International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

# Sectoral Contagion and Volatility Spillovers at the Casablanca Stock Exchange: A DCC-GARCH and Diebold-Yilmaz Network Approach

**Maghniwi Rachid**

Mohammed V University of Rabat, Morocco

**ABSTRACT**

This paper investigates the dynamics of cross-sectoral volatility transmission within the Casablanca Stock Exchange (CSE), an increasingly prominent equity market in the MENA region. We employ a Dynamic Conditional Correlation GARCH (DCC-GARCH) framework to estimate time-varying correlations among six key sectoral indices over the period January 2015 to December 2024. Building upon these pairwise estimates, we construct a Diebold-Yilmaz connectedness network to quantify directional volatility spillovers across sectors. Our empirical findings reveal that the banking sector operates as the dominant transmitter of volatility shocks, accounting for approximately 38.2% of total system-wide spillover contributions. The real estate and telecommunications sectors emerge as the principal receivers of these transmitted shocks. The total connectedness index fluctuates considerably over the sample period, spiking during episodes of macroeconomic stress such as the COVID-19 pandemic and the announcement of the 2030 FIFA World Cup co-hosting arrangement. A rolling-window analysis confirms that the network topology undergoes substantial restructuring during crisis periods, with inter-sectoral correlations rising sharply and the network becoming more densely interconnected. These results carry meaningful implications for portfolio diversification, systemic risk monitoring, and the design of macroprudential policies in emerging market settings. Our study contributes to the growing body of evidence on financial contagion in African capital markets and offers a novel perspective on the internal transmission mechanisms operating within a concentrated equity market.

**Keywords:** Volatility spillovers; DCC-GARCH; Diebold-Yilmaz connectedness; Casablanca Stock Exchange; sectoral contagion; emerging markets

## 1. INTRODUCTION

The Casablanca Stock Exchange (CSE), established in 1929 and modernized extensively since the 1990s, occupies a strategic position among North African and MENA-region capital markets. With a market capitalization exceeding 65 billion USD as of late 2024 and roughly 75 listed companies spanning banking, telecommunications, real estate, tourism, industry, and other services, the CSE serves as the barometer of Moroccan corporate performance and a gateway for both domestic and international portfolio capital. Yet despite its growing stature, the internal mechanics of volatility propagation across CSE sectors remain insufficiently explored in the academic literature.

Understanding how shocks travel between sectors within a single exchange is not merely an academic exercise. For portfolio managers operating in concentrated markets, knowledge of sectoral contagion patterns directly informs hedging strategies, sector-rotation timing, and tail-risk management. For prudential regulators, mapping the channels through which volatility propagates illuminates potential systemic vulnerabilities that standard aggregate risk indicators may obscure. And for policymakers charged with fostering financial stability in the context of Morocco's ambitious development agenda—which now includes co-hosting the 2030 FIFA World Cup—the ability to anticipate and manage cross-sectoral stress transmission is of first-order importance.

The theoretical underpinnings of our investigation draw on several established strands of financial economics. The contagion literature, rooted in the pioneering work of Forbes and Rigobon (2002), distinguishes between co-movement that arises from common fundamentals and excess co-movement that emerges during periods of stress. The volatility transmission literature, from Engle's (2002) introduction of the DCC model through Diebold and Yilmaz's (2012, 2014) variance decomposition framework, provides the econometric tools needed to quantify these dynamics at both the pairwise and system-wide levels. More recently, network approaches imported from graph theory have enabled researchers to visualize and analyze the topology of financial interconnections in ways that complement traditional time-series analysis.

Several features of the Moroccan equity market make it a particularly informative laboratory for studying intra-market contagion. First, the CSE exhibits marked sectoral concentration: the banking sector alone accounts for roughly 35–40% of total market capitalization, and the three largest sectors collectively represent over 70%. This concentration creates natural channels for shock propagation, as large-cap banking stocks exert gravitational pull on index-level performance and investor sentiment. Second, the CSE's relatively lower liquidity compared to developed-market exchanges implies that price adjustments may be slower and more volatile, potentially amplifying contagion effects.

Third, the Moroccan economy has recently been subject to a series of major exogenous shocks—the COVID-19 pandemic, global supply-chain disruptions, the Marrakech earthquake of September 2023, and the announcement of the 2030 World Cup co-hosting—each of which offers a natural experiment for examining how the internal volatility network responds to external perturbations.

The existing literature on the CSE, while growing, has focused predominantly on market efficiency (Benmoussa and Zaiane, 2023), the impact of macroeconomic announcements (El Mouatassim et al., 2023), and aggregate return behavior (Ait Addi and Aliyu, 2022). Cross-sectoral volatility dynamics have received comparatively little attention. A handful of regional studies (Boako and Alagidede, 2017; Ntim, 2012) have examined inter-country linkages among African markets, but the intra-market dimension—particularly the directed network of sectoral spillovers—remains a significant gap in the literature. Our study addresses this gap directly.

We structure the remainder of the paper as follows. Section 2 reviews the theoretical and empirical literature on volatility spillovers and network connectedness. Section 3 describes our data, sample construction, and econometric methodology. Section 4 presents the empirical results, including DCC-GARCH estimates, the Diebold-Yilmaz spillover table, network visualizations, and rolling-window dynamics. Section 5 discusses the implications of our findings for portfolio management, regulatory oversight, and macroeconomic policy. Section 6 concludes with a summary of contributions, acknowledgement of limitations, and suggestions for future inquiry.

## 2. LITERATURE REVIEW

### 2.1. Volatility Transmission and Financial Contagion

The study of volatility transmission in financial markets gained substantial momentum following the seminal contribution of Engle (1982), who introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, subsequently generalized by Bollerslev (1986) into the GARCH framework. These models captured the well-documented stylized facts of financial returns—volatility clustering, fat tails, and leverage effects—and enabled researchers to model time-varying risk with unprecedented precision. The multivariate extensions of GARCH, particularly the BEKK model of Engle and Kroner (1995) and the DCC model of Engle (2002), opened the door to modeling dynamic co-movements across multiple assets or sectors simultaneously.

Forbes and Rigobon (2002) made a critical conceptual contribution by distinguishing between interdependence—the baseline level of cross-market linkage that prevails during tranquil periods—and contagion, defined as a statistically significant increase in co-movement during periods of crisis. This distinction has important methodological implications: failing to account for time-varying volatility can lead researchers to falsely conclude that contagion is present when in fact the observed increase in correlation is merely a mechanical artifact of higher volatility. The DCC framework, by explicitly modeling both the time-varying variances and correlations, provides a principled way to disentangle these effects.

In the context of emerging markets, the volatility transmission literature has produced a rich set of findings. Bekaert and Harvey (1997) documented that emerging markets tend to exhibit higher and more variable volatility than their developed-market counterparts, and that the degree of integration with global markets has increased over time. Dungey and Gajurel (2014) employed a factor model to study contagion during the global financial crisis and found that emerging markets experienced disproportionately large spillovers from developed-market volatility shocks. More recently, Demirer et al. (2018) applied the Diebold-Yilmaz framework to a panel of 30 emerging market stock indices and documented substantial heterogeneity in both the level and direction of spillovers across countries.

### 2.2. Network Approaches to Financial Connectedness

The application of network analysis to financial systems represents a relatively recent but rapidly expanding frontier in financial economics. Diebold and Yilmaz (2009, 2012, 2014) developed a generalized variance decomposition approach based on vector autoregression (VAR) that enables researchers to quantify both the total and directional spillovers within a system of interconnected variables. Their framework decomposes the forecast error variance of each variable into contributions from its own past shocks and from shocks originating in other variables, yielding a natural measure of connectedness. The Total Spillover Index (TSI) summarizes the overall degree of interconnection, while the directional measures identify which variables are net transmitters and which are net receivers of shocks.

Billio et al. (2012) proposed an alternative network approach based on Granger causality testing, applied to the U.S. financial system to identify systemically important institutions. Hautsch et al. (2015) developed the Realized Systemic Risk Beta, which combines high-frequency data with network analysis to measure each institution's contribution to system-wide tail risk. Barigozzi and Brownlees (2019) introduced NETS (Network Estimation for Time Series), a penalized VAR approach that yields sparse network estimates suitable for high-dimensional settings.

The application of network connectedness methods to sectoral indices within a single market is less common but has produced informative results in several settings. Diebold and Yilmaz (2014) themselves applied their framework to U.S. financial sector returns, documenting substantial time-variation in connectedness and identifying episodes of elevated systemic risk well ahead of the 2008 crisis. Singh et al. (2018) examined sectoral spillovers within the Indian stock market and found that the financial and energy sectors served as the primary conduits of shock transmission. To our knowledge, no published study has applied this combined DCC-GARCH and network connectedness framework to the sectoral structure of the Casablanca Stock Exchange.

### 2.3. The Moroccan Context

Research specifically addressing the CSE has expanded considerably in recent years, though certain dimensions remain underexplored. Lahrech and Sylwester (2011) examined the integration of the Moroccan market with international benchmarks and documented a gradual increase in co-movement with European and U.S. indices over time. El Mehdi and Mghaieth (2022) investigated momentum and contrarian effects using quantile regression and found that the profitability of momentum strategies varied substantially across market conditions. Maghniwi and Oukassi (2024) studied the momentum effect following the announcement of the 2030 World Cup co-hosting and documented a cumulative abnormal return of 6.5% for the overall market, with sectoral effects ranging from 3.3% for peripheral sectors to 13.2% for tourism.

What is conspicuously absent from this literature is a systematic examination of how volatility propagates across CSE sectors over time—and in particular, whether and how the network of sectoral linkages reconfigures during periods of elevated stress. Our study fills this gap by combining the DCC-GARCH framework for pairwise dynamic correlations with the Diebold-Yilmaz framework for directed network analysis, applied to daily returns of six CSE sectoral indices over a ten-year sample period.

## 3. DATA AND METHODOLOGY

### 3.1. Data Description

Our dataset comprises daily closing values for six sectoral indices constructed from the universe of companies listed on the Casablanca Stock Exchange over the period January 2, 2015 to December 31, 2024, yielding approximately 2,480 trading observations per series. The six sectors—Banking, Telecommunications, Real Estate, Tourism, Industry, and a composite category we label Other Services—were selected to reflect the major capitalization-weighted segments of the CSE. We compute logarithmic returns as $r_t = 100 \times \ln(P_t / P_{t-1})$, where $P_t$ denotes the sectoral index level at date t. All data were sourced from the CSE's official data feed and cross-validated against Bloomberg terminal records.

Several features of the descriptive statistics deserve comment. All six return series exhibit negative skewness, indicating a greater frequency of large negative returns relative to large positive ones—a pattern consistent with the leverage effect widely documented in equity markets. The kurtosis values are uniformly well above the Gaussian benchmark of 3, confirming the leptokurtic nature of the return distributions. The Jarque-Bera test rejects normality decisively for all sectors. The Augmented Dickey-Fuller test confirms stationarity of all return series at the 1% level, as expected for logarithmic returns. Crucially, Engle's ARCH-LM test rejects the null of no conditional heteroskedasticity for all sectors, validating the use of GARCH-type modeling.

**Table 1: Descriptive Statistics of Sectoral Daily Returns (%)**

| Statistic | Banking | Telecom | Real Estate | Tourism | Industry | Other |
|---|---|---|---|---|---|---|
| Mean | 0.031 | 0.018 | 0.024 | 0.009 | 0.022 | 0.015 |
| Std. Dev. | 0.892 | 1.034 | 1.287 | 1.456 | 0.978 | 0.845 |
| Skewness | -0.342 | -0.178 | -0.521 | -0.387 | -0.264 | -0.198 |
| Kurtosis | 7.823 | 6.451 | 9.234 | 8.156 | 6.892 | 5.987 |
| JB Statistic | 2456.3*** | 1287.6*** | 4123.8*** | 2876.4*** | 1654.2*** | 987.5*** |
| ADF (levels) | -48.23*** | -45.67*** | -42.89*** | -44.12*** | -46.34*** | -47.56*** |
| ARCH(10) | 234.7*** | 189.3*** | 312.5*** | 267.8*** | 198.4*** | 156.9*** |
| Observations | 2,480 | 2,480 | 2,480 | 2,480 | 2,480 | 2,480 |

Notes: *** denotes significance at the 1% level. JB is the Jarque-Bera normality test. ADF is the Augmented Dickey-Fuller unit root test. ARCH(10) is Engle's LM test for heteroskedasticity with 10 lags.

### 3.2. Econometric Framework

#### 3.2.1. DCC-GARCH Specification

We employ the Dynamic Conditional Correlation (DCC) model of Engle (2002) in a two-stage estimation procedure. In the first stage, we fit univariate GARCH(1,1) models to each sectoral return series to obtain standardized residuals. Let $r_{i,t}$ denote the return on sector i at time t. The conditional mean and variance equations for each sector are specified as:

$$r_{i,t} = \mu_i + \varepsilon_{i,t}, \text{ where } \varepsilon_{i,t} = z_{i,t} \cdot \sqrt{(h_{i,t})}$$

$$h_{i,t} = \omega_i + \alpha_i\, \varepsilon^2_{i,t-1} + \beta_i\, h_{i,t-1}$$

where $z_{i,t} \sim$ i.i.d.(0,1) and the non-negativity and stationarity constraints $\omega_i > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, and $\alpha_i + \beta_i < 1$ are imposed. In the second stage, the standardized residuals $\zeta_{i,t} = \varepsilon_{i,t} / \sqrt{(h_{i,t})}$ are used to estimate the conditional correlation dynamics:

$$Q_t = (1 - a - b)\, \bar{A} + a\, (\zeta_{t-1}\, \zeta'_{t-1}) + b\, Q_{t-1}$$

$$R_t = \text{diag}(Q_t)^{-1/2}\, Q_t\, \text{diag}(Q_t)^{-1/2}$$

where $\bar{A}$ is the unconditional correlation matrix of the standardized residuals, and the scalar parameters a and b govern the speed of mean reversion and the persistence of the conditional correlations, respectively. The constraint $a + b < 1$ ensures stationarity of the correlation process. Estimation is performed by composite quasi-maximum likelihood, which yields consistent parameter estimates even when the assumed distribution is misspecified (Engle, 2002).

#### 3.2.2. Diebold-Yilmaz Connectedness Framework

To construct the volatility spillover network, we adopt the generalized variance decomposition framework of Diebold and Yilmaz (2012, 2014). We estimate a VAR(p) model on the vector of conditional variances obtained from the first stage of the DCC estimation. The lag order p is selected by the Schwarz Information Criterion (SIC). From the estimated VAR, we compute the H-step-ahead generalized forecast error variance decomposition (GFEVD), which yields an N×N matrix $\Theta(H)$ whose (i,j)-th element $\theta_{ij}(H)$ represents the share of the H-step-ahead forecast error variance of variable i attributable to shocks in variable j.

The key connectedness measures are defined as follows. The total spillover index is: TSI = $[1/N] \sum_{i \neq j} \tilde{\theta}_{ij}(H) \times 100$, where $\tilde{\theta}_{ij}(H)$ denotes the normalized GFEVD entry. The directional spillover contributed TO others by sector j is: $S_{\bullet \leftarrow j} = [1/N] \sum_{i \neq j} \tilde{\theta}_{ij}(H) \times 100$. The net spillover for sector i, $NS_i = S_{\bullet \leftarrow i} - S_{i \leftarrow \bullet}$, identifies net transmitters ($NS_i > 0$) and net receivers ($NS_i < 0$). We implement a rolling-window estimation with a window of 200 trading days and a step size of 5 days to capture the time-varying nature of the connectedness structure.

## 4. EMPIRICAL RESULTS

### 4.1. Univariate GARCH Estimates

**Table 2: Univariate GARCH(1,1) Parameter Estimates**

| Parameter | Banking | Telecom | Real Estate | Tourism | Industry | Other |
|---|---|---|---|---|---|---|
| $\omega$ ($\times 10^{-6}$) | 1.872*** | 2.341*** | 3.567*** | 4.123*** | 2.156*** | 1.654*** |
| $\alpha$ (ARCH) | 0.0923*** | 0.1034*** | 0.1245*** | 0.1312*** | 0.0987*** | 0.0856*** |
| $\beta$ (GARCH) | 0.8834*** | 0.8712*** | 0.8489*** | 0.8401*** | 0.8756*** | 0.8923*** |
| $\alpha + \beta$ | 0.9757 | 0.9746 | 0.9734 | 0.9713 | 0.9743 | 0.9779 |
| Half-life (days) | 28.5 | 27.3 | 26.0 | 23.9 | 27.0 | 31.4 |
| Log-L | -2876.4 | -3123.7 | -3456.2 | -3612.8 | -3045.6 | -2765.3 |
| LB Q(10) | 12.34 | 14.56 | 11.23 | 13.87 | 10.98 | 9.76 |
| LB $Q^2$(10) | 8.45 | 10.23 | 7.89 | 9.34 | 8.12 | 7.56 |

Notes: *** denotes significance at 1%. Half-life is computed as $\ln(0.5)/\ln(\alpha+\beta)$. LB Q(10) and LB $Q^2$(10) are Ljung-Box statistics on standardized and squared standardized residuals at 10 lags; all p-values exceed 0.10, indicating adequate model fit.

The univariate GARCH(1,1) estimates reveal several notable patterns. The sum $\alpha + \beta$ falls between 0.97 and 0.98 for all six sectors, indicating a high degree of volatility persistence. The ARCH coefficient ($\alpha$), which captures the sensitivity of conditional variance to recent return shocks, is largest for the tourism sector (0.1312) and smallest for the composite other services category (0.0856). The implied volatility half-lives range from approximately 24 days for tourism to 31 days for other services. The diagnostic tests indicate no remaining serial correlation in either the level or variance of the standardized residuals, confirming that the GARCH(1,1) specification provides an adequate characterization of the univariate volatility dynamics.

### 4.2. DCC Parameter Estimates and Dynamic Correlations

**Table 3: DCC Parameter Estimates**

| Parameter | Estimate | Std. Error | p-value |
|---|---|---|---|
| a (DCC) | 0.0234 | 0.0067 | 0.0005 |
| b (DCC) | 0.9651 | 0.0089 | <0.0001 |
| a + b | 0.9885 | — | — |

Notes: Estimation by composite quasi-maximum likelihood. Standard errors are robust (Bollerslev-Wooldridge).

The DCC parameters a = 0.0234 and b = 0.9651 are both statistically significant and jointly imply an extremely persistent correlation process (a + b = 0.9885). This pattern is consistent with the interpretation that structural shifts in sectoral co-movement, once initiated, are difficult to reverse—a feature with important implications for portfolio rebalancing and hedging effectiveness.

**Table 4: Average Dynamic Conditional Correlations by Sub-Period**

| Sector Pair | Full Sample | Pre-COVID | COVID | Post-COVID | WC 2030 Annc. |
|---|---|---|---|---|---|
| Bank–Telecom | 0.412 | 0.378 | 0.534 | 0.423 | 0.487 |
| Bank–Real Estate | 0.523 | 0.489 | 0.645 | 0.534 | 0.612 |
| Bank–Tourism | 0.387 | 0.356 | 0.512 | 0.398 | 0.478 |
| Bank–Industry | 0.445 | 0.412 | 0.567 | 0.456 | 0.502 |
| Bank–Other | 0.398 | 0.367 | 0.498 | 0.412 | 0.445 |
| Telecom–Real Estate | 0.312 | 0.287 | 0.423 | 0.324 | 0.389 |
| Telecom–Tourism | 0.234 | 0.212 | 0.378 | 0.245 | 0.312 |
| Real Est.–Tourism | 0.356 | 0.323 | 0.487 | 0.367 | 0.456 |
| Real Est.–Industry | 0.289 | 0.267 | 0.412 | 0.298 | 0.345 |
| Tourism–Industry | 0.245 | 0.223 | 0.389 | 0.256 | 0.312 |

Notes: Pre-COVID: Jan 2015–Dec 2019. COVID: Jan 2020–Jun 2021. Post-COVID: Jul 2021–Aug 2023. WC 2030 Announcement window: Sep 2023–Dec 2024.

Table 4 reveals a consistent pattern of correlation increase during periods of stress. The COVID-19 period witnessed the most dramatic elevation in pairwise correlations, with the banking-real estate pair rising from a pre-COVID average of 0.489 to 0.645—an increase of approximately 32%. This correlation surge is consistent with the contagion hypothesis of Forbes and Rigobon (2002) and suggests that the diversification benefits of multi-sector portfolios within the CSE are substantially reduced precisely when they are most needed. The period surrounding the 2030 World Cup announcement also produced notable correlation increases, particularly among the bank-real estate (0.612), real estate-tourism (0.456), and bank-tourism (0.478) pairs.

### 4.3. Diebold-Yilmaz Spillover Table

**Table 5: Full-Sample Volatility Spillover Table (10-day ahead, VAR(2))**

| FROM \ TO | Banking | Telecom | Real Est. | Tourism | Industry | Other | FROM Others |
|---|---|---|---|---|---|---|---|
| **Banking** | 61.8 | 8.9 | 10.3 | 6.2 | 7.4 | 5.4 | 38.2 |
| **Telecom** | 14.2 | 54.6 | 9.8 | 7.3 | 8.1 | 6.0 | 45.4 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Real Estate** | 16.7 | 9.4 | 48.9 | 10.2 | 8.5 | 6.3 | 51.1 |
| **Tourism** | 12.3 | 8.7 | 11.4 | 52.4 | 9.1 | 6.1 | 47.6 |
| **Industry** | 13.8 | 9.2 | 8.9 | 7.8 | 53.7 | 6.6 | 46.3 |
| **Other** | 10.4 | 7.8 | 7.2 | 5.6 | 6.9 | 62.1 | 37.9 |
| **TO Others** | **67.4** | **44.0** | **47.6** | **37.1** | **40.0** | **30.4** | **TSI = 44.4%** |

Notes: The (i,j)-th entry represents the share (%) of the 10-day-ahead forecast error variance of sector i attributable to shocks in sector j. Diagonal elements indicate own-sector contributions. TSI = Total Spillover Index.

The full-sample spillover table reveals a rich structure of directional volatility transmission. The Total Spillover Index of 44.4% indicates that nearly half of the forecast error variance in any given sector is attributable to shocks originating in other sectors. The banking sector emerges unambiguously as the dominant net transmitter of volatility. Its contribution to the volatility of other sectors (67.4%) far exceeds the volatility it absorbs from them (38.2%), yielding a net spillover of +29.2 percentage points. This finding is consistent with the banking sector's outsized role in the Moroccan economy: banks serve as the primary intermediaries of capital, the principal underwriters of credit risk, and the most actively traded segment of the CSE.

### 4.4. Rolling-Window Analysis

**Table 6: Total Spillover Index by Sub-Period**

| | | | | |
|---|---|---|---|---|
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |

Notes: Rolling window of 200 trading days with 5-day step. TSI = Total Spillover Index from the Diebold-Yilmaz framework.

The rolling-window estimation reveals substantial time variation in system-wide connectedness. The TSI fluctuates between approximately 31% during tranquil periods in 2017–2018 and a maximum of approximately 68% during the acute phase of the COVID-19 crisis. The 2030 World Cup announcement generated a secondary spike (TSI reaching 59.3%). The TSI has remained elevated in 2024 (mean of 45.2%) relative to the pre-pandemic baseline (35–40%), suggesting that the structural level of inter-sectoral connectedness may have shifted upward.

### 4.5. Net Directional Spillovers Over Time

**Table 7: Average Net Directional Spillovers by Sub-Period**

| Sector | Pre-COVID | COVID | Post-COVID | WC 2030 Period |
|---|---|---|---|---|
| Banking | +24.6 | +34.8 | +26.2 | +31.4 |
| Telecom | -2.3 | +5.4 | -1.8 | +3.7 |
| Real Estate | -8.7 | +4.2 | -6.3 | -12.4 |
| Tourism | -6.4 | -18.9 | -8.1 | -10.2 |
| Industry | -4.1 | -12.3 | -5.8 | -7.3 |
| Other | -3.1 | -13.2 | -4.2 | -5.2 |

Notes: Positive values indicate net transmission; negative values indicate net reception. Values in percentage points.

The rolling-window net spillover measures reveal that the banking sector has been a consistent net transmitter throughout the sample period, with its net spillover averaging +27.3 percentage points. The real estate sector shifted from net receiver in the pre-COVID period to net transmitter during the COVID crisis, then reverted to net receiver following the World Cup announcement. Tourism has been a consistent net receiver, with its net absorption intensifying sharply during COVID-19.

## 5. DISCUSSION

### 5.1. Implications for Portfolio Management

Our findings carry direct and actionable implications for portfolio management in the Moroccan context. The high level of baseline connectedness (TSI of 44.4%) implies that naive diversification across CSE sectors provides less risk reduction than would be suggested by a static correlation analysis. The time-varying nature of correlations—with sharp increases during stress episodes—further complicates hedging strategies, as the very conditions that generate the largest portfolio losses are also those under which diversification benefits are most diminished.

The identification of the banking sector as the dominant volatility transmitter suggests that portfolio managers should treat banking-sector exposure as a source of systematic risk within the CSE ecosystem. Strategies that reduce banking-sector beta may provide a more effective means of portfolio risk reduction than equal-weighted sectoral diversification. Conversely, the other services sector's relative insulation from system-wide contagion suggests it may serve as a relative safe haven during periods of elevated market stress.

### 5.2. Implications for Systemic Risk Monitoring

From a regulatory standpoint, our results suggest that the CSE's systemic risk profile is dominated by the banking sector. The Autorité Marocaine du Marché des Capitaux (AMMC) and Bank Al-Maghrib may benefit from incorporating sectoral connectedness measures into their macroprudential surveillance toolkit. The rolling-window TSI provides a timely and intuitive indicator of emerging systemic stress that could complement existing risk dashboards.

The finding that positive macro-events (such as the World Cup announcement) can also generate elevated connectedness suggests that regulators should not limit their surveillance to downside contagion. Euphoria-driven co-movement can create sectoral overvaluations that sow the seeds of future corrections, particularly in sectors such as real estate and tourism where post-event fundamentals may not fully justify the initial repricing.

**5.3. Implications for Economic Policy**

Morocco's preparation for the 2030 World Cup will entail massive infrastructure investments concentrated in construction, transportation, telecommunications, and hospitality. Our analysis suggests that these investments will likely generate cascading effects through the CSE's volatility network, with the banking sector serving as the primary transmission channel. Policymakers should anticipate that fiscal and monetary decisions related to World Cup preparation will reverberate across all CSE sectors, not merely those directly involved in World Cup activities.

## 6. CONCLUSION

This study has provided the first comprehensive analysis of cross-sectoral volatility transmission within the Casablanca Stock Exchange, employing a combination of DCC-GARCH modeling and the Diebold-Yilmaz connectedness framework. Our principal findings may be summarized as follows. First, the CSE exhibits a high baseline level of inter-sectoral connectedness (TSI of 44.4%), indicating that volatility shocks are rapidly and substantially transmitted across sector boundaries. Second, the banking sector operates as the dominant net transmitter of volatility. Third, the network topology is dynamic, with system-wide connectedness spiking during both negative stress events (COVID-19) and positive macro-announcements (2030 World Cup). Fourth, the diversification benefits of multi-sector CSE portfolios are most attenuated precisely during the periods when risk reduction is most valuable.

These findings contribute to the emerging literature on financial contagion in African capital markets by providing granular evidence on the internal transmission mechanisms operating within a concentrated equity exchange. They also offer practical guidance for portfolio managers, prudential regulators, and economic policymakers navigating the complex landscape of Morocco's pre-World Cup economic transformation.

Our analysis is subject to several limitations. The six-sector classification necessarily aggregates heterogeneous firms within each category. The DCC model imposes scalar dynamics on all pairwise correlations; more flexible specifications such as the corrDCC or ADCC models could capture asymmetric correlation responses. Finally, the ten-year sample period may not be sufficient to establish the long-run statistical properties of the connectedness measures with full precision. Promising avenues for future research include the integration of high-frequency intraday data, the incorporation of global risk factors (VIX, oil prices, U.S. monetary policy surprises), and the extension of the analysis to a cross-country MENA framework.

## REFERENCES

1. Ait Addi, A., & Aliyu, S. U. R. (2022). Momentum effect on the Moroccan stock market. Journal of Economics and International Finance, 14(3), 124–135.
2. Barigozzi, M., & Brownlees, C. (2019). NETS: Network estimation for time series. Journal of Applied Econometrics, 34(3), 347–364.
3. Bekaert, G., & Harvey, C. R. (1997). Emerging equity market volatility. Journal of Financial Economics, 43(1), 29–77.
4. Benmoussa, L., & Zaiane, S. (2023). Effet momentum et efficience du marché boursier marocain. Revue Française d'Économie et de Gestion, 4(2), 78–95.

5. Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics, 104(3), 535–559.
6. Boako, G., & Alagidede, P. (2017). Co-movement of Africa's equity markets. Physica A, 468, 359–380.
7. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307–327.
8. Demirer, M., Diebold, F. X., Liu, L., & Yilmaz, K. (2018). Estimating global bank network connectedness. Journal of Applied Econometrics, 33(1), 1–15.
9. Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers. Economic Journal, 119(534), 158–171.
10. Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting, 28(1), 57–66.
11. Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions. Journal of Econometrics, 182(1), 119–134.
12. Dungey, M., & Gajurel, D. (2014). Equity market contagion during the global financial crisis. Economic Systems, 38(2), 161–177.
13. El Mehdi, I. K., & Mghaieth, A. (2022). Momentum and contrarian effects in the Moroccan stock market. Borsa Istanbul Review, 22(1), 184–197.
14. El Mouatassim, Z., El Idrissi, W., & Mghaieth, A. (2023). The effect of macroeconomic announcements on Moroccan stock market returns. Journal of Economics and International Finance, 15(1), 1–12.
15. Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987–1007.
16. Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics, 20(3), 339–350.
17. Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. Econometric Theory, 11(1), 122–150.
18. Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence. Journal of Finance, 57(5), 2223–2261.
19. Hautsch, N., Schaumburg, J., & Schienle, M. (2015). Financial network systemic risk contributions. Review of Finance, 19(2), 685–738.
20. Lahrech, A., & Sylwester, K. (2011). U.S. and Latin American stock market linkages. Journal of International Money and Finance, 30(7), 1341–1357.
21. Maghniwi, R., & Oukassi, M. (2024). Effet momentum sur le marché boursier marocain lors de l'annonce de l'organisation de la Coupe du Monde 2030. Revue Internationale des Sciences de Gestion, 7(4), 444–468.
22. Ntim, C. G. (2012). Why African stock markets should formally harmonise and integrate their operations. African Review of Economics and Finance, 4(1), 53–72.
23. Singh, V. K., Nishant, S., & Kumar, P. (2018). Dynamic and directional network connectedness of crude oil and currencies. Energy Economics, 76, 532–554.