) emerged as the primary determinant of cross-crisis variation in safe-haven effectiveness, confirming theoretical predictions derived from the stock-bond correlation literature. Investors should adopt dynamic, market-specific, and horizon-calibrated portfolio allocation strategies rather than relying on any single traditional safe-haven asset. For macroprudential authorities, the dominance of U.S. equity market shocks in cross-asset risk transmission and the instability of traditional safe-haven classifications during inflationary regimes underscore the importance of maintaining internationally coordinated monitoring frameworks.

7. Policy Implications

The results have important implications for financial regulators and policymakers. The strong spillover transmission from the U.S. equity market underscores the importance of international coordination in monitoring systemic risk. Because shocks originating in the United States propagate rapidly into other equity markets and into the pricing of candidate safe-haven assets themselves, no single national regulator can adequately monitor or contain this transmission in isolation. This points to a need for closer information-sharing arrangements among central banks and securities regulators, particularly around real-time volatility and cross-asset correlation data, so that early signs of stress in one major market can inform supervisory responses elsewhere before contagion fully materializes.

The conditional nature of safe haven effectiveness suggests that financial systems remain exposed to global shocks despite the presence of traditional refuge assets, reinforcing the need for robust macroprudential frameworks. If gold, government bonds, or reserve currencies only provide protection in some crises and at some investment horizons rather than uniformly, then policymakers cannot treat the presence of these assets in the financial system as a substitute for active macroprudential oversight. Capital buffers, countercyclical capital requirements, and stress-testing scenarios should therefore be calibrated to account for the possibility that traditional hedges fail precisely during the crisis types or horizons where they are most needed, rather than assuming a fixed, always-available cushion against equity market stress.

The limited safe haven role of Bitcoin indicates that cryptocurrencies currently function more as alternative investment assets than systemic stabilizers, warranting appropriate regulatory oversight. This has direct implications for how digital assets are classified and supervised. Regulators should be cautious about policy narratives, whether from industry advocates or from investors themselves, that position Bitcoin and similar assets as reliable portfolio protection during equity market downturns. Instead, oversight frameworks should treat cryptocurrencies primarily through the lens of investor protection and market conduct risk, similar to other volatile speculative instruments, while continuing to monitor whether this role evolves as crypto markets mature and institutional adoption deepens.

Finally, strengthening market depth and institutional resilience in emerging economies can further reduce vulnerability to global financial spillovers. Shallow markets, thin trading volumes, and underdeveloped domestic institutional investor bases tend to amplify the transmission of external shocks rather than absorb them. Policymakers in emerging markets can therefore reduce their exposure to global spillovers not only through capital flow management tools but also through longer-term structural measures, such as deepening local bond and derivatives markets, encouraging domestic institutional investment, and improving market microstructure and liquidity provision, so that domestic financial systems are better positioned to absorb external shocks rather than simply transmitting or amplifying them.

8. Limitations and Suggestions for Future Research

Despite the comprehensive empirical framework adopted in this study, several limitations should be acknowledged. First, the analysis focuses on a limited set of traditional and alternative safe-haven assets. Other

potential hedging instruments, such as commodities, volatility indices, or alternative currencies, were not included and may offer additional insights into diversification strategies. Second, the study considers only four major equity markets, which may not fully capture the dynamics of smaller or frontier financial markets. Finally, the analysis concentrates on two major crisis periods (the COVID-19 pandemic and the Russia–Ukraine geopolitical conflict) while other macroeconomic or financial shocks may influence safe-haven behavior differently.

Future research can extend this study in several directions. First, a broader set of safe-haven assets, including oil, volatility indices such as the VIX, stablecoins, and other cryptocurrencies, could be examined to deepen insights into diversification opportunities. Second, expanding the sample to include frontier and regional equity markets may reveal how safe-haven dynamics vary with levels of financial development. Third, alternative portfolio risk management approaches, such as downside risk hedging, expected shortfall optimization, and regime-switching models, could be applied to better capture nonlinear risk dynamics.

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