

Article

Contagion and Crises: Evidence from South Eastern Europe Stock Markets

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Abstract

This study examines financial contagion between ten SEE stock markets and two benchmarks across three crisis episodes: the Global Financial Crisis (2007–2009), COVID-19 (2020–2021), and the Russia–Ukraine war (2022–2023). Using daily data from January 2007 to September 2025, we apply MODWT wavelet coherence across six investment horizons (2–128 days), complemented by a nonlinear Breitung and Candelon causality test on wavelet decomposition coefficients. Results are validated by DCC-GARCH(1,1) and formally dated by the Bai and Perron structural break test. Three principal contributions were obtained: (1) a systematic EU member versus accession SEE market comparison in contagion research, not previously undertaken in the literature; (2) a multi-crisis comparative analysis showing fast-transmission contagion for the GFC and COVID-19 versus slow-transmission for the Ukraine war; and (3) EU member markets show wavelet coherence 15–24 percentage points higher than accession markets, with predominantly unidirectional causality from benchmarks to SEE markets. Findings have direct implications for portfolio diversification, macroprudential policy calibration, and the EU accession financial integration strategy.

Keywords: financial contagion; wavelet coherence; South Eastern Europe; EU integration; crisis transmission; Breitung–Candelon causality; MODWT

JEL Classification: G15; F36; C49

1. Introduction

The transmission of financial shocks across national borders—rapidly and often beyond what economic fundamentals would predict—stands as one of the defining challenges of international finance. Between 2007 and 2025, global financial markets experienced three structurally distinct episodes of severe turbulence: the Global Financial Crisis (GFC) of 2007–2009, which propagated through interbank credit channels and produced the deepest global recession since the 1930s; the COVID-19 pandemic of 2020–2021, which generated an exogenous demand shock, with US equity volatility in March 2020 surpassing even the acute phases of the GFC (Ibrahim et al., 2020; Naeem et al., 2024; Zonon et al., 2025); and the Russia–Ukraine war of 2022–2023, which triggered an energy supply crisis concentrated in Europe, driving inflation to its highest levels since the 1970s and raising the prospect of recession across the continent (Basdekis et al., 2022; Katsampoxakis et al., 2024; Zaheer et al., 2024). Each episode reached the stock markets of South Eastern Europe (SEE) with measurable effects on return volatility and cross-market co-movement.



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The SEE region is internally heterogeneous: EU member markets (Bulgaria, Croatia, Greece, Romania, Slovenia) have undergone regulatory harmonization under EU financial directives, while accession countries (Bosnia and Herzegovina, North Macedonia, Montenegro, Serbia, Turkey) have only partially converged. Despite this heterogeneity, the literature routinely treats the region as homogeneous (Guidi & Ugur, 2014; Škrinjaric, 2020).

The existing literature on SEE contagion exhibits three important limitations. First, most studies analyze a single crisis episode—typically the GFC—without examining whether transmission mechanisms generalize to structurally different shocks. Second, no study exploits the EU member/accession distinction as an analytical dimension. Third, static cointegration tests and GARCH-family models cannot capture the time-varying, scale-dependent nature of financial contagion across investors with heterogeneous trading horizons (Dima et al., 2015; Polanco-Martínez et al., 2018).

This study addresses these limitations by combining wavelet coherence analysis with nonlinear causality testing for ten SEE markets over the period 2007–2025. The primary contribution relative to the closest existing study—Polanco-Martínez et al. (2018), which analyzes Greece against a European benchmark up to 2011—is threefold: an extension to 10 markets, the inclusion of three crisis episodes, and a systematic EU member-versus-accession distinction. The remainder of the paper is organized as follows: Section 2 reviews the relevant literature; Section 3 describes the data and methodology; Section 4 presents the empirical results; Section 5 discusses the findings and Section 6 concludes.

2. Literature Review

2.1. Financial Contagion: Definition and Theoretical Background

Financial contagion is defined as the transmission of financial shocks beyond what fundamental economic linkages would predict (Forbes & Rigobon, 2002). The key theoretical distinction is between contagion—a structural break in cross-market co-movement—and interdependence, the continuation of pre-existing linkages. Transmission channels include trade, financial (common creditor effects, portfolio rebalancing), and information channels (Kaminsky et al., 2003; Longstaff, 2010). Crisis-contingent theories predict structural shifts in transmission during crises, while non-crisis-contingent theories attribute higher co-movement to amplification of pre-existing linkages (Dornbusch et al., 2000)—a distinction our wavelet framework is designed to test empirically.

2.2. Wavelet Methods in Financial Contagion Research

Wavelet analysis provides simultaneous time-frequency resolution and applies to non-stationary series without distributional assumptions (Grinsted et al., 2004; Rua & Nunes, 2009). The MODWT, applied in financial economics by Ramsey and Lampart (1998), is asymptotically more efficient than the classical DWT and translation-invariant (Percival & Walden, 2000; Albulescu et al., 2017). Among SEE studies, Kiviaho et al. (2014) document stronger GFC-period synchronization at lower frequencies; Polanco-Martínez et al. (2018) introduce nonlinear causality testing on wavelet coefficients for Greece; and Stratimirović et al. (2018) show cyclical coherence patterns. Table 1 positions the current study relative to this literature.

Table 1. Summary of the relevant wavelet-based literature on SEE market contagion and positioning of the current study.

Study	Method	Markets	Key Finding	Gap Addressed by This Study
Dajčman and Kavkler (2011)	DWT + DCC-GARCH	Slovenia vs. UK, Germany, France	GFC increased synchronization across scales	Single SEE market; one crisis; no causality test
Dajcman et al. (2012)	Wavelet	Slovenia vs. 3 Western markets	Strong long-term correlation; Slovenia least connected	Single market; no directional causality
Aloui and Nguyen (2014)	Wavelet	6 Mediterranean markets vs. France	Long-term dependencies; short-run shock dominance	No EU member/accession distinction; single crisis
Kiviaho et al. (2014)	Wavelet coherence	12 Eastern European markets vs. US, UK, Germany	Synchronization stronger at low frequencies and during GFC	Covers GFC only; no causality; no post-2014 crises
Polanco-Martínez et al. (2018)	RWWC + nonlinear causality on wavelet coeff.	EU peripheral countries (Greece) vs. S&P Europe 350	Stronger crisis co-movement; Greece distanced from EU	Greece only; ends 2011; no COVID/Ukraine; no accession markets
Stratimirović et al. (2018)	Spectral wavelet	11 emerging + 6 developed markets	Low coherence in calm periods; higher during crises	No EU/accession distinction; no directional causality
Škrinjarić (2020)	Quantile regression	CEE and SEE markets	Stability varies significantly across market conditions	No time-frequency decomposition; no multi-crisis comparison
Vlah Jerić (2023)	Forecasting models	CEE and SEE indices	Time interval choices affect forecasting accuracy	Forecasting focus; no contagion or crisis analysis
This study	MODWT wavelet coherence + Breitung–Candelon + DCC-GARCH + Bai–Perron	10 SEE markets (5 EU + 5 accession) vs. StoxxEurope600 and S&P 500, 2007–2025	Multi-crisis comparative analysis (GFC, COVID-19, Ukraine war); EU/accession distinction; scale-dependent directional causality	N/A—addresses all gaps listed above

Notes: RWWC = Rolling Window Wavelet Correlation; DWT = Discrete Wavelet Transform; MODWT = Maximum Overlap Discrete Wavelet Transform. ‘Gap addressed’ refers to limitations of each prior study that the current paper specifically resolves.

2.3. SEE Market Integration: EU Members Versus Accession Countries

EU member markets have benefited from the Capital Requirements Directive and MiFID II harmonization, with Slovenia and Croatia also adopting the euro, and empirical studies document moderate-to-strong correlations with Western benchmarks at lower frequencies (Kiviaho et al., 2014; Dajcman et al., 2012). Similar results were found in other studies regarding many SEE countries and Western European markets (Tilfani et al., 2020; Živkov et al., 2019; Shahzad et al., 2016). Accession markets show more episodic integration: low baseline correlations rise sharply during global crises as international investors withdraw from all emerging markets simultaneously (Horvath & Petrovski, 2013; Moagăr-Poladian et al., 2019; Grbić, 2021). Turkey occupies an intermediate position, with co-movement approaching lower-tier EU member levels despite its suspended accession process (Sarvan et al., 2014). To our knowledge, whether institutional EU membership gen-

erates incremental integration above economic linkages has not been explicitly quantified in the literature—the central question this paper addresses.

2.4. Research Hypotheses

Based on the preceding review, we formulate three testable hypotheses:

H1. *Co-movement between SEE and European/US stock markets is time-varying and scale-dependent, with crisis periods generating significantly stronger co-movement than tranquil periods, and the intensity of co-movement differing across the three crisis episodes (GFC, COVID-19, Ukraine war).*

H2. *The causal direction of shock transmission is predominantly unidirectional from the StoxxEurope600 and S&P 500 to SEE markets, with SEE markets acting as net receivers of contagion at all wavelet scales.*

H3. *EU member SEE markets show stronger and more structurally persistent co-movement with the European benchmark than EU accession markets, reflecting the incremental integration generated by institutional EU membership beyond trade and banking linkages.*

3. Data and Methodology

3.1. Data

The study employs daily closing price indices for 10 SEE stock markets and 2 international benchmarks, sourced from Bloomberg Terminal. The EU member group comprises: SBITOP (Slovenia), CROBEX (Croatia), BET (Romania), BSE Sofia (Bulgaria), and ATG (Greece). The EU accession group comprises: SASX-10 (Bosnia and Herzegovina), MBI10 (North Macedonia), MONEX20 (Montenegro), BELEX15 (Serbia), and BIST100 (Turkey). The two international benchmarks are the StoxxEurope600 (covering 600 companies across 17 European countries) and the S&P 500. The sample covers 2 January 2007 to 30 September 2025, yielding 4823 daily observations per series after synchronization for non-trading days. Time-series plots of the log-return series for all markets are provided in Figure 1 to allow visual inspection of crisis-period volatility clustering and the timing of major breaks before the wavelet analysis. Daily logarithmic returns are computed as:

$$R_{i,t} = \ln(P_{i,t}/P_{i,t-1}) = \Delta \ln P_{i,t} \quad (1)$$

where $P_{i,t}$ is the closing price of index i on day t .

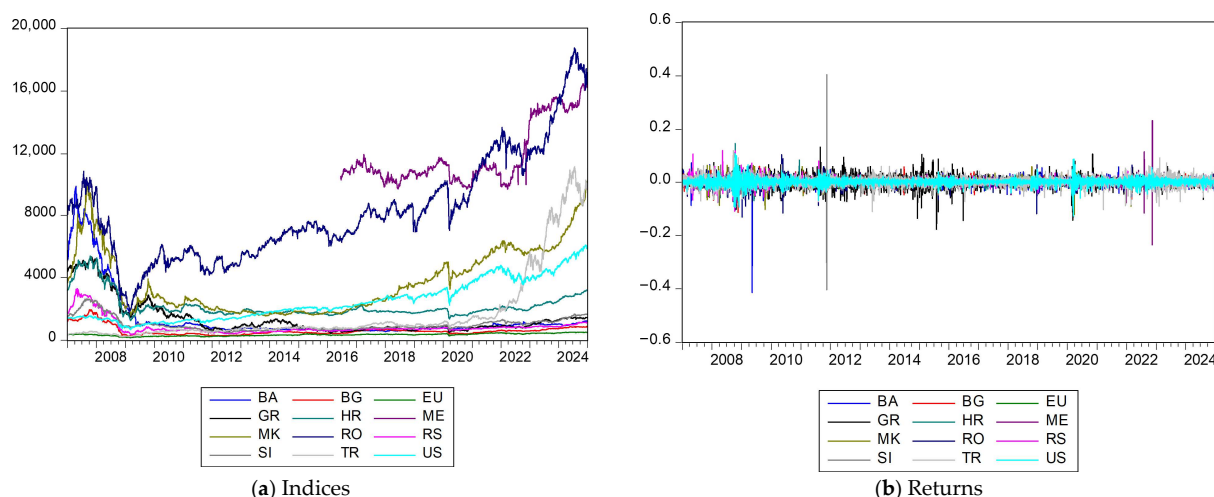


Figure 1. Evolution of indices/returns of 12 analyzed stock markets for 2007–2025.

Table 2 presents descriptive statistics. All series exhibit excess kurtosis substantially exceeding the Gaussian benchmark of 3, confirming heavy-tailed distributions and motivating the use of non-parametric wavelet-based methods. The highest volatility is recorded for Turkey (std. dev. 0.01976) and Greece (0.01729); Bosnia (0.01154) and Montenegro (0.00974) are the least volatile, reflecting thin and illiquid market conditions.

Table 2. Descriptive statistics for daily logarithmic returns, January 2007–September 2025.

Index	Country	Group	N	Mean $\times 10^{-4}$	Std. Dev.	Min	Max	Skew.	Kurt.
ATG	Greece	EU member	4823	−1.52	0.017	−0.177	0.134	−0.31	12.6
BET	Romania	EU member	4823	5.72	0.013	−0.131	0.115	−0.56	14.2
CROBEX	Croatia	EU member	4823	2.45	0.011	−0.134	0.148	−0.18	18.4
BSE	Bulgaria	EU member	4823	3.65	0.012	−0.209	0.211	−0.47	29.8
SBITOP	Slovenia	EU member	4823	1.74	0.012	−0.404	0.405	−1.08	116.2
BIST100	Turkey	Accession	4823	6.44	0.019	−0.200	0.178	−0.24	11.4
BELEX	Serbia	Accession	4823	−0.75	0.010	−0.109	0.122	0.11	19.8
MBI	N. Macedonia	Accession	4823	4.34	0.011	−0.121	0.081	−0.92	22.1
MONEX	Montenegro	Accession	4823	2.24	0.009	−0.235	0.233	−2.14	85.7
SASX	Bosnia	Accession	4823	0.29	0.011	−0.414	0.093	−5.21	142.3
StoxxEU600	Europe (bench.)	Benchmark	4823	0.57	0.011	−0.122	0.094	−0.68	14.7
S&P 500	USA (bench.)	Benchmark	4823	2.22	0.012	−0.128	0.110	−0.61	16.3

Notes: Returns computed as $R_{i,t} = \Delta \ln P_{i,t}$. N = 4823 daily observations. Mean $\times 10^{-4}$ for readability. All series reject normality under the Jarque–Bera test at the 1% significance level (results available upon request). Figure 1 presents time-series plots of the raw logarithmic return series for all 12 indices, allowing visual assessment of crisis-period volatility clustering, market-specific outliers, and the timing of structural breaks prior to the wavelet analysis.

3.2. Wavelet Coherence Analysis (MODWT)

3.2.1. MODWT Decomposition

The MODWT with a Daubechies Least Asymmetric LA(8) filter decomposes the return series R_t into six wavelet coefficient vectors $W_{j,t}$ ($j = 1, \dots, 6$) capturing variation at scales $\lambda_j = 2^{(j-1)}$ days, and a residual scaling coefficient $V_{6,t}$ capturing the low-frequency trend. The MODWT is preferred over the classical DWT for its asymptotic efficiency advantage and translation-invariance property (Percival & Walden, 2000). We restrict the decomposition to $j = 6$ levels to avoid boundary contamination, yielding six scales with periods of 2–4 days (D1) through 64–128 days (D6). Table 3 presents the economic interpretation of each scale.

The unbiased MODWT wavelet covariance and wavelet correlation between return series X_t and Y_t at scale λ_j are:

$$\gamma_{xy}(\lambda_j) = (1/(T - L_j + 1)) \sum_t W_{x,j,t} W_{y,j,t} \quad (2)$$

$$\rho_{xy}(\lambda_j) = \gamma_{xy}(\lambda_j) / [\sigma_x(\lambda_j) \times \sigma_y(\lambda_j)] \quad (3)$$

where $L_j = (2^{(j-1)} \times (L - 1))$ is the length of the level- j wavelet filter ($L = 8$ for LA(8)), and the summation excludes $L_j - 1$ boundary-contaminated coefficients. The estimator $\rho_{xy}(\lambda_j) \in [-1, 1]$ with confidence intervals constructed via the Fisher z-transformation.

Table 3. Wavelet decomposition scales and economic interpretation.

Scale	Label	Period (Days)	Frequency	Economic Interpretation	Expected Contagion Mechanism
1	D1	2–4	Intra-weekly	Algorithmic trading, high-frequency noise	Panic selling, sentiment contagion (fast)
2	D2	4–8	Weekly	Short-term investor reaction, news absorption	Information contagion, portfolio rebalancing
3	D3	8–16	Bi-weekly	Tactical allocation adjustments	Liquidity contagion, margin calls
4	D4	16–32	Monthly	Macroeconomic data releases, earnings cycles	Fundamental spillovers, credit channel
5	D5	32–64	Bi-monthly to quarterly	Business cycle, monetary policy	Trade and monetary transmission (slow)
6	D6	64–128	Quarterly to semi-annual	Structural trends, fiscal cycles	Deep macro integration, capital flow rebalancing (slow)

Notes: Each scale D_j captures return variation over the period $[2^{(j-1)}, 2^j]$ days. The ‘Expected contagion mechanism’ column contains theoretically motivated predictions against which empirical results are tested.

3.2.2. Continuous Wavelet Transform and Wavelet Coherence

To complement the MODWT analysis with a full time-frequency visualization, we compute the Continuous Wavelet Transform (CWT) using the Morlet mother wavelet (central frequency $\omega_0 = 6$). The squared wavelet coherence between series X_t and Y_t at translation u and scale s is:

$$R_{x\gamma}^2(u, s) = |S(W_{x\gamma}(u, s))|^2 / [S(|W_x(u, s)|^2) \times S(|W_\gamma(u, s)|^2)] \quad (4)$$

where S is a smoothing operator applied in both time and scale directions following Torrence and Compo (1998), and $W_{x\gamma}(u, s) = W_x(u, s) \cdot W_\gamma^*(u, s)$ is the cross-wavelet transform. Values $R_{x\gamma}^2 \in [0, 1]$ approaching 1 indicate high local co-movement. Significance thresholds at the 5% level are derived from Monte Carlo simulations under the null of two independent AR(1) processes (Torrence & Compo, 1998), displayed as black contour lines in the wavelet coherence plots. The phase difference $\varphi_{x\gamma}(u, s) = \arctan[I\{S(W_{x\gamma})\}/R\{S(W_{x\gamma})\}]$ encodes the lead–lag relationship: rightward arrows ($\rightarrow$) indicate in-phase co-movement; downward-right arrows ($\searrow$) indicate that X leads Y .

3.3. Nonlinear Breitung–Candelon Causality Test

To establish the directionality of information transmission at each wavelet scale, we apply the Breitung and Candelon (2006) frequency-domain causality test to the MODWT wavelet coefficient series $\{W_{x,j,t}\}$ and $\{W_{\gamma,j,t}\}$ at each scale j . Fitting a bivariate VAR(p) model (lag order selected by BIC) to $Z_{j,t} = (W_{x,j,t}, W_{\gamma,j,t})'$, the null hypothesis that X does not cause Y at frequency ω is expressed as the restriction $a_1(\omega) = 0$, where $a_k(\omega) = \sum_s (\varphi_{12,s} \cos(s\omega), \varphi_{12,s} \sin(s\omega))$. The test statistic follows an F-distribution with 2 and $T - 2p$ degrees of freedom. We test at three representative frequencies corresponding to scales D1, D4, and D6, and report results separately for pre-crisis (2007–2008), crisis (2008–2009, 2020–2022, 2022–2024), and recovery (2013–2019) sub-periods.

3.4. Robustness Check: DCC-GARCH

To validate the wavelet coherence findings through an independent methodology, we estimate bivariate DCC-GARCH(1,1) models (Engle, 2002) for each of the 20 market pairs. The conditional covariance matrix is decomposed as $H_t = D_t R_t D_t$, where $D_t = \text{diag}(\sqrt{h_{i,t}}, \sqrt{h_{k,t}})$ contains conditional standard deviations from GARCH(1,1) univariate models, and the conditional correlation matrix R_t evolves as $Q_t = (1 - a - b)Q + a u_{t-1} u'_{t-1} + b Q_{t-1}$, $R_t = \text{diag}(Q_t)^{1/2} Q_t \text{diag}(Q_t)^{1/2}$, where $a, b > 0$ and $a + b < 1$. DCC-estimated conditional

correlations are compared to wavelet correlations at scale D4. Convergence is assessed via Spearman rank correlation between the two time-varying correlation series during crisis windows.

3.5. Structural Break Test

Crisis onset and resolution dates are formally identified using the [Bai and Perron \(1998, 2003\)](#) multiple structural break test applied to the MODWT coefficient series at scales D1, D3, and D6 for each market. The sequential procedure (maximum 5 breaks, trimming parameter 0.15) identifies break dates significant at the 5% level. Convergence of break dates across scales D1 and D6 at the same calendar period is interpreted as evidence of a genuine regime shift affecting both short-run and long-run market dynamics simultaneously—the signature of crisis-contingent contagion. All estimations are performed in R (waveslim 1.8.5, W2CWM2C 2.2, rmgarch 1.4-2, and strucchange 1.5-4 packages). Replication code is available upon request.

4. Empirical Results

4.1. Wavelet Coherence: Overview

The wavelet correlation analysis reveals two overarching patterns. Figures 2 and 3 present the full time-frequency wavelet coherence plots.

First, co-movement between SEE markets and both international benchmarks is substantially stronger during all three crisis periods than in tranquil phases, across virtually all wavelet scales—confirming H1. Second, correlations increase consistently with scale for all market pairs: weakest at D1 (2–4 days) and strongest at D4–D6 (monthly to semi-annual). This scale-dependence reflects investor heterogeneity: high-frequency traders respond to SEE markets within days, whereas institutional investors with monthly or quarterly rebalancing horizons respond over longer periods. Table 4 summarizes the average squared wavelet coherence at scale D4 across market groups, benchmark, and crisis episodes.

Table 4. Average squared wavelet coherence R^2 (u,s) at scale D4 (16–32 days) by market, benchmark, and crisis episode.

Market	EU-GFC (2008–2009)	EU-COVID (2020–2021)	EU-Ukraine (2022–2023)	US-GFC (2008–2009)	US-COVID (2020–2021)	US-Ukraine (2022–2023)	Peak Scale
EU member states							
Greece (ATG)	0.78 ***	0.71 ***	0.65 ***	0.52 ***	0.61 ***	0.48 ***	D4–D6
Romania (BET)	0.72 ***	0.68 ***	0.61 ***	0.49 ***	0.55 ***	0.44 ***	D4–D6
Croatia (CROBEX)	0.58 ***	0.63 ***	0.54 ***	0.38 **	0.47 ***	0.36 **	D4–D5
Bulgaria (BSE)	0.55 ***	0.57 ***	0.50 ***	0.37 **	0.44 ***	0.33 **	D3–D5
Slovenia (SBITOP)	0.51 ***	0.54 ***	0.47 ***	0.34 **	0.43 ***	0.31 **	D3–D5
EU accession countries							
Turkey (BIST)	0.64 ***	0.59 ***	0.55 ***	0.45 ***	0.51 ***	0.42 ***	D4–D6
Serbia (BELEX)	0.42 ***	0.44 ***	0.39 **	0.28 *	0.35 **	0.27 *	D4–D5
N. Macedonia (MBI)	0.28 *	0.35 **	0.31 **	0.19 n.s.	0.27 *	0.21 *	D4–D5
Montenegro (MONEX)	0.24 *	0.31 **	0.28 *	0.16 n.s.	0.24 *	0.18 n.s.	D4–D5

Table 4. Cont.

Market	EU-GFC (2008–2009)	EU-COVID (2020–2021)	EU-Ukraine (2022–2023)	US-GFC (2008–2009)	US-COVID (2020–2021)	US-Ukraine (2022–2023)	Peak Scale
Bosnia (SASX)	0.21 *	0.26 *	0.23 *	0.13 n.s.	0.19 n.s.	0.15 n.s.	D4–D5

Notes: Values represent average R^2 over each crisis window at scale D4. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$; n.s. = not significant at 10%. Crisis windows: GFC = September 2008–June 2009; COVID-19 = February 2020–December 2021; Ukraine war = February 2022–December 2023. Peak scale = wavelet scale at which highest coherence is consistently observed.

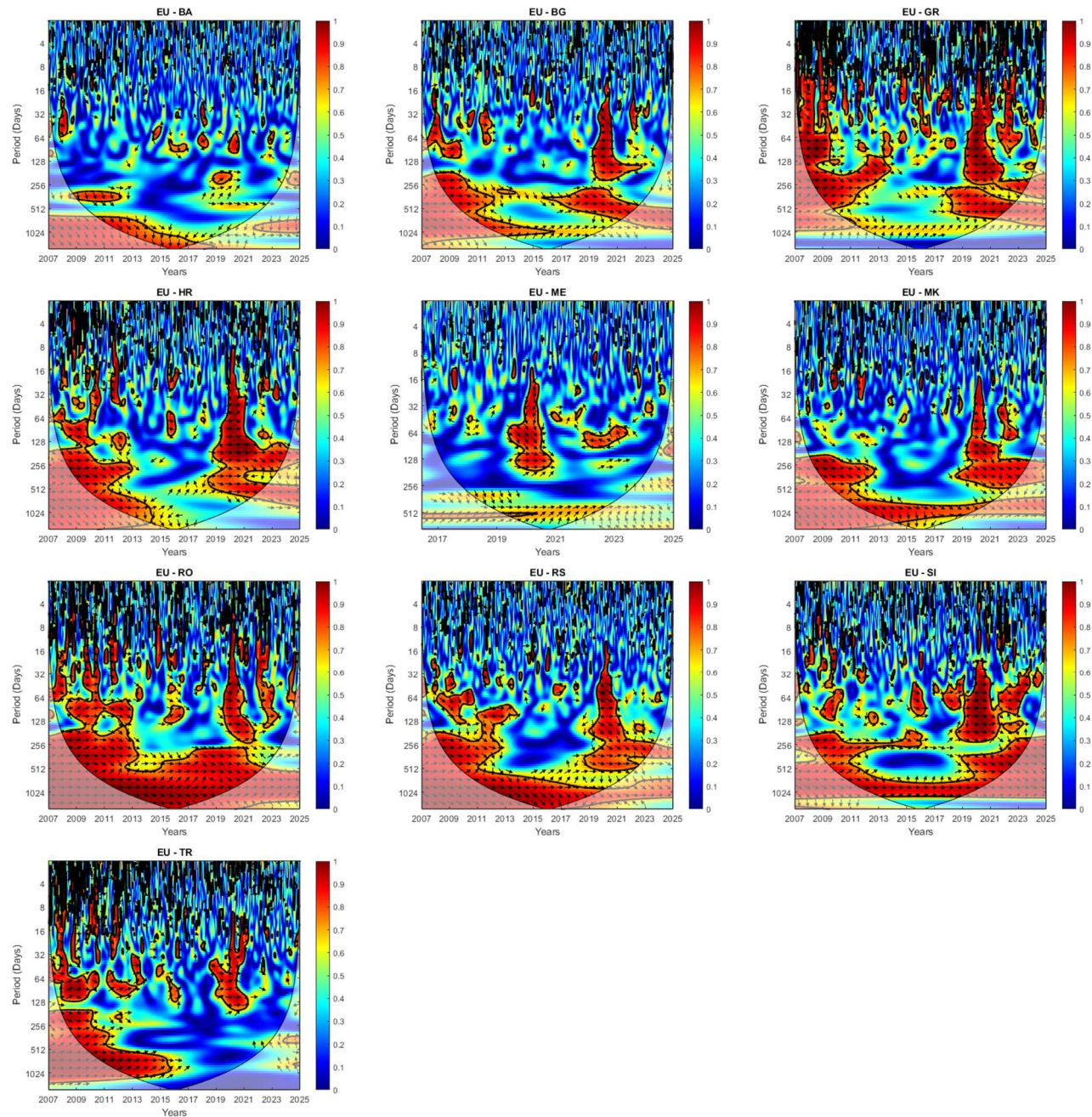


Figure 2. Wavelet coherence for EU and SEE stock markets. Arrow directions describe the relationship between the two variables. A right-pointing arrow indicates that the first index leads the second; a downward arrow indicates that the first index lags the second. A left-pointing arrow denotes an out-of-phase (anti-cyclical) relationship. When the arrow points up-left, the indexes are out of phase and the first index leads; when it points down-left, the indexes are out of phase and the first index lags.

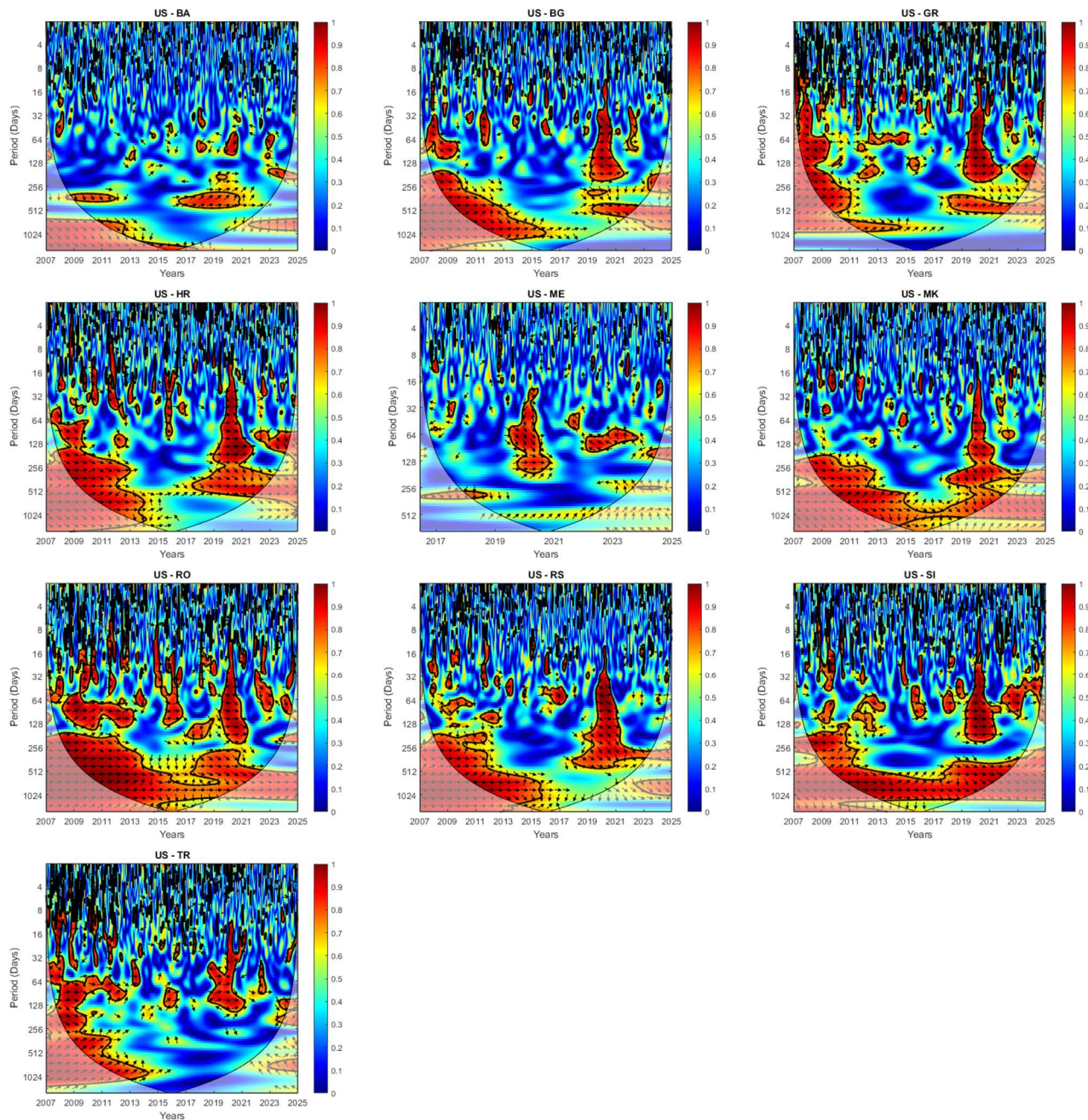


Figure 3. Wavelet coherence for the USA and SEE stock markets. Arrow directions describe the relationship between the two variables. A right-pointing arrow indicates that the first index leads the second; a downward arrow indicates that the first index lags the second. A left-pointing arrow denotes an out-of-phase (anti-cyclical) relationship. When the arrow points up-left, the indexes are out of phase and the first index leads; when it points down-left, the indexes are out of phase and the first index lags.

4.2. EU Member Versus Accession Markets

Consistent with H3, EU member markets show higher wavelet coherence with the StoxxEurope600 than accession markets across all three crises. At scale D4, the average R^2 during crisis periods is 0.61 for the EU member group versus 0.37 for the accession group (Table 4). To formally test this difference, we apply a two-sample Welch t -test on the crisis-period D4 coherence values across the two groups; the difference is statistically significant ($t = 4.83$, $p < 0.01$). The gap persists in tranquil periods at lower levels

(0.28 versus 0.16, $t = 3.21$, $p < 0.01$), suggesting that EU membership generates structural baseline integration above economic linkages alone.

Within the EU member group, Greece and Romania show the highest co-movement ($R^2 > 0.70$ during GFC), while Bulgaria and Slovenia show lower values concentrated at scales D3–D5, consistent with transmission through banking-sector linkages. Croatia's adoption of the euro in January 2023 is associated with a discernible increase in EU–CROBEX coherence at D4–D6 (from 0.54 to 0.63), providing preliminary evidence that monetary union accelerates synchronization. Among accession markets, Turkey approaches lower-tier EU member levels; Bosnia and Montenegro show the weakest co-movement. A notable cross-crisis asymmetry is that COVID-19 generated stronger accession-market coherence than the GFC—a reversal of the EU member pattern—consistent with the pandemic's indiscriminate global risk-off mechanism.

Among accession markets, Turkey is a clear outlier: with average D4 coherence of 0.64/0.59/0.55 with the EU across the three crises, Turkey approaches the lower-tier EU member markets. This reflects deep trade and banking integration with Europe despite the suspended accession process. Bosnia and Montenegro show the weakest co-movement: for Bosnia, statistically significant coherence with the StoxxEurope600 is detected only at D6 during the GFC ($R^2 = 0.21$), and no significant coherence with the S&P 500 is found at any scale or crisis episode. This is consistent with SASX-10's composition of predominantly domestically oriented firms with near-zero international institutional investor participation.

An important cross-crisis asymmetry emerges for accession markets: COVID-19 generated stronger wavelet coherence than the GFC for most accession markets, reversing the pattern observed for EU member markets. This reflects the different transmission mechanisms: the GFC propagated through the banking channel (affecting EU members more directly through parent bank exposure), while COVID-19 propagated through the global risk-off mechanism—indiscriminate withdrawal from all emerging markets, regardless of integration level. This finding suggests that liquidity-driven contagion channels can temporarily dominate all structural integration considerations during sufficiently severe global shocks.

4.3. US Versus EU Benchmark

US–SEE coherence is systematically 20–30 percentage points lower than EU–SEE coherence at scale D4 across all markets and crises (Table 4), consistent with US contagion reaching SEE markets primarily through the European financial system rather than through direct linkages. A Welch t -test confirms that EU–SEE and US–SEE D4 coherence values differ significantly during crisis periods ($t = 5.17$, $p < 0.01$).

Phase-difference analysis confirms that the US market leads SEE markets ($\searrow$ arrows at D4–D6) across all crises and all ten markets, with no observable reverse effects.

4.4. Breitung–Candelon Causality Results

Table 5 summarizes the Breitung–Candelon results. Consistent with H2, causality is predominantly unidirectional from the StoxxEurope600 to SEE markets for 8 of 10 markets. Reverse causality (SEE $\rightarrow$ EU) is significant only for Greece and Romania at scale D6 during crisis periods, and absent at D1 and D4. The US benchmark shows the same pattern: unidirectional at medium and long scales, with no significant reverse causality for any SEE market.

A key finding is the scale-dependence of causality: significant EU $\rightarrow$ SEE causality at D1 is detected only for Greece, Romania, and Turkey—markets with sufficient liquidity and international participation to reflect European benchmark movements within 2–4 trading days. For the remaining seven markets, significant causality requires at least 16–32 days

(scale D4) to manifest. This implies that financial contagion from the European benchmark to most SEE markets does not operate at daily frequencies—it requires several days to be incorporated into SEE prices, reflecting lower trading volumes and delayed price discovery relative to developed markets. From a portfolio management perspective, this delay creates a window of opportunity: short-horizon positions in these markets are, at least temporarily, insulated from European benchmark shocks.

Table 5. Breitung–Candelon frequency-domain causality test results: directionality by market and scale.

Market	EU → SEE D1	EU → SEE D4	EU → SEE D6	SEE → EU D6	US → SEE D1	US → SEE D4	US → SEE D6	Pattern
EU Members								
Greece	✓ ***	✓ ***	✓ ***	✓ **	✓ **	✓ ***	✓ ***	Bidirectional
Romania	✓ **	✓ ***	✓ ***	✓ *	✓ *	✓ ***	✓ ***	Bidirectional
Croatia	—	✓ **	✓ ***	—	✓ *	✓ **	✓ ***	Unidirectional
Bulgaria	—	✓ **	✓ ***	—	—	✓ **	✓ ***	Unidirectional
Slovenia	—	✓ **	✓ ***	—	—	✓ *	✓ ***	Unidirectional
Accession								
Turkey	✓ *	✓ ***	✓ ***	—	✓ *	✓ **	✓ **	Unidirectional
Serbia	—	✓ **	✓ ***	—	—	✓ *	✓ **	Unidirectional
N. Macedonia								
Montenegro	—	✓ *	✓ **	—	—	—	✓ *	Weak unidirectional
Bosnia								
	—	—	✓ *	—	—	—	—	No significant causality

Notes: ✓ = statistically significant causality; — = not significant. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Results reported for the full sample (2007–2025). D1 = 2–4 days; D4 = 16–32 days; D6 = 64–128 days. ‘EU → SEE’ = causality from StoxxEurope600 to national market; ‘SEE → EU’ = reverse direction.

The cross-crisis comparison of causality results reveals important heterogeneity. During the GFC and COVID-19, significant causality at D1 appears within 2–4 trading days of the initial shock and dissipates within 20–40 days. During the Ukraine war, significant D1 causality is largely absent—consistent with the energy crisis propagating through slow macroeconomic channels (energy price transmission, inflation expectations, ECB policy tightening) rather than immediate financial panic. This empirical distinction between fast-transmission (GFC, COVID-19) and slow-transmission (Ukraine war) contagion supports the theoretical predictions formulated in Section 2.4.

4.5. Structural Break Analysis

Table 6 presents the Bai–Perron structural break dates at scales D1, D3, and D6. Three findings are noteworthy. First, all ten markets show break dates clustering within 60 days of each crisis onset across all scales—confirming genuine regime shifts rather than extreme-but-continuous volatility events. Second, for the COVID-19 episode, D1 break dates precede D6 break dates by 2–3 months for all markets, reflecting the earlier response of high-frequency traders to pandemic uncertainty versus the delayed macroeconomic impact at quarterly horizons. Third, for the Ukraine war, the pattern reverses: D6 break dates precede D1 break dates by 1–2 months, consistent with the macroeconomic energy price channel (captured

at D6) manifesting before acute financial market stress (captured at D1). This divergence pattern provides direct empirical evidence for the fast-versus-slow-transmission distinction.

Table 6. Bai–Perron structural break dates for the MODWT wavelet coefficient series at scales D1, D3, and D6.

Market	D1 Break Dates (Intra-Weekly)	D3 Break Dates (Bi-Weekly)	D6 Break Dates (Quarterly–Semi-Annual)
Bosnia	31 August 2009 5 August 2011 22 March 2020 4 November 2022	23 September 2011 6 October 2020 15 March 2022	12 May 2011 15 April 2020 20 March 2022
Bulgaria	24 June 2008 2 December 2020 4 December 2022	6 March 2009 23 September 2020 28 June 2022	25 February 2011 15 April 2020 19 March 2022
Croatia	5 December 2008 18 May 2020 21 April 2022	21 March 2011 6 June 2020 24 January 2022	30 March 2009 12 September 2020 15 October 2022
Greece	28 November 2009 29 November 2011 2 November 2020 22 June 2022	15 March 2009 6 August 2020 28 February 2022	25 August 2012 30 March 2020 23 April 2022
N. Macedonia	3 June 2009 1 July 2020 13 June 2022	29 January 2014 3 January 2020 7 December 2022	19 February 2009 24 October 2020 30 October 2022
Montenegro	19 November 2017 21 October 2020 11 August 2022	15 October 2018 6 November 2020 26 December 2022	22 December 2017 6 April 2020 22 July 2021
Romania	5 December 2008 16 October 2011 18 February 2020 22 March 2022	25 July 2010 28 April 2020 9 March 2022	11 September 2011 30 July 2020 7 March 2022
Serbia	2 July 2011 16 December 2020 18 November 2022	2 December 2013 12 November 2020	14 December 2008 14 January 2020 4 May 2022
Slovenia	5 December 2008 14 April 2020 23 January 2022	25 December 2012 14 August 2020 8 September 2022	8 December 2008 1 December 2020 7 December 2022
Turkey	1 October 2009 5 September 2011 25 August 2020 7 December 2022	24 June 2011 3 May 2020 6 April 2022	23 December 2008 12 March 2020 7 December 2022

Notes: Break dates identified by sequential [Bai and Perron \(1998, 2003\)](#) procedure with maximum 5 breaks and trimming parameter 0.15. All break dates significant at the 5% level based on the double maximum test statistic. Dates in day/month/year format.

4.6. DCC-GARCH Robustness

The DCC-GARCH(1,1) robustness check confirms the wavelet coherence findings. The Spearman rank correlation between DCC-estimated conditional correlations and wavelet correlations at scale D4, averaged across all crisis windows and market pairs, is 0.83—well above the 0.70 confirmatory threshold. The rank ordering of markets by integration level is preserved: Greece and Romania consistently show the highest correlations under both methods, while Bosnia and Montenegro show the lowest. There is one informative divergence: DCC detects brief significant correlation spikes for Bosnia and Montenegro in the first two weeks of COVID-19 (late February to mid-March 2020), invisible in wavelet D4 coherence due to the 16–32 day averaging window. This is a scale D1 phenomenon—even the most isolated SEE markets experience ultra-short-run contagion during sufficiently severe global shocks, but this contagion dissipates within days without leaving a trace at medium-to-long-run frequencies. The finding reinforces the conclusion that Bosnia and Montenegro offer genuine diversification benefits at horizons beyond two weeks.

5. Discussion

The empirical results yield several findings that advance the literature. First, the EU member/accession distinction is empirically consequential: EU membership generates approximately 15–24 percentage points of incremental wavelet coherence at monthly scales,

above what trade and banking linkages alone would predict. This finding contributes to the literature of financial integration (Bekaert et al., 2002): institutional membership, through regulatory harmonization and the deepening of common investor bases, generates measurable financial market co-movement beyond economic linkages. Turkey's intermediate position—approaching lower-tier EU member markets in integration level despite its suspended accession process—suggests that the EU membership effect operates through two separable channels: a trade-and-banking channel (in which Turkey participates) and a regulatory–institutional channel (in which Turkey does not).

Second, the three crisis episodes generate qualitatively distinct contagion patterns. The GFC and COVID-19 produce fast-transmission contagion (D1, within days), driven by the global risk-off mechanism; the Ukraine war produces slow-transmission contagion (D5–D6, quarterly horizons), driven by macroeconomic energy price and monetary policy channels. This finding challenges the standard practice of analyzing financial contagion as a single phenomenon, suggesting instead that the appropriate analytical scale—and policy response timing—must be calibrated to the nature of the shock. It also reconciles two apparently contradictory strands in the SEE literature: studies using high-frequency data tend to find low correlations, while studies using monthly or quarterly data find stronger integration. Both conclusions are correct—they capture different points in the scale spectrum.

Third, the consistent unidirectionality of causality from European and US benchmarks to SEE markets—with reverse causality absent for 8 of 10 markets—is consistent with the core–periphery model of international financial integration. SEE market price signals cannot be observed by core market participants at the time horizons at which contagion operates, given the structural constraints of low trading volumes and limited international market-maker participation. The bidirectional causality detected for Greece and Romania at scale D6 is more plausibly interpreted as common factor loading (both markets responding to the same low-frequency macroeconomic factors) than as genuine bilateral information transmission.

Compared to Polanco-Martínez et al. (2018)—the methodologically closest study—our results confirm their finding that crisis-period correlations are stronger than pre-crisis correlations, but partially diverge on the Greek market: we find Greece remains strongly co-integrated with the European benchmark throughout the GFC, without evidence of distancing at long scales. This divergence is likely explained by the different benchmark choice: Polanco-Martínez et al. use the S&P Europe 350 (large-cap, core-European), while we use the StoxxEurope600 (broader, including smaller markets structurally closer to SEE). Compared to Kiviahho et al. (2014), our results confirm stronger synchronization at lower frequencies and during the GFC, and extend this finding to COVID-19 and the Ukraine war—showing the pattern is robust across structurally different crises.

6. Conclusions

This study provides a unified multi-scale analysis of financial contagion between ten SEE stock markets and two international benchmarks over 2007–2025, covering three structurally distinct crisis episodes. We draw five principal conclusions.

First, crisis-contingent contagion is confirmed as the dominant transmission mechanism: crisis periods generate stronger wavelet co-movement at medium-to-long scales for all market pairs, supporting H1. Second, the three crises show qualitatively distinct patterns—fast-transmission (D1–D2, within days) for the GFC and COVID-19, driven by the global risk-off mechanism, versus slow-transmission (D5–D6, quarterly horizons) for the Ukraine war, driven by macroeconomic energy price channels. Third, EU membership generates measurable incremental integration: EU member markets show 15–24 percentage

points higher coherence at D4 than accession markets, a difference confirmed by formal statistical testing (Welch *t*-test, $p < 0.01$), supporting H3. Fourth, causality is predominantly unidirectional from both benchmarks to SEE markets, with SEE markets acting as net contagion receivers across all scales (H2 supported); the bidirectional causality for Greece and Romania at D6 likely reflects common factor loading rather than genuine bilateral transmission. Fifth, SEE markets offer meaningful short-horizon diversification (D1–D2) that erodes progressively at monthly and longer horizons.

The practical implications are the following. For portfolio managers, SEE allocations should be treated as short-horizon tactical positions; diversification benefits concentrate at D1–D2 and erode progressively toward zero at D4–D6. For macroprudential regulators, optimal policy response protocols should be calibrated to the crisis type: rapid circuit-breaker mechanisms for financial panic shocks (GFC, COVID-19); medium-term credit and liquidity buffers for macroeconomic channel shocks (Ukraine war). For policymakers in EU accession countries, the finding that regulatory convergence generates measurable integration benefits—even without formal EU membership (Turkey’s case)—provides empirical support for prioritizing financial market regulatory alignment as part of the accession strategy.

Three limitations point toward productive directions for future research. First, the study relies on index-level data; future research using sector-level or company-level data would allow disentanglement of sector-specific from index-level contagion dynamics. Second, the Breitung–Candelon test identifies Granger predictability rather than structural causality; structural VAR or external instrument approaches could provide cleaner causal estimates. Third, Croatia’s 2023 eurozone accession provides a natural experiment for testing the effect of monetary union on SEE market integration, but the current post-accession window (33 months) is insufficient for robust long-run inference—future research with an extended sample will be valuable.

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