1 DYNAMIC CONDITIONAL CORRELATIONS AND RISK SPREAD BETWEEN INTERNATIONAL FINANCIAL MARKETS: A DCC-GARCH ANALYSIS

Bogdan DIMA[1]

Lucian Liviu ALBU[2]

Ştefana Maria DIMA[3*]

Roxana IOAN[4]

Anca SARAOLU IONAŞCUŢI[5]

Marian Ilie SIMINICA[1]

Abstract

The paper studies the dynamic conditional correlations (DCC Multivariate GARCH models) of risks for 31 major financial markets, using Expected Shortfall as proxies for these markets' risk. We selected several specifications of the Generalized Orthogonal GARCH model and of the Copula Asymmetric Generalized DCC model. Most of the GARCH-Copula models outperform standard DCC-GARCH and GO-GARCH models. We further study the nature of the processes driving these correlation series, finding the correlations non-stationary (but not 'explosive') and exhibiting multifractal properties. Moreover, some DCCs may act as triggers (at least in a 'nonlinear' Granger sense) for others. Finally, we show evidence of cross-market risk spread during the 2007-2010 turmoil, pandemic and Ukrainian war crises.

Keywords: GO-GARCH DCC, Copula-GARCH DCC, multivariate affine Normal-Inverse Gaussian distribution, Expected Shortfall, financial crises

JEL Classification: C10; C13; G15; G32

[1] *West University of Timisoara, Faculty of Economics and Business Administration, Timisoara, Romania; bogdan.dima@e-uvt.ro*

[2] *Institute for Economic Forecasting, Romanian Academy, albul@ipe.ro*

[3*] *West University of Timisoara, Faculty of Economics and Business Administration; East European Center for Research in Economics and Business (ECREB), Timisoara, Romania; Institute of Advanced Environmental Research, West University of Timișoara. Email:stefana.dima@e-uvt.ro Corresponding author.*

[4] *West University of Timisoara, Faculty of Economics and Business Administration, Timisoara, roxana.ioan@e-uvt.ro*

[5] *West University of Timisoara, Doctoral School of Economics and Business Administration, Timisoara, anca.ionascuti96@gmail.com*

[1] *University of Craiova. Email: marian.siminica@edu.ucv.ro*

1. Introduction

A bitter lesson of the latest crises, such as the 2007-2010 financial and real turmoil, the pandemic crisis, or the Ukrainian war, is that large endogenous and exogenous shocks affect the ecosystem of international financial markets. Such shocks can push these markets 'far from equilibrium' for significant periods and disrupt their 'business as usual' mechanisms. Worst, even if the shocks initially originate at the level of a single market, various contagion mechanisms may lead to a worldwide spread of risks. Hence, studying risk connectivity between international financial system's globalized components is a hot topic nowadays.

Engle (2002)'s Dynamic Conditional Correlation Multivariate GARCH (DCC-GARCH) is a popular model frequently used in the literature to study cross-market dynamic correlations and to estimate interconnections between different types of assets, markets, and countries. Compared to the ARCH and GARCH models, the so-called DCC-GARCH embraces several models that estimate covariations between assets based on different approaches. According to Andersson-Säll and Lindskog (2019), the first DCC-GARCH models were the Vector Error Correction (VEC-GARCH), the BEKK models, and Bollerslev ' Constant Conditional Correlation (CCC-GARCH). Based on the CCC-GARCH, the DCC-GARCH was developed to give a computational advantage regarding large covariance matrix estimation. This advantage resides in the number of estimated parameters independent of the number of series to be assessed in the correlation process. The DCC-GARCH model describes the time-varying nature of conditional correlations among markets that arise under the impact of various regional or international driving forces. Large time-varying covariance matrices are essential for researchers in vector auto-regressions. Considering that asset allocation and risk assessment mostly rely on correlations, forecasted return covariance matrices are, as Engle (2002) argued, also required for building and managing optimal portfolios. As Sabkha and Peretti (2018) reasoned, this model is suitable when investigating financial phenomena, such as risk spillover, co-movements, and contagion. For instance, Kocaarslan et al. (2017) investigate the impacts of volatility expectations in oil, gold, currency, and the U.S. stock markets on time-varying conditional correlations between BRIC and U.S. stock markets. Syllignakis and Kouretas (2011) review the time-varying conditional correlations to the weekly index returns of seven emerging stock markets of Central and Eastern Europe. Cai et al. (2016) consider the DCCs between U.S. and eight emerging East Asian stock markets and analyze their dynamic equicorrelation. Song et al. (2018) examine the dynamic conditional correlations between the U.S. and Korean financial markets. Karfakis and Panagiotidis (2015) study the effects of the 2007-2010 crisis on the conditional correlations between three exchange rate returns (USD/EUR, JPY/USD, and USD/GBP). Kim et al. (2015) identify the spillover effects of the recent U.S. financial crisis on five emerging Asian countries based on an approach that simultaneously estimates the conditional correlation coefficient and the effects of its determining factors over time.

Nevertheless, despite its extended content, we note some limitations of this literature. For instance, the markets' returns are often involved in studies. However, the cross-sectional correlations of the returns are not the ultimate proof of risk spread and contagion. Two markets may have similar return dynamics but very different risk profiles .

Also, most studies make use of standard DCC-GARCH models, but there are other models that can be used as well. For instance, van der Weide (2002)'s Generalized Orthogonal GARCH model or the Copula Asymmetric Generalized DCC, as they might provide more robust and consistent results. Perhaps, more importantly, once estimates of dynamic correlations are obtained, their nature and specific properties are not always studied in detail. Considering that the two models, Generalized Orthogonal GARCH model and the Copula Asymmetric Generalized DCC, were underutilized in the literature, we can only consider few studies. For example, Jondeau and Rockinger (2006) used the Copula-GARCH model to test for conditional dependencies, Messaoud and Aloui (2015) used the Copula-GARCH model to analyze asymmetric dependence, Nasri and Rémillard (2019) used copula-based dynamic models in order to capture the dependencies between various time series, Isenah and Olubusoye (2016) used the GO-GARCH model in order to analyze and forecast the exchange rate dynamics. However, we go beyond these studies that mostly involve markets' returns, by focusing on the dynamic conditional correlations of risks.

Therefore, we propose a three-fold contribution to this topic:

1. We involve the Expected Shortfall (ES) for each financial market as a coherent measure of risk to provide estimates for the 31 major developed and emergent stock markets (of international or regional importance) within the sample. We employ the ES measure in contrast to the literature where Value at Risk (VaR) is mainly used as a risk estimation measure (such as, Boman (2019), Afzal et al. (2021) and so on). Why? Because the ES implies the main properties a risk measure should fulfil in order to be coherent, namely, monotonicity, translation invariance, homogeneity and subadditivity (according to Acerbi and Tasche (2002), only the ES measure can assure the last property).

2. Compared to the current research where dynamic conditional correlations of risks are analyzed based on multivariate GARCH models, we contribute to the literature by selecting several DCC-GARCH models that were underutilized (namely, 8 GO-GARCH DCC models and one Copula-GARCH DCC model). We obtain dynamic correlations between these markets' individual ES series based on their best (as selected by the average log-likelihood differences between them and the constant mean model). The use of the GO-GARCH DCC models and Student Copula Asymmetric Generalized DCC models might provide better results in terms of log-likelihood.

3. We examine in detail the main features displayed by the series of these correlations and additional checks for potential causality linkages among DCC series. A key contribution here is that we test the spread of risk between some international/regional relevant markets, both developed and emerging.

We find that the results of DCC analysis are significantly sensitive to model selection, with a Copula-GARCH model providing the best estimates. We also find that particular DCC series between pairs of markets can be driven by non-stationary (but not "explosive") processes with multifractal features and may be causally (at least in a non-linear Granger sense) interlinked.

The following section describes the methodology and the international dataset's leading properties. Section 3 reports the main results and checks for causality between the DCC series and comments, while the last section concludes.

2. Methodology and international data

To empirically assess the existence of co-movements between financial markets risks, two issues should be addressed beforehand. The first one is related to properly selecting an adequate risk estimator. The second refers to involving a robust technique for detecting the connections between individual markets' risk estimates.

For tackling the first issue, we consider the Expected Shortfall (ES) as a suitable measure of risk. The ES's main advantages will be further emphasized. Moreover, we involve two different versions of the Dynamic Conditional Correlation (DCC) models to address the second issue.

Expected Shortfall as a risk estimator

As Yamai and Yoshiba (2002:182) argue: "It is a well-known fact that value-at-risk (VaR) models do not work under market stress. VaR models are usually based on normal asset returns and do not work under extreme price fluctuations". Indeed, several problems are raised by VaR models. Among these: the assumption that assets' returns follow a normal distribution and disregard the fat-tails properties of observed returns; the fact that, by definition, VaR only measures the distribution quantile and ignores extreme loss beyond the VaR level; VaR can be criticized for not being sub-additive (Acerbi and Tasche (2002)), which means that, for a portfolio of financial assets, global risk can be larger than the sum of the stand-alone risks of its components measured by VaR (see Embrechts (2000) for an overview of some possible criticism).

To alleviate such limits of VaR, the notion of *coherent* risk measures was introduced by Artzner et al. (1997, 1999). Such a *coherent spectral measure* of financial portfolio risk (i.e. a risk measure satisfying the four axioms of translation invariance, subadditivity, positive homogeneity, and monotonicity), which is also easy to estimate, is the *Expected Shortfall* (ES). For a specified level α, ES is the "average loss in the worst 100 α % cases" (Acerbi and Tasche (2002:1488)).

From relation (1), it can be noticed that ES exclusively depends on the distribution of X and the level α, but not on a particular definition of quantiles.

Although the involvement of ES provides several advantages over VaR, it should be mentioned that this does not represent the only available *coherent* measure of risk. For instance, Ahmadi-Javid (2012) proposes an "entropic Value-at-Risk" (corresponding to the tightest possible upper bound obtained from the Chernoff inequality for the VaR as well as the conditional value-at-risk (CVaR)), which is also coherent. Nevertheless, we argue that investors widely know and use ES compared to alternative measures. Therefore, their ES estimation is more likely to account for their decision to select and trade their portfolios of financial assets. Hence, we further consider ES as the involved measure of risk. To assess the association between ES's values for several markets, we further consider the framework of *Dynamic Conditional Correlation* (DCC) with a particular focus on two models, namely the *GO-GARCH* model and, respectively, the *Student Copula Asymmetric Generalized DCC* model (see Galanos(2022a) for model details).

Dynamic Conditional Correlation Models

The conditional correlation (CC) models decompose the covariance matrix into conditional standard deviations and correlations. The aim is to express the univariate and multivariate dynamics distinctively and to ease the estimation process.

Nevertheless, Aielli (2011) argues that the estimation of DCC model might be inconsistent. Hence, a version of the DCC model is proposed (cDCC), which includes a corrective step to eliminate this inconsistency. However, the price to be paid here is that variance targeting cannot be used. We further refer to this version of the DCC models as baseline.

The GO-GARCH Model

The Factor ARCH models originally introduced by Engle et al. (1990) are designed to deal with time series for which the "structural errors" (unobserved underlying *factors*) are conditionally heteroscedastic. In the *Orthogonal GARCH* (O-GARCH) model proposed by Alexander (2001), uncorrelated and independent factors are involved. Similarly, the *Generalized Orthogonal GARCH* (GO-GARCH) model of van der Weide (2002) places the factors in an independent setting. Such a flexible approach provides several advantages as separability and weighted density convolution. As van der Weide (2002:549) argues: "potentially large covariance matrices can be parameterized with a fairly large degree of freedom while estimation of the parameters remains feasible. The model can be seen as a natural generalization of the O-GARCH model, while it is nested in the more general BEKK model".

However, the GO-GARCH framework's involvement in modelling financial data should be done with caution. As Lanne and Saikkonen (2007:61) warn, models like the one of van der Weide (2002) are "rather restrictive for financial data in that they allow for no idiosyncratic shocks". Therefore, we consider an alternative to this framework, namely the *Copula Asymmetric Generalized DCC* models.

The Student Copula Asymmetric Generalized DCC model

The extension of the static copula approach to dynamic models, particularly GARCH, was proposed by Patton (2006). This paper extends the validity of the Sklarś theorem for the conditional case. Later developments address the relevance of using the GARCH framework with skewed Student distribution for studying financial data. For example, we mention Chollete et al. (2009), which uses GARCH with skewed Student distribution in the first stage and a regime-switching model with a Canonical vine copula for the high dependence regime and a Normal copula for the low dependence regime in order to capture observed asymmetric dependence in international financial returns. The aim was to ensure that any founded asymmetry in the dependence structure truly reflects dependence and cannot be attributed to poor modelling of the marginals. The negative skew captures that the tails of some of the marginal distributions are typically longer on the left side.

In this framework, the set x_t of risk estimates can be supposed to follow a copula GARCH model with joint distribution given by:

$$F(x_t|m_t,h_t) = C\big(F_1(x_{1t}|m_{1t},h_{1t}),\ldots,F_N(x_{Nt}|m_{Nt},h_{Nt})\big) \qquad (1)$$

Here F_i,i=1,2,...,N is the conditional distribution of the i^{th} marginal series density, while *C* is the N-dimensional Copula. m_t, h_t are the conditional mean and the conditional variance. h_t follows a GARCH process. If, for instance, such process is a GARCH(1,1) one, then:

$$x_{\text{it}} = m_{\text{it}} + \varepsilon_{\text{it}}, \varepsilon_{\text{it}} = \sqrt{h_{\text{it}} z_{\text{it}}}$$
$$h_{\text{it}} = \omega + \alpha\varepsilon^2{}_{\text{it-1}} + \beta h_{\text{it-1}} \qquad (2)$$

z_{it} are i.i.d. random variables which conditionally follow a standardized skew Student distribution with skew and shape parameters ξ_i, v_i, $z_{\text{it}} \sim f_i(0,1,\xi_i,v_i)$.

The dependence structure of the margins is presumed to follow a Student copula with constant shape parameter. Meanwhile, its conditional correlation dynamics follows an Asymmetric Generalized DCC model.

International data

The daily closing returns of 31 major developed and emergent stock markets' indexes (S&P 500, DAX, NIKKEI 225, IBOVESPA, MERVAL, HANG SENG, AEX, Austrian Traded Index, S&P/ASX 200, BEL 20, S&P BSE SENSEX, CAC 40, FTSE 100, S&P/TSX, IBEX 35, ISEQ All Share, Jakarta Composite Index, FTSE Bursa Malaysia KLCI, KOSPI, IPC MEXICO, S&P/NZX 50, OMX Stockholm 30, SMI PR, STI, TSEC, SSE, JSE, PSEi, USD/TND, USD/BDT and BIST 100) are collected from Yahoo Finance (https://finance.yahoo.com/) for a period between 2005/01/01 and 2022/11/30 by using the R package "yfR" (Perlin, 2021). We remove the non-available data, ending with 1980 observations. In addition, as entirely exogenous variables, we collect for the same period and from the same source data related to Brent Crude Oil and natural gas prices (as traded on New York Mercantile Exchange).

As displayed in Table 1, all these tests reject the assumption of multivariate normality. Nevertheless, we need to account that multivariate GARCH (MGARCH) models are usually estimated under multivariate normality. If data violate such an assumption, the obtained estimates might be biased. Hence, all the MGARCH specifications derived from such an assumption should be considered with caution for our dataset.

Table 1. Multivariate normality (MVN) tests for market ES (full sample)

Test	Test value	p-value	Conclusion for multivariate normality
Mardia Skewness	708575.188	0	NO
Mardia Kurtosis	1650.179	0	NO
Henze-Zirkler	9.795	0	NO
Doornik-Hansen	539173.2	0	NO
E-statistic	270.896	0	NO

Notes: *This table reports for the entire dataset the results from Mardia (1970; 1974), Henze and Zirkler (1990), Doornik and Hansen (2008) and "E-statistic" (Szekely and Rizzo, 2005; 2013;2017, Rizzo and Szekely, 2016, Mori et al., 2021) tests of multivariate normality in markets Expected Shortfall data. The null hypothesis of all the tests is that the data sample comes from a multivariate normal distribution. Mardia test shows multivariate skewness and kurtosis coefficients and their corresponding statistical significance. The Henze-Zirkler (HZ) test is based on a non-negative functional distance that measures the distance between two distribution functions. The test statistic HZ is approximately log-normally distributed if the data is multivariate normal. The energy test of multivariate normality is an affine invariant test based on a characterization of equal distributions by energy distance. All these tests are implemented by Korkmaz et al. (2014).*

3. Results and comments

Main results

We further proceed to the estimation of GO-GARCH and GARCH-Copula models. Table 2 reports the main features of various specifications for such models.

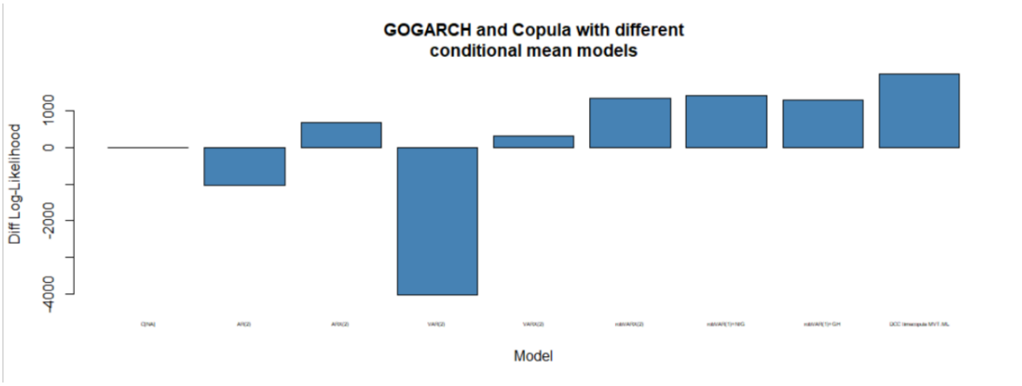
Table 2. Various GO-GARCH and GARCH-Copula models specification

Model nr.	Model label	Mean specification	Variance model	Distribution model	Transformations	External regressors in mean model
1	"C"	Constant	Glosten-Jagannathan-Runkle (GJR) GARCH; GARCH[1,1]; no variance targeting	Multivariate distribution with generalized hyperbolic margins	No	No
2	"AR(2)"	AR(2)	Glosten-Jagannathan-Runkle (GJR) GARCH; GARCH[1,1]; no variance targeting	Multivariate affine Normal-Inverse Gaussian	No	No
3	"ARX(2)"	AR(2)	Glosten-Jagannathan-Runkle (GJR) GARCH; GARCH[1,1]; no variance targeting	Multivariate distribution with generalized hyperbolic margins	No	Yes
4	"VAR(2)""	The mean vector is derived from a VAR(2) model	Glosten-Jagannathan-Runkle (GJR) GARCH; GARCH[1,1]; no variance targeting	Multivariate distribution with generalized hyperbolic margins	No	No
5	"VARX(2)""	The mean vector is derived from a VAR(2) model	Glosten-Jagannathan-Runkle (GJR) GARCH; GARCH[1,1]; no variance targeting	Multivariate affine Normal-Inverse Gaussian	No	Yes

Model nr.	Model label	Mean specification	Variance model	Distribution model	Transformations	External regressors in mean model
6	"robVARX(2)""	The mean vector is derived from a robust version of VAR(2) model	Glosten-Jagannathan-Runkle (GJR) GARCH; GARCH[1,1]; no variance targeting	Multivariate affine Normal-Inverse Gaussian	No	Yes
7	"robVARX(1)+NIG"	The mean vector is derived from a robust version of VAR(1) model	Asymmetric power ARCH; GARCH[1,1]; no variance targeting	Multivariate affine Normal-Inverse Gaussian	No	Yes
8	"robVARX(1)+GH""	The mean vector is derived from a robust version of VAR(1) model	Asymmetric power ARCH; GARCH[1,1]; no variance targeting	Multivariate affine Normal-Inverse Gaussian	No	Yes
9	"DCC timecopula MVT:ML"	ARMA(1,5); ARCH volatility included in mean model	Glosten-Jagannathan-Runkle (GJR) GARCH; GARCH[1,1]; variance targeting	Student Copula	Pseudo ML transformation	Yes

Notes: *All models from 1 to 8 are GO-GARCH models. Model 9 is a time-varying DCC GARCH-Copula. The Independent Component Analysis (ICA) method for estimating the orthogonal matrix U (FastICA of Hyvärinen and Oja, 2000) or the Robust Accurate, Direct ICA aLgorithm (RADICAL) (Learned-Miller and Fisher III, 2003) applies for estimations. As exogenous variables, Brent Crude Oil and natural gas prices from New York Mercantile Exchange are involved. These models are implemented in R package "rmgarch" (Galanos, 2022b).*

Figure 1. Difference of average log-likelihood versus constant mean and multivariate normal model for different models



Notes: *The figure reports the average log-likelihood differences between various multivariate generalized orthogonal GARCH and GARCH-Copula models described in Table 2 and the constant mean model.*

Of all the models, the GARCH-Copula model 9 provides the best log-likelihood. It is important to note that this model uses a Student Copula to model data distribution. As it concerns the GO-GARCH models, the best fit occurs for model 7, including a VARX(1) specification in mean and a multivariate affine Normal-Inverse Gaussian distribution. These two models display the best marginal explanatory power compared with a baseline constant mean specification GO-GARCH model. Thus, we will supplementary involve these two models and compare their outcomes. However, for the cases of Standard and Poor's 500 (S&P 500) and Brazilian Bovespa Index

(IBOVESPA) markets, the two methods provide to a certain extent different results. Several differences and similarities between the outcomes of these two methods can be highlighted here.

First, for all estimates, the GARCH-Copula model 9 shows levels of DCCs that are significantly lower (in absolute terms) than GO-GARCH model 7. In addition, for some periods, there are important divergences in the evolving pattern of conditional correlations displayed by these two methods. It is interesting to note that such divergences tend to be placed during the 2011-2012 markets' recovery period and, respectively, in 2015 and in 2018's episode of significant volatility. Nevertheless, for the 2007-2010 financial crises, both methods illustrate dynamic processes of decoupling/coupling of different markets' evolutions with rapid changes in estimates from low to high (and back to low at the end of 2010) levels. This last outcome can be associated with individual markets' non-uniform post-crisis recovery speed. Hence, these two methods possess different capacities to capture the divergences in markets' evolutionary patterns.

Second, the shape of DCCs estimates provided by the GO-GARCH model suggests higher volatility of the considered relationships between markets than those corresponding to the GARCH-Copula model. Indeed, there are several spikes in the GO-GARCH estimates evolution, and this model displays significantly more pattern shifts than the GARCH-Copula model. In other words, the connections between markets are estimated to be less stable by the first model in comparison with the second model.

Third, both methods show important differences in the dynamic correlations between developed and emerging markets during the entire analysis period. This last type of correlation is far less stable and is subjected to high amplitude estimates' changes. In addition, these two methods show that the risk spread across markets was taking place at different speeds until the crisis reached its global dimension.

Fourth, both models capture a peak in the dynamic correlations between markets' risk during March-May 2020, followed by a downward trend of these correlations and a new upward evolution during the Ukrainian war. In other words, these models can capture the effects of large exogenous shocks on the bi-univocal spread of risks between financial markets. As such shocks arise, the markets' risk profiles become more correlated.

Fifth, as the differences in log-likelihoods between models including or not the Brent Crude Oil and natural gas prices as external regressors show, these two variables play more than a 'decorative' role and they can change estimations' outcomes. Of course, we do not explicitly account for the involved mechanisms and do not formally investigate their impact. Nevertheless, we argue that it is highly plausible that their dynamics can influence investors' expectations about future market status and, henceforth, their current trading decisions.

Sixth, a justified question can be phrased as follows: What is the nature of the DCCs processes connecting the market risks? In order to attempt to answer such a question, we further test the null hypothesis of non-stationary processes versus the alternative hypothesis of the presence of "explosive" evolutions in the DCCs series. Table 3 reports the results of three tests (Augmented Dickey-Fuller test, Supremum ADF test and the generalized SADF test) for the pairs of S&P 500 ES values versus the corresponding values for the other markets in our dataset. These results show that (with the possible exceptions of the correlation between the risks of S&P 500 and two financial markets, namely Austrian Traded Index and MERVAL risks), the association between markets' risks are driven by unit root processes. Therefore, at least for this subset of markets, one can account for the existence of a "long-run" functional instability in the connection between their specific risks.

Nevertheless, if we consider instead a subset of data formed by the pairs between a key Latin America market (IBOVESPA) risk and the other markets' risks, the same conclusions can be derived (as shown in Table 4).

Therefore, the outcome of the "long-run" instability of markets' risks appears to be robust across different sub-samples[2]. However, such functional instability does not imply the existence of "explosive" processes in DCCs' underlying mechanisms.

Table 3. Tests of unit root versus "explosive" processes in GARCH-Copula model 9 estimates for S&P 500 ES pairs

Pair of markets	ADF test value	SADF test value	GSADF test value
S&P 500/ AEX	-11.7 Accept H0	-1.70 Accept H0	1.11 Accept H0
S&P 500/ Austrian Traded Index	-12.5 Accept H0	-2.07 Accept H0	3.27 Reject H0 at the 5%; accept H0 at 10% and 1%
S&P 500/ S&P/ASX 200	-11.8 Accept H0	-1.56 Accept H0	0.503 Accept H0
S&P 500/ BEL 20	-11.5 Accept H0	-2.99 Accept H0	0.088 Accept H0
S&P 500/ S&P BSE SENSEX	-12.3 Accept H0	-1.63 Accept H0	0.777 Accept H0
S&P 500/ IBOVESPA	-10.8 Accept H0	-1.77 Accept H0	0.992 Accept H0
S&P 500/ CAC 40	-11.2 Accept H0	-2.14 Accept H0	2.09 Accept H0
S&P 500/ FTSE 100	-10.5 Accept H0	-1.64 Accept H0	1.06 Accept H0
S&P 500/ DAX	-11.5 Accept H0	-2.24 Accept H0	0.816 Accept H0
S&P 500/ S&P/TSX	-11.5 Accept H0	-2.04 Accept H0	1.40 Accept H0
S&P 500/ HANG SENG	-11.8 Accept H0	-1.51 Accept H0	0.053 Accept H0
S&P 500/ IBEX 35	-11.2 Accept H0	-1.80 Accept H0	2.10 Accept H0
S&P 500/ ISEQ All Share	-11.2 Accept H0	-2.51 Accept H0	1.29 Accept H0
S&P 500/ Jakarta Composite Index	-11.1 Accept H0	-2.24 Accept H0	1.55 Accept H0
S&P 500/ FTSE Bursa Malaysia KLCI	-12.0 Accept H0	-2.05 Accept H0	0.492 Accept H0
S&P 500/ KOSPI	-11.4 Accept H0	-0.776 Accept H0	1.13 Accept H0
S&P 500/ MERVAL	-10.6 Accept H0	-1.95 Accept H0	2.69 Reject H0 at the 10%; accept H0 at 5% and 1%
S&P 500/ IPC MEXICO	-10.3	-0.991	2.44

[2] *All the equivalent results for the GO-GARCH model 7, not reported here but available by request from authors, are similar.*

Pair of markets	ADF test value	SADF test value	GSADF test value
	Accept H0	Accept H0	Accept H0
S&P 500/ Nikkei 225	-11.5 Accept H0	-1.40 Accept H0	1.68 Accept H0
S&P 500/ S&P/NZX 50	-11.9 Accept H0	-1.58 Accept H0	0.826 Accept H0
S&P 500/ OMX Stockholm 30	-12.3 Accept H0	-1.49 Accept H0	1.02 Accept H0
S&P 500/ SMI PR	-10.6 Accept H0	-1.37 Accept H0	0.878 Accept H0
S&P 500/ STI	-11.8 Accept H0	-1.23 Accept H0	1.70 Accept H0
S&P 500/ TSEC	-11.9 Accept H0	-2.92 Accept H0	1.59 Accept H0
S&P 500/ SSE	-12.6 Accept H0	-1.87 Accept H0	0.968 Accept H0
S&P 500/ JSE	-11.5 Accept H0	-1.34 Accept H0	1.76 Accept H0
S&P 500/ PSEi	-12.7 Accept H0	-2.68 Accept H0	0.536 Accept H0
S&P 500/ USD/TND	-11.9 Accept H0	-1.70 Accept H0	1.36 Accept H0
S&P 500/ USD/BDT	-11.6 Accept H0	0.260 Accept H0	0.577 Accept H0
S&P 500/ BIST 100	-12.5 Accept H0	-3.60 Accept H0	0.608 Accept H0

Notes: *The table reports the values of the Augmented Dickey-Fuller (ADF) test, Supremum ADF test (SADF) of Phillips, Wu, and Yu (2011), and the generalized SADF (GSADF) of Phillips, Shi, and Yu (2015a, b). Finite-sample critical values based on the Monte Carlo method are considered. The null hypothesis of the tests is the presence of unit root. The alternative hypothesis is the presence of "explosive" dynamics during the entire period (ADF) or "explosive" dynamics in some part(s) of the sample (SADF and GSADF). The tests are implemented in the R package "exuber" (Vasilopoulos et al. (2020a,b)). The settings include a minimum window size equal to 36 days (around one and a half conventional trading months); a lag length equal to one, and the choice of the minimum duration of an episode of the „explosive" process using the rule of Phillips et al. (2015a). The critical values of ADF test are: -0.401 (at 10%); 0.002 (at 5%) and 0.761 (at 1%). For the SADF test, these values are at 10%, 5% and 1%: 1.44, 1.64 and 2.21, while for GADF, these are 2.59, 2.80 and, respectively, 3.36.*

Table 4. Tests of unit root versus "explosive" processes in GARCH-Copula model 9 estimates for IBOVESPA ES pairs

Pair of markets	ADF test value	SADF test value	GSADF test value
IBOVESPA/ AEX	-10.3 Accept H0	-1.67 Accept H0	0.957 Accept H0
IBOVESPA/ Austrian Traded Index	-11.0 Accept H0	-2.60 Accept H0	0.685 Accept H0
IBOVESPA/ S&P/ASX 200	-11.0 Accept H0	-1.39 Accept H0	1.31 Accept H0
IBOVESPA/ BEL 20	-9.86	-2.47	0.974

Pair of markets	ADF test value	SADF test value	GSADF test value
	Accept H0	Accept H0	Accept H0
IBOVESPA/ S&P BSE SENSEX	-11.6 Accept H0	-1.55 Accept H0	0.301 Accept H0
IBOVESPA/ CAC 40	-10.1 Accept H0	-2.44 Accept H0	1.45 Accept H0
IBOVESPA/ FTSE 100	-9.99 Accept H0	-2.89 Accept H0	1.29 Accept H0
IBOVESPA/ DAX	-10.4 Accept H0	-1.68 Accept H0	0.916 Accept H0
IBOVESPA/ S&P/TSX	-10.5 Accept H0	-2.26 Accept H0	0.993 Accept H0
IBOVESPA/ HANG SENG	-11.0 Accept H0	-1.39 Accept H0	1.24 Accept H0
IBOVESPA/ IBEX 35	-11.2 Accept H0	-2.01 Accept H0	0.441 Accept H0
IBOVESPA/ ISEQ All Share	-10.9 Accept H0	-1.95 Accept H0	1.29 Accept H0
IBOVESPA/ Jakarta Composite Index	-11.0 Accept H0	-0.567 Accept H0	0.714 Accept H0
IBOVESPA/ FTSE Bursa Malaysia KLCI	-11.8 Accept H0	-2.32 Accept H0	0.546 Accept H0
IBOVESPA/ KOSPI	-11.1 Accept H0	-1.39 Accept H0	0.186 Accept H0
IBOVESPA/ MERVAL	-10.6 Accept H0	-1.96 Accept H0	1.03 Accept H0
IBOVESPA/ IPC MEXICO	-10.8 Accept H0	-1.59 Accept H0	1.57 Accept H0
IBOVESPA/ Nikkei 225	-11.4 Accept H0	-1.68 Accept H0	1.66 Accept H0
IBOVESPA/ S&P/NZX 50	-10.5 Accept H0	-2.20 Accept H0	0.353 Accept H0
IBOVESPA/ OMX Stockholm 30	-10.1 Accept H0	-1.66 Accept H0	1.91 Accept H0
IBOVESPA/ SMI PR	-10.7 Accept H0	-2.19 Accept H0	1.45 Accept H0
IBOVESPA/ STI	-10.9 Accept H0	-1.27 Accept H0	1.35 Accept H0
IBOVESPA/ TSEC	-11.4 Accept H0	-1.63 Accept H0	0.637 Accept H0
IBOVESPA/ SSE	-11.5 Accept H0	-3.34 Accept H0	0.579 Accept H0
IBOVESPA/ JSE	-11.3 Accept H0	-1.94 Accept H0	0.750 Accept H0
IBOVESPA/ PSEi	-9.99 Accept H0	-1.92 Accept H0	2.10 Accept H0
IBOVESPA/ USD/TND	-10.0 Accept H0	-2.19 Accept H0	1.12 Accept H0
IBOVESPA/ USD/BDT	-10.6 Accept H0	-1.64 Accept H0	0.955 Accept H0
IBOVESPA/ BIST 100	-11.4 Accept H0	-2.66 Accept H0	0.451 Accept H0

Note: *The specifications and the interpretation of the results are the same as in Table 3.*

Causality checks between DCCs: The Variable-Lag Transfer Entropy Ratio approach

Until this point, we analyzed the DCCs between autonomous pairs of markets. Nevertheless, are the dynamic correlations between these markets fully independent with respect to others? If we consider the case of international investors trading geographically diversified portfolios and using different markets to implement their hedging strategies, the answer to such question is negative.

In order to check for the potential causality between DCCs, we involve the *Transfer Entropy* (TE) approach. This approach can be viewed as a non-linear extension of Granger causality (Amornbunchornvej et al. (2021)) and it is a model-free measure designed as the Kullback-Leibler distance of transition probabilities (Dimpfl and Peter (2013)). In the implementation, we follow the arguments from Amornbunchornvej et al. (2021:1). According to these arguments, a typical operationalization of the TE: "make a strong assumption that every time point of the effect time series is influenced by a combination of other time series with a fixed time delay… However, the assumption of the fixed time delay does not hold in many applications, such as collective behavior, financial markets, and many natural phenomena". To address this issue, they propose a *Variable-Lag Transfer Entropy* (VL-TE) that relaxes the assumption of the fixed time delay and it allows causes to influence effects with arbitrary time delays.

In this framework, for two time series "X" and "Y" a *VL-TE Ratio* can be involved for causality inference such as:

$$VL\text{-}TE(X,Y)Ratio = \frac{VL\text{-}TE_{X\rightarrow Y}}{VL\text{-}TE_{Y\rightarrow X}} \tag{4}$$

If there is a value of this ratio greater than 1, this implies that "X" causes "Y" based on the VL-TE approach. Higher the value of this ratio, greater the strength of the involved causality. Table 5 reports the values of the *VL-TE Ratio* for several DCCs series, which are estimated based on GARCH-Copula model 9.

The results depict a heterogeneous framework, with only some DCCs as predictors of other DCCs' evolutions. For instance, the dynamic conditional correlations between the United States S&P 500 and Brazilian IBOVESPA appear to be (nonlinear) Granger triggers of the DCCs occurring between each of these markets and other developed and emerging ones. Meanwhile, other pairs (like FTSE 100 and SEE or DAX and S&P/ASX 200) are not predictors of other DCCs. Overall, no strong regularity regarding potential causality running between different DCCs can be inferred based on these results. Yet these results reveal that the trading decisions adopted by investors operating on international markets may lead to pair synchronization in risk evolution amongst these markets.

Table 5. Variable-lag Transfer Shannon Entropy Ratio causality tests for some DCCs (estimation based on GARCH-Copula model 9)

Hypothesis	***Transfer Entropy Ratio***	**Conclusion**
S&P 500/ IBOVESPA causes S&P 500/ DAX	7.077	True
S&P 500/ IBOVESPA causes S&P 500/ Nikkei 225	0.974	False
S&P 500/ IBOVESPA causes S&P/ASX 200/ BEL 20	2.681	True
DAX/ S&P/ASX 200 causes Nikkei 225/ KOSPi	0.826	False
FTSE 100/ MERVAL causes DAX/ STI	0.598	False
Nikkei 225/ Jakarta Composite Index causes CAC 40/ AEX	1.212	True
HSI/ IBOVESPA causes S&P 500/ JSE	0.834	False

Hypothesis	*Transfer Entropy Ratio*	Conclusion
S&P 500/ PSEi causes HSI/ TSEC	1.121	True
FTSE 100/ SEE causes Nikkei 225/ PSEi	0.517	False
FTSE 100/ S&P BSE SENSEX causes KOSPI/ STI	0.894	False
S&P 500/ DAX causes S&P 500/ ISEQ All Share	4.838	True
BEL 20/ Austrian Traded Index causes OMX Stockholm/ SMI PR	1.661	True
S&P 500/ KOSPi causes S&P BSE SENSEX/ USD/BDT	1.010	True
FTSE 100/ BEL 20 causes CAC 40/ USD/TND	1.473	True
CAC 40/ IBEX 35 causes DAX/ BIST 100	1.749	True
S&P 500/ S&P/TSX causes S&P/ASX 200/ S&P BSE SENSEX	1.298	True
S&P 500/ MERVAL causes STI/ FTSE Bursa Malaysia KLCI	1.810	True
S&P 500/ FTSE 100 causes IBOVESPA/ SSE	1.481	True
DAX/ S&P/TSX causes HSI/ KOSPI	0.971	False
FTSE 100/ BEL 20 causes AEX/ ISEQ All Share	3.146	True
S&P 500/ DAX causes IBOVESPA/ S&P/TSX	1.256	True
FTSE 100/ CAC 40 causes HSI/ JSE	1.234	True
S&P/TSX/ KOSPi causes S&P/ASX 200/ STI	1.144	True
S&P 500/ FTSE 100 causes USD/BDT/ BIST 100	0.909	False
DAX/ IBOVESPA causes STI/ Jakarta Composite Index	5.467	True

Notes: *If the Transfer Entropy Ratio exceeds 1, then series "X" causes series "Y". The maximum possible time delay is chosen using cross-correlation. The significant-level threshold for Transfer Entropy bootstrapping by Dimpfl and Peter (2013) is set to be 5%. The number of times bootstrapping is equal to 10. The method is described by Amornbunchornvej et al. (2021) and implemented by Amornbunchornvej (2022).*

Comments

We find that major financial markets display bi-univocal dynamic correlations between their risks, as captured by ES estimators. We also find that such correlations are not stable on "long-run", and some substantial endogenous and exogenous shocks are driven by their evolutions. Nonetheless, several comments must be made in regard to the plausibility of these findings.

First, "correlation" is not the same as "causality": we do not explicitly address the issue of our dataset's leading markets' identification. However, some DCCs may act as triggers (at least in a (nonlinear) Granger sense) for others. Therefore, this analysis suggests that a rise in risk spread between two individual markets can trigger the spread of risk between other connected markets. This is particularly true for the major United States and European markets and, to a lesser extent, for the conditional correlations between Latin America and South-Asia markets. Such outcome may reflect the deepening of international market inter-linkages driven by financial globalization, the increased activity of international traders and a higher sophistication of their hedging strategies, as well as the fact that some of the markets included in our dataset play a global role, while others are mainly regionally relevant. Nonetheless, such potential bi and multi-vocal causality does not appear stable on "long-run". As large endogenous and exogenous shocks arise, accommodation adjustments in the implied mechanisms occur.

Second, significant international bubbles/crashes seem to be periods of markets' risk profile synchronization: phenomena like overreactions/panic lead the trading decisions during such periods (with variations that can be influenced by various factors; the behavioral factors for instance include: herding behavior, bounded rationality, risk-seeking trading decisions, resistance to new information or overconfidence, and social and cultural factors). Notably, we find strong evidence of cross-market risk spread during the 2007-2010 financial and real turmoil, the pandemic and the Ukrainian war. This outcome contrasts with the "no contagion, only interdependence" result of Forbes and Rigobon (2002). However, it is supported by other findings in the literature such as, Syllignakis and Kouretas (2011); Naoui et al. (2010); Maghyereh et al. (2022); Cai et al. (2016); Tantipaiboowong et al. (2021); Ji et al. (2022). Therefore, we do not view the high inter-market co-movements during crisis periods as a simple continuation of previous cross-market linkages. Instead, we argue that crises' specific mechanisms drive risk contagion processes during such periods. However, our data sample does not cover the three crises studied by Forbes and Rigobon (2002) (the 1997 East Asian crisis, the 1994 Mexican peso collapse, and the 1987 U.S. stock market crash). So, an extended analysis might be required to clarify if such crisis-related mechanisms are or not specific to the post-2000s period.

Third, the results display specific sensitivity to the choice of DCCs estimation. Overall, most of the GARCH-Copula models outperform both standard and GO-GARCH models. Jointly with the multivariate non-normal distribution of data, it points toward the requirement of a careful selection of the models employed to capture cross-correlations between markets.

Fourth, the differences between models, which involve or not the Brent Crude Oil and natural gas prices as external regressors, suggest that these two variables may play an essential role in the mechanisms driving the occurrence of DCCs. We argue that such a role can be related to a rise in the uncertainty surrounding the economic environment, directly associated with a shock at the level of these prices. Such uncertainty may directly impact investors' trading decisions and related trading performances. In fact, the literature includes evidence of this (see Chiweza and Aye (2018); Bashar et al. (2013); Caporale et al. (2015)). Nevertheless, this argument does not involve any particular transmission channel for the effects induced by these two prices. Thus, a more extended study is required to highlight the potential mechanisms and better clarify the DCCs' response reactions to adjustments in their levels.

Fifth, we learn that the DCCs are driven by non-stationary (but not "explosive") processes. In addition, such processes show multifractal properties. This result is perhaps not a surprise: on high frequencies (daily), one can typically expect only small amplitude adjustment processes in the linkages between markets' risk. Of course, this does not hold during market crash periods when significant changes in risk occur. Consequently, any analysis over a time span covering both "business as usual" and crisis periods might reveal distinctive behaviors and characteristic scaling exponents in different parts of the risk series.

Therefore, one interesting implication is that a standard hedge strategy efficiency might substantially vary over time under the impact of markets' risk association. However, the opposite might also be true: while the investors from international markets implement more sophisticated trading strategies and build up more geographically diversified portfolios, the inter-linkages between markets' risks become less stable. Broadly, the "fundamentals" that govern the markets may substantially change over time. This variation of the driving forces can affect the connections between markets and their corresponding risks. Based on our findings, it can be seen that market interconnectivity leads to prolonged instability of the financial systems at the global level. In this regard, more prudential supervision measures should be implemented in order to reduce financial market stress and volatility, and further to avoid the occurrence of bubbles and crises. Nonetheless, the design of improved policies should be carried out carefully and their capacity of implementation should also be considered. This could be a challenging task especially for emerging countries where transparency, market discipline and financial institutions internal controls are weak. In this sense, emerging countries should take as example and follow the steps of developed countries in what concerns the strategies, the policies and the regulations they implemented..

4. Conclusions

The DCC-GARCH models provide a flexible framework that allows the study of dynamic conditional correlations between international financial markets' risks. For a group of 31 key markets, we find that such correlations occur and, at least for some pairs, they may be causally linked. However, the time series containing these correlations are not necessarily stable on the "long-run" and exhibit multifractal properties.

Several limitations of our study can be mentioned here. First, we only consider a limited number (although relevant) of markets. An extension of our dataset may help to obtain more insights. Second, our analysis covers periods of high financial turmoil. Nevertheless, there are some significant differences between the 2007-2010, the pandemic and the Ukrainian war crises. A deeper examination of these crises' consequences on cross-market risk spread is required. Third, the robustness of our findings concerning alternative measures of risk and estimation techniques should be checked. Fourth, the potential influence of various macroeconomic conditions is not examined here. However, such examination can lead to a better understanding of the exogenous perturbations.

Despite such limitations, the key implication of our findings is that markets' interconnectivity provides opportunities for global financial assets' trade and it may also facilitate a prolonged instability of the international financial systems as a whole. Therefore, more concrete and prudential supervision measures may be helpful to promote corrective mechanisms and prevent extended periods of financial crises and functional instability.

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