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The Nexus between Sovereign CDS and Stock Market Volatility: New Evidence

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Abstract: This paper extends the studies published to date by performing an analysis of the causal relationships between sovereign CDS spreads and the estimated conditional volatility of stock indices. This estimation is performed using a vector autoregressive model (VAR) and dynamically applying the Granger causality test. The conditional volatility of the stock market has been obtained through various univariate GARCH models. This methodology allows us to study the information transmissions, both unidirectional and bidirectional, that occur between CDS spreads and stock volatility between 2004 and 2020. We conclude that CDS spread returns cause (in the Granger sense) conditional stock volatility, mainly in Europe and during the sovereign debt crisis. This transmission dynamic breaks down during the COVID-19 period, where there are high bidirectional relationships between the two markets.

Keywords: CDS sovereign spread; conditional volatility; GARCH; VAR; Granger causality

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1. Introduction

The great global crisis of 2008 was characterized by a dramatic drop in equity prices, high credit risk values, and strong levels of cross-market contagion, due in part to increasing international financial integration. In recent years, the observed interconnections derived from the latest crises have increased and the risk transmission channels have intensified.

As a consequence, the risk of adverse contagion flowing from a large negative shock has increased [1]. This has shown that it is essential to understand contagion mechanisms in order to identify systemic risk and anticipate future financial crises and their evolution, as well as to be able to design regulations that improve financial stability.

In this context, CDSs have played a key role as drivers of systemic risk. The excessive exposure of financial institutions to these derivative instruments during the subprime crisis led to a rapid transfer of credit risk worldwide, which spread to all areas of the global market for both public and private debt. During the subsequent sovereign debt crisis in the eurozone, the role of sovereign CDSs was also evidenced as a possible destabilizing element of the reference countries [2].

As a consequence, both analysts and regulators have focused their attention on these instruments, whose trading volume has grown notably over the last twenty years. According to data from the ISDA (International Swaps and Derivatives Association, 2018), the volume of CDSs has increased from 2.2 trillion dollars in 2002 to around 50 trillion dollars today, with the maximum of 62.2 billion dollars reached in 2017. CDSs occupy a prominent place in global financial regulation (including, among others, the Basel III guidelines and the European Markets in Financial Instruments Directive (MiFID), which is applicable across the EU), and nowadays, they are the most liquid derivative products, representing approximately half of all credit derivatives traded in the market [3]. They are considered important indicators of credit quality [4–6] and also reflect the market's perception of the financial health of the company or country to which they are referenced.

As a result, interest has been rekindled in understanding the CDS market as a proxy for credit risk and its dependency on other markets, among which the equity market stands out. The literature has mainly focused on the analysis of returns and generally uses corporate US data. Most studies, such as [7–9], among others, point to the leadership of stocks over CDSs, which is in line with the results of [10,11] for sovereign CDS data. However, the literature on the relationship in terms of volatility is scarce and provides contradictory results. Using corporate data, in [12–14], significant causality from the CDS market to stock market volatility is found [15], showing the opposite relationship when using the VIX Index as a proxy for the volatility of the equity market, and in [16,17], a bidirectional relationship between the two markets is found. There is also no consensus among the authors analyzing sovereign CDS data. In [18], it is concluded that VIX significantly causes sovereign CDSs, while in [11], it is found that sovereign CDSs anticipate the conditional volatility of equity returns, and in [10], no evidence of a connection is found.

Given this background, the importance of adding additional insight into the interaction between equity volatility and sovereign CDS returns is evident. Specifically, the aim of this paper is to analyze that relationship for both the US and Europe, while also distinguishing between the eurozone and the non-eurozone, during the period from 2004 to 2020. Following the study in [19], we estimate the conditional volatility series of stock returns using various GARCH econometric models. The interrelationship between markets is analyzed by estimating the VAR models (in line with the studies in [20] or [12], among others). In particular, the VAR methodology is carried out in a context of rolling windows, which allows us to analyze the temporal evolution of the causality between the two markets (in line with the studies in [21] and [11]). The large sample period considered also enables us to examine the connection between the two markets during good and bad economic times, among which the recent COVID-19 pandemic stands out. As a health crisis, it has several unique characteristics that distinguish it from previous financial crises.

The results of the study show how sovereign CDS spread returns lead to the anticipation of information about the estimated conditional volatility of stocks. This effect is more evident in Europe and has a greater impact if the stock market conditional volatility is estimated using a model that captures the different impact of negative shocks on volatility. The greatest anticipation of the CDS market on volatility in the US and Europe occurs during the sovereign debt crisis, albeit with a less significant transmission impact in the US. For Europe, there is also a high level of causality during the post-crisis period, a symptom of the fact that this region still maintained significant levels of credit risk. Interestingly, the results during the COVID-19 period break the transmission dynamics seen so far, showing a high bidirectional relationship between CDS returns and the conditional volatility of stock market indices. The European currency zones follow the line of the results for Europe, although we observe high causal relationships for the eurozone (non-eurozone) during the global financial crisis (sovereign debt crisis).

This paper has the following structure. In Section 2, the most relevant works on which the study was based are analyzed. In Section 3, the data used are specified, and a preliminary analysis of them is conducted. Section 4 develops the methodology used, and Section 5 details the results obtained in the study. In Section 6, the conclusions obtained in the analysis are presented.

2. Literature Review

In [22], the first study on the theoretical relationship between credit risk and stock prices at the corporate level was published, noting that the value of credit derivatives is linked to the probability of the entity's exposure to a credit event and that for companies with listed shares, the probability is estimated using information from that market. Given these predictions, in [23], it is argued that the size of the CDS spread and its empirical relationship with the value and volatility of the underlying stock portfolio is of interest. In the specific case of volatility, one would expect a large CDS index spread when the stock market valuation is low, and the volatility is high, and vice versa.

From these works, an important branch of literature has developed focusing on investigating this relationship from a causality/anticipation perspective from one market to another. Initial studies, such as those in [24] (using data from US firms) and [25] (with an international sample of US, European, and Asian firms) show that price discovery transmission flows from stock markets to CDSs and then to bond spreads. The latter also conclude that this effect is stronger for US firms than for European ones.

Focusing exclusively on the relationship between CDS and stock returns, most studies point to the leadership of stocks over CDSs. In this line, some of the most recent papers also provide additional interesting results. In [7], with a sample of US firms, a strong anticipation of information for stocks over CDS returns is found, mainly due to the aggregate and positive information in the equity market. In [8], it is also established that it is equity returns that respond to CDS returns, but not the other way around. In a more recent study [9], it is confirmed that for all US industries, the equity market leads the CDS market, and it is concluded that this causality has a dynamic character and is counter cyclical. Using the same sample, in [21], the determinants of this causality are studied, finding that the volatility of the stock market, the business conditions, the default premiums, the Treasury bond rate, and the slope of the yield curve are the major explanatory factors of this relationship. For the European case, in [26], the iTraxx CDS Index is used, and the leadership of the stock market is revealed, with an increasing effect during the subprime crisis. The few authors that consider sovereign CDS returns, instead of corporate data, reach the same conclusion, namely, that the stock market leads the sovereign CDS market [10,11]. A detailed description of this branch of the literature that analyzes the relationship in terms of returns between the equity and CDS markets can be found in [11].

However, the literature that analyzes the transmission process in terms of volatilities is quite limited, focusing mostly on the US, and provides mixed results. In [12], US corporate data are considered, and it is found that volatilities of both the investment-grade and the high-yield CDX indices lead stock market volatility. In the same spirit, although using exclusively US and European banks, in [13], the connection between the CDX and iTraxx indices is analyzed, and it is concluded that CDS volatilities are the leaders of the transmission. In [14], the same unidirectional relationship of CDS returns to equity volatility for US sectoral data is found, with a higher impact during the period of the post-Lehman crisis. However, more recently, in [15], the opposite relationship from VIX to CDS returns for most US sectors was found. They also conclude that utilities and industrial sectors are the ones with the weakest relationship, while cyclical industries, such as basic materials, are highly connected. Following the study of this nexus at the US sectorial level, the analysis in [16] even reveals bidirectional Granger causality in variance for all the sectors. The same bidirectional volatility spillover result is achieved in [17] using European corporate data, although with a predominant leadership of the CDS market over the stock market.

There is also no consensus among the authors considering sovereign CDS data. In [18], the causal relationship between the VIX Index and sovereign CDS returns for 56 countries is analyzed, finding that, for most countries, the VIX leads transmission significantly. In contrast, in [11], the lead-lag connection between conditional volatilities of equity returns and sovereign CDS returns for 14 European countries and the US is studied, showing the leadership of CDSs, both for the US and Europe. Finally, in [10], no evidence of a connection between CDS returns and implied market volatility is found.

We further note that there is also no agreement on whether to consider CDS returns or volatilities. While the use of CDS volatilities means that the data for both markets are expressed in terms of volatilities, examining CDS returns is especially appropriate when it comes to analyzing the transmission of information in terms of risks. Note that equity volatilities measure equity market risk, while CDSs are already a proxy of credit risk.

Our paper contributes to the studies published to date by conducting an exhaustive empirical analysis of the causal relationships between sovereign CDS returns and the estimated conditional volatility of equity indices, approximating the latter through various GARCH models. Previous studies have focused primarily on the connection in returns using US corporate data and have paid little attention to the sovereign relationship in terms of volatility. As far as we know, only three papers have carried out such an analysis [10,11,18], although in different ways. They use a variety of methodologies, data, and sample periods, obtaining such different results that it is exceedingly difficult to draw conclusions. We improve on the literature in several ways. First, we adopt a rolling window approach to analyze the existing interaction dynamically. This enables us to obtain the temporal evolution of the causality. Second, the long sample period considered (2004 to 2020) also allows us to draw comparisons between good and bad economic times, among which the global financial crisis of 2008, the European sovereign debt crisis of 2010, and, above all, the recent COVID-19 pandemic stand out. To date, this is the only paper that includes the COVID-19 era in the study. As a health crisis, it has several unique characteristics that distinguish it from previous financial crises, which can condition the interaction between markets, both in terms of magnitude and the direction of information transmission. Third, we conduct the study for different geographical areas, both the US and Europe, and distinguish between the eurozone and the non-eurozone.

3. Data

We use two major datasets collected from the Thomson Datastream database. First, we have daily data of 5-year sovereign CDS spreads for the US and 14 developed European countries: ten belong to the eurozone (Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain) and four to the non-eurozone (Denmark, Norway, Sweden, and the UK). We consider CDS contracts maturing in five years, since they are the most liquid and the most traded credit risk derivative [25,27]. The beginning of the negotiation of CDS contracts in the different countries marks the beginning of the sample period, which runs from 6 January 2004 to 22 October 2020 for European countries and from 11 December 2007 to 22 October 2020 for the US. Next, given that the analysis will be carried out by geographical area, we proceed to form equally weighted CDS portfolios for Europe, as well as for the eurozone and non-eurozone. The three resulting series, together with the US sovereign CDSs, measure the average sovereign credit risk of each of the four zones.

The second dataset consists of daily data of stock indices for each geographical area: S&P 500 for the US, Stoxx Europe Total Market for Europe, Euro Stoxx 50 for the eurozone, and Stoxx Europe Ex Euro Total Market for the non-eurozone. Henceforth, we will use the abbreviations, SPX, STOXX, Euro-STOXX, and Non-Euro-STOXX, respectively, to refer to them.

The long sample period considered (from 2004 to 2020) allows us to dynamically study the evolution of the transmission between the CDS market and the volatility of the equity market, as well as to make a comparison between good and bad economic times, and ultimately analyze to what extent the existence and magnitude of the lead-lag causality depends on the economic cycle. We establish a total of five sub-periods. From January 2004 to June 2007. We have the pre-crisis period of relative stability, followed by two periods of financial turmoil, the global financial crisis from July 2007 to December 2009, and the European sovereign debt crisis from January 2010 to December 2013. These two financial crises are followed by six years of economic stability, which we denote as the post-crisis period, from January 2014 to November 2019. The last period, from December 2019 to October 2020, corresponds to the COVID-19 crisis, thus covering the first two waves of the pandemic.

Table 1 reports, in Panel A, the summary statistics of the sovereign CDS spreads data, while Figure 1 (Panel A) shows their daily time evolution. After the pre-crisis period of stability, characterized by low credit risk values, we observe a marked increase in the CDS series of the four regions during the global financial crisis period (specifically, after the bankruptcy of Lehman Brothers in September 2008). It is in this period that US CDSs reach their maximum value. With the sovereign debt crisis and its uneven effect in different regions, fragmentation in Europe becomes evident. The eurozone is by far the most affected area. Their CDSs increase considerably to a record high of 1893.6 bps. This is mainly due to the particular case of Greece, whose instability during that period led to the country's massive default. Greek CDSs reached the unanticipated level of 37,000 bps (in March 2012), which triggered a suspension in trading. The sovereign debt problems of the eurozone are also evident in the high standard deviation observed during both the sovereign debt crisis and the post-crisis period. This last result is exclusively due to Italy and Portugal, countries that still faced serious debt problems, and which is reflected by their high levels of credit risk during 2014 and early 2015. The reaction of CDSs to the Covid-19 crisis was much lower and not at all comparable to what was observed during previous financial crises. All CDS series show an increase in credit risk at the end of March 2020, although they stabilize on average, returning to values similar to those obtained in the global financial crisis period. Panel B of Table 1 shows the basic statistics of the stock market indices calculated as log-returns, both for the total sample and by sub-periods, while Panel B of Figure 1 shows their daily time evolution. In general terms, what stands out is the high variability observed during bad economic times, due to the instability in the financial markets caused by the existing uncertainty. This is especially so during the sub-periods of the global financial crisis and the Covid-19 crisis and, to a lesser extent, during the sovereign debt crisis.

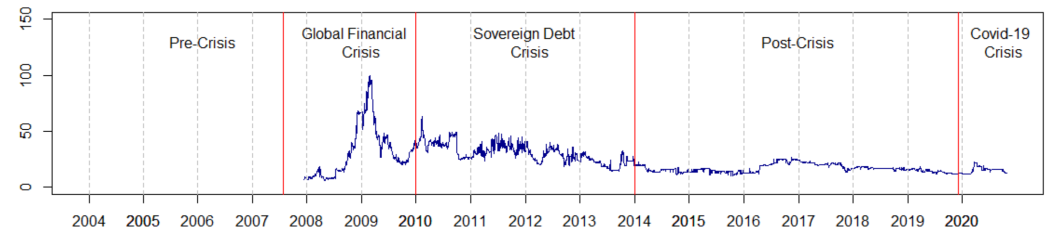
Table 1. Main descriptive statistics of daily sovereign CDS spreads and stock indices returns [1].

Panel A	Sovereign CDS Spreads					Panel B	Stock Indices Returns				
	Obs.	Min.	Max.	Mean	Std. Deviation		Obs.	Min.	Max.	Mean	Std. Deviation
Complete sample period (2004–2020)											
US	3358	5.80	100.00	23.38	12.71	SPX	4382	−0.128	0.110	0.000	0.012
Europe	4383	2.89	1374.72	404.32	507.09	STOXX	4382	−0.122	0.093	0.000	0.012
Eurozone	4383	2.64	1893.60	556.46	707.88	Euro-STOXX	4382	−0.132	0.104	0.000	0.013
Non-Eurozone	4383	1.39	134.55	24.09	21.87	Non-Euro-STOXX	4382	−0.114	0.087	0.000	0.011
Pre-Financial Crisis (January 2004–June 2007)											
US	-	-	-	-	-	SPX	908	−0.035	0.021	0.001	0.007
Europe	909	2.89	22.05	6.04	3.00	STOXX	908	−0.031	0.026	0.001	0.007
Eurozone	909	2.64	13.61	5.28	1.13	Euro-STOXX	908	−0.034	0.026	0.001	0.008
Non-Eurozone	909	1.39	60.91	8.12	9.78	Non-Euro-STOXX	908	−0.031	0.028	0.001	0.007
Global Financial Crisis (July 2007–December 2009)											
US	538	5.80	100.00	31.21	22.65	SPX	654	−0.095	0.110	−0.000	0.020
Europe	654	8.16	173.79	50.80	41.92	STOXX	654	−0.079	0.093	−0.001	0.018
Eurozone	654	2.70	189.49	55.78	46.33	Euro-STOXX	654	−0.082	0.104	−0.001	0.020
Non-Eurozone	654	6.80	134.55	38.89	31.73	Non-Euro-STOXX	654	−0.079	0.087	−0.001	0.018
Sovereign Debt Crisis (January 2010–December 2013)											
US	1043	14.32	63.28	30.80	8.45	SPX	1043	−0.069	0.046	0.000	0.011
Europe	1043	73.18	1374.72	740.56	482.17	STOXX	1043	−0.049	0.068	0.000	0.011
Eurozone	1043	85.43	1893.60	1019.09	675.19	Euro-STOXX	1043	−0.063	0.098	0.000	0.014
Non-Eurozone	1043	18.31	93.11	44.25	18.83	Non-Euro-STOXX	1043	−0.044	0.053	0.000	0.010
Post-Financial Crisis (January 2014–November 2019)											
US	1543	10.02	26.48	16.86	3.56	SPX	1543	−0.042	0.048	0.000	0.008
Europe	1543	30.66	1141.17	617.27	532.90	STOXX	1543	−0.072	0.041	0.000	0.009
Eurozone	1543	38.81	1589.78	857.95	744.61	Euro-STOXX	1543	−0.090	0.046	0.000	0.011
Non-Eurozone	1543	8.22	27.71	15.60	4.28	Non-Euro-STOXX	1543	−0.067	0.039	0.000	0.009
COVID Crisis (December 2019–October 2020)											
US	235	11.81	22.76	15.29	2.70	SPX	235	−0.128	0.090	0.000	0.022
Europe	235	28.03	55.39	36.48	6.92	STOXX	235	−0.122	0.081	−0.001	0.018
Eurozone	235	36.06	70.90	46.74	8.66	Euro-STOXX	235	−0.132	0.088	−0.001	0.020
Non-Eurozone	235	7.81	18.99	10.83	2.69	Non-Euro-STOXX	235	−0.114	0.081	−0.001	0.017

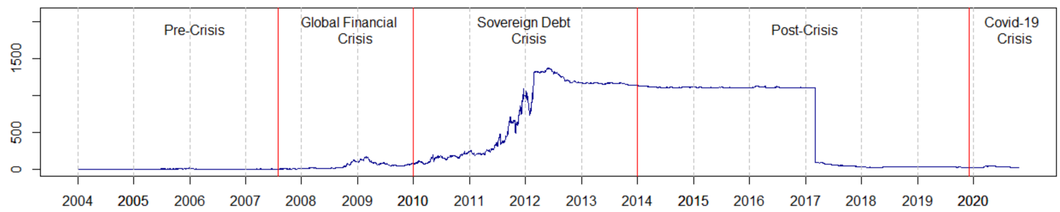
[1] This table provides the descriptive statistics of sovereign CDS spreads and stock indices returns for US and Europe. The sample period is from 6 January 2004 to 22 October 2020 for European CDS spreads and from 11 December 2007 to 22 October 2020 for US CDS spreads.

Panel A: CDS spreads

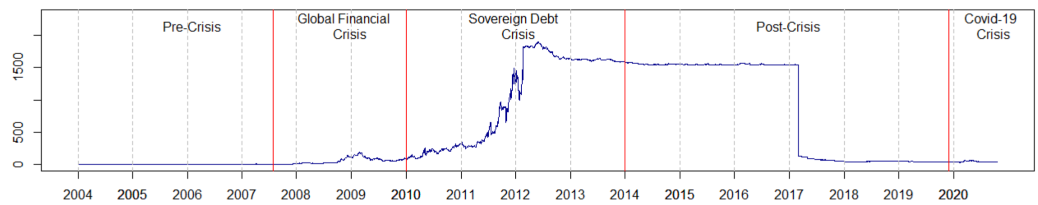
US



Europe



Eurozone



Non-Eurozone

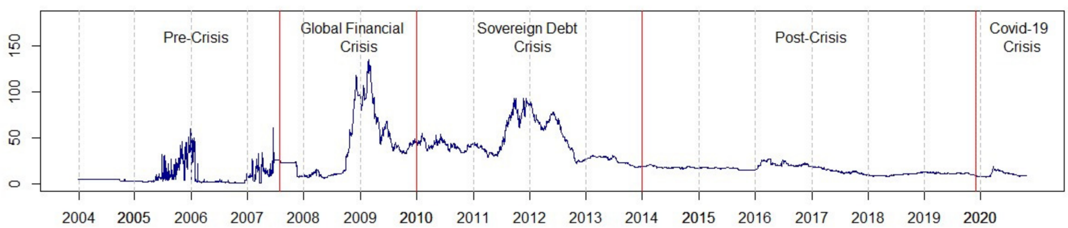
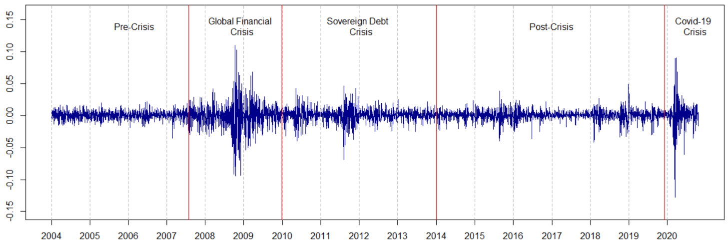


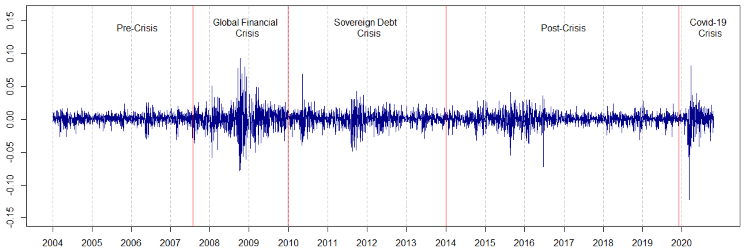
Figure 1. *Cont.*

Panel B: Stock indices returns

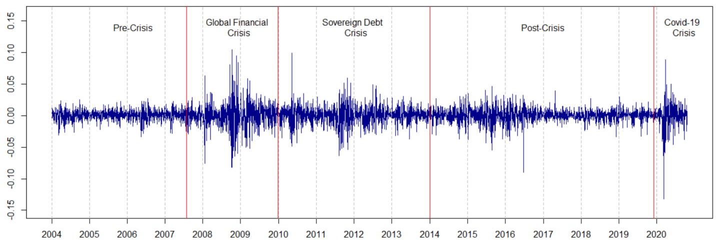
SPX Index



STOXX Index



Euro-STOXX Index



Non-Euro-STOXX Index

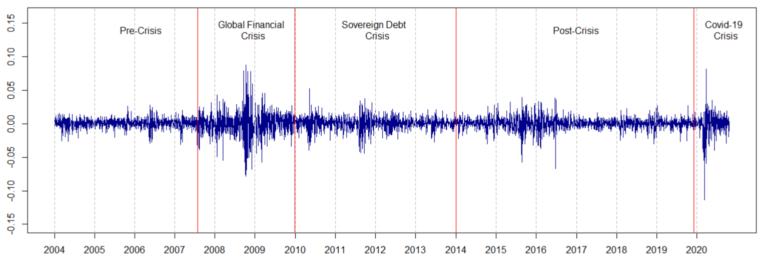


Figure 1. Daily time evolution of the sovereign CDS spreads expressed in basis points and stock indices returns. The sample period is from 6 January 2004 to 22 October 2020 for European CDS spreads and from 11 December 2007 to 22 October 2020 for US CDS spreads. The vertical lines mark the beginning of the different sub-periods: pre-crisis, global financial crisis, sovereign debt crisis, post-crisis, and COVID-19 periods.

4. Methodology

This section explains the two steps followed in the methodology to analyze the nexus between sovereign CDS returns and stock market volatility.

4.1. Estimation of the Conditional Volatility of Stock Market Returns

The first step consists in estimating the conditional volatility of the returns of each of the four stock market indices. To allow volatility to change over time, volatility is extracted using four alternative models. Following the study in [28], we consider the exponentially weighted moving average (EWMA) model, the generalized autoregressive conditional heteroscedasticity (GARCH) model, and two models derived from the latter, the exponential GARCH or EGARCH and the GJR GARCH (Glosten-Jagannathan-Runkle GARCH) model.

4.1.1. EWMA Model

The EWMA model is a particular case of the ARCH(m) model proposed in [29]. The variance estimate is based on a long-run average variance using m observations, in which more recent observations have greater weight on the variance:

$$\sigma_t^2 = \omega + \sum_{i=1}^{m} \alpha_i u_{t-i}^2 \tag{1}$$

The u_i is defined as the continuously compounded return during day i, and the weights α_i decrease exponentially as we move away in time. Specifically, $\alpha_{i+1} = \lambda \alpha_i$, where λ is a constant between zero and one, which is called the smoothing parameter. This particularity ensures a variance that is weighted or biased toward more recent data using the following recursive formula:

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1-\lambda)\, u_{t-1}^2 \tag{2}$$

In a general way, the EWMA volatility model can also be formulated as:

$$\sigma_t^2 = (1-\lambda) \sum_{i=1}^{m} \lambda^{i-1} u_{t-i}^2 + \lambda^m \sigma_{t-m}^2 \tag{3}$$

where the weights decrease at rate λ as we move away in time, and each time is λ times the previous weight.

4.1.2. GARCH Model

In [19], the GARCH (p,q) model is proposed, in which the conditional variance is estimated with the most recent p observations of squared returns and the most recent q estimates of the variance. This allows the conditional variance to be dependent on previous delays and captures information contained in the historical values of the variance. The GARCH (1,1) model is given by the following equation:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4}$$

where $\omega > 0$, $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. These constraints for the coefficients ensure the non-negativity of the variance. The GARCH (1,1) model is by far the most used model, since it avoids a large number of delays, which in general were related, and hence, it is our choice within the GARCH family of models.

Note that the EWMA model is a particular case of the GARCH (1,1) model, where $\omega = 0$, $\alpha = 1 - \lambda$, and $\beta = \lambda$. The most notable difference between the two is that unlike the EWMA model, the GARCH model includes a mean reversion term.

4.1.3. EGARCH Model

For the EGARCH model proposed in [30] and, in particular, for the specific case of the EGARCH (1,1) model considered, the conditional volatility specification is given by the following equation:

$$ln(\sigma_t^2) = \omega + \alpha\left(|u_{t-1}| - \sqrt{\frac{2}{\pi}}\right) + \beta\, ln(\sigma_{t-1}^2) + \gamma u_{t-1} \tag{5}$$

This model does not require any sign restriction for its parameters, since it is specified for the logarithm of variances. The use of the EGARCH model also has the advantage of allowing the effects of information asymmetries to occur, which are captured by the leverage parameter γ. The main contribution of this model is that if γ is below zero, this reflects the greatest impact on the volatility of negative shocks, compared to positive ones.

4.1.4. GJR GARCH Model

The GJR GARCH model proposed in [31] is an extension of the GARCH model by adding an additional term to account for the asymmetries observed in the financial markets. The model is presented as follows:

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})u_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

where $\omega > 0,\ \alpha, \beta \geq 0$, and I_t is a dummy variable, which is equal to 1 if $u_t < 0$ (negative shocks) and 0 if $u_t \geq 0$ (positive shocks).

In this model, conditional volatility is allowed to have different reactions to past innovations based on their signs. The effect of good and bad news is captured through α and $\alpha + \gamma$, respectively, so that γ is the parameter that measures the impact of news arrival and collects the possible asymmetry in variance. If it is positive (negative), the volatility response is greater (lower) in the face of negative shocks. It is in the first case (when $\gamma > 0$) that volatility is marked by a leverage effect.

4.2. Granger Causality Test

The second step is to carefully examine, for each of the four geographic zones, the existence of a causality relation between sovereign CDS returns and stock market volatility, identifying which of the two series is leading and which is lagging, and whether that relationship changes over time. To that end, a bivariant vector autoregressive VAR(p) model is estimated, in which each dependent variable is explained by its own lags and the lags of the other dependent variable:

$$Y_t = \alpha + \sum_{j=1}^{p} \Theta_j Y_{t-j} + \varepsilon_t \qquad t = 1,\ \ldots, T \tag{7}$$

where Y_t is the $m \times 1$ vector composed of the m stationary series to be analyzed (in our case, $m = 2$), α is the vector of intercept terms 2×1, Θ_j is the matrix of estimated coefficients 2×2, and ε_t is the vector of innovations (2×1) that follows a multivariate normal distribution with variance Σ. In this particular case, Θ_j is given by the 2×2 matrix with coefficient $\beta_{1,j},\ \delta_{1,j}, \beta_{2,j}$, and $\delta_{2,j}$.

As usual, the optimal VAR lag p is chosen following the Akaike Information Criterion (AIC) and the Bayesian information criterion (BIC). Next, the causality test in [32] is used. Specifically, sovereign CDS returns would cause, in the Granger sense, equity volatility, when the nullity of the $\beta_{1,j}$ coefficients is rejected, that is, when the null hypothesis $H_0 = \beta_{1,1} = \ldots = \beta_{1,j} = \ldots = \beta_{1,p} = 0$ is rejected. Equity volatility would cause, in the Granger sense, sovereign CDS returns, when the nullity of the $\delta_{2,j}$ is rejected, that is, when the null hypothesis $H_0 = \delta_{2,1} = \ldots = \delta_{2,j} = \ldots = \delta_{2,p} = 0$ is rejected.

The VAR estimation has been carried out dynamically using rolling windows of 250 observations in order to obtain causality results over time. We verify the robustness of the results by modifying the size of the rolling window to 200 days (in line with [27] or [33]). With this approach, two time series of p-values associated with each of the two null hypotheses mentioned above are obtained for each geographical zone. In this way, three types of lead–lag relationships can be extracted in each rolling window, the two aforementioned unidirectional ones, and the bidirectional transmission that occurs when the nullity of both coefficients $\beta_{1,j}$ and $\delta_{2,j}$ is rejected in the same window. Finally, with the aim of studying to what extent the observed transmissions vary over time, we quantify the number of times that a particular causality is observed. These causality results are calculated in percentage terms for both the full sample period and five important sub-periods (the pre-crisis period, the global financial crisis, the European sovereign debt crisis, the post-crisis period, and the COVID-19 crisis).

5. Results

5.1. Conditional Volatility of Stock Indices Returns

In this section, we proceed to estimate, for each of the four zones, the conditional volatility of stock index returns using the EWMA, GARCH, EGARCH, and GJR GARCH models. Table 2 shows the results of the estimated coefficients for each model and the residual diagnosis based on the Ljung-Box and Engle's tests for the standardized residuals. In all cases, a β coefficient is obtained that is significant, positive, and close to unity, indicating a high persistence in volatility. In the case of the EGARCH and GJR GARCH models, significant asymmetry coefficients are also obtained (negative and positive, respectively), indicating that there is a greater volatility response to negative shocks. The Ljung-Box tests and the tenth order ARCH reveal that the residuals are free of conditional heteroskedasticity and autocorrelation, both in level and squared returns. Furthermore, the ARCH test for the EWMA model reveals that GARCH structure models with time-varying volatility would be more appropriate.

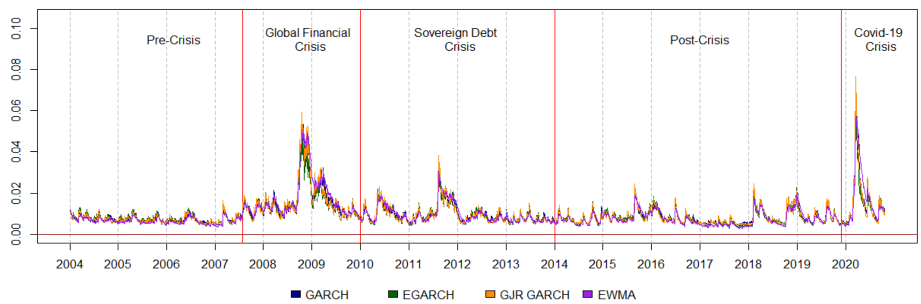
Table 2. Conditional volatility coefficients of stock indices returns and summary statistics for the standardized residuals [2].

Index	ω	α	β	γ	$Q(10)$	$Q^2(10)$	**ARCH(10)**
			EWMA model				
SPX			0.928903 ***		16.25 *	28.32 ***	27.35 ***
STOXX			0.920915 ***		6.78	25.63 ***	24.10 ***
Euro-STOXX			0.934051 ***		5.31	27.78 ***	27.99 ***
Non-Euro-STOXX			0.915599 ***		10.83	27.22 ***	25.23 ***
			GARCH model				
SPX	0.000002	0.129490 ***	0.848774 ***		15.28	15.14	15.50
STOXX	0.000002	0.122425 ***	0.863031 ***		6.50	10.87	11.03
Euro-STOXX	0.000003	0.107732 ***	0.877657 ***		6.26	16.29 *	17.30 *
Non-Euro-STOXX	0.000002	0.13224 ***	0.852468 ***		9.73	7.68	7.77
			EGARCH model				
SPX	−0.258846 ***	0.174039 ***	0.971792 ***	−0.138552 ***	20.83 **	10.54	10.19
STOXX	−0.235340 ***	0.140450 ***	0.974470 ***	−0.145770 ***	7.38	8.17	8.13
Euro-STOXX	−0.199304 ***	0.111591 ***	0.977376 ***	−0.156721 ***	7.03	12.04	12.54
Non-Euro-STOXX	−0.243860 ***	0.165230 ***	0.973600 ***	−0.127130 ***	10.55	8.16	8.08
			GJR-GARCH model				
SPX	0.000002	0.014196	0.872510 ***	0.174651 ***	13.99	8.77	8.83
STOXX	0.000002	0.000023	0.881795 ***	0.193467 ***	7.66	9.26	9.16
Euro-STOXX	0.000003	0.000000	0.893193 ***	0.182704 **	7.28	15.15	15.71
Non-Euro-STOXX	0.000002	0.014959	0.871363 ***	0.179087 ***	10.29	6.22	6.27

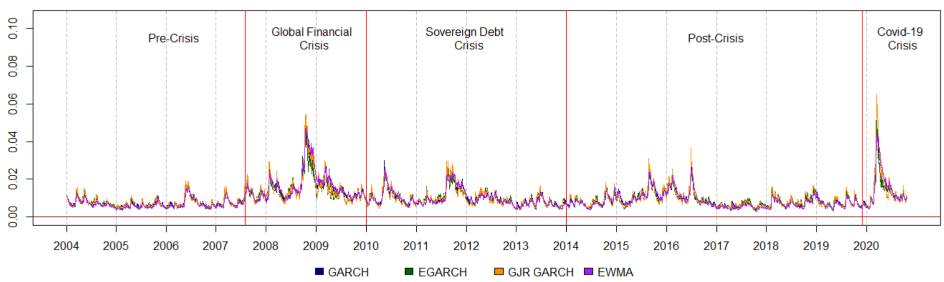
[2] This table reports the estimation parameters of the conditional volatility models for European and US stock indices returns. In the models, ω is the constant, α and β are the ARCH and GARCH terms, and γ is the asymmetric term. For the EWMA model, note that $\beta = \lambda$. $Q(10)$ and $Q^2(10)$ are Ljung-Box tests for tenth-order serial correlation in the standardized residuals and squared residuals. ARCH(10) is Engle's test for tenth-order ARCH, distributed as $X^2(10)$. ***, ** and * indicate significance at the level of 1%, 5%, and 10%, respectively.

Figure 2 shows the estimated volatility series. In general terms, we observe a similar behavior, although it is true that the volatilities obtained with the asymmetric models (especially with the GJR GARCH model) are slightly higher than those obtained with the other models, and this fact is observed to a greater extent in times of financial instability. The asymmetric models seem to better capture the greater impact on volatility of the negative shocks, characteristic of bad economic times. It can be seen how the onset of the global financial crisis at the end of 2007, together with the subsequent collapse of Lehman Brothers in September 2008, increased the volatility of stock market indices, especially in the United States. The sovereign debt crisis in Europe also substantially increased the index volatility, although to a lesser extent. Finally, in March 2020, with the onset of the COVID-19 crisis, the volatility in all stock market indices shot up, even more than during the global financial crisis.

Panel A: SPX Index



Panel B: STOXX Index



Panel C: Euro-STOXX Index

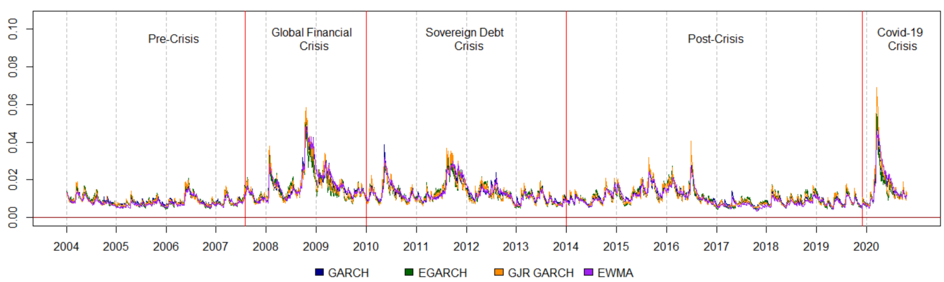


Figure 2. *Cont.*

Panel D: Non-Euro-STOXX Index

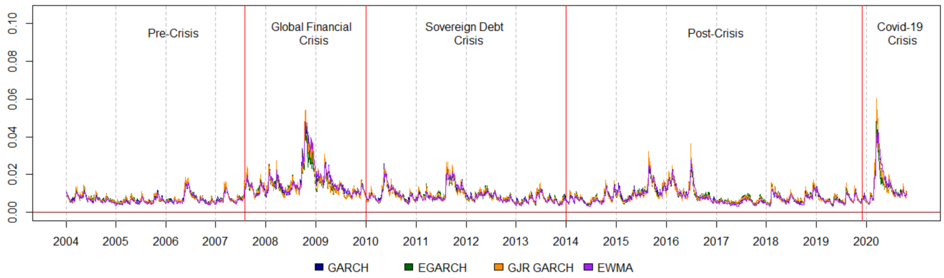


Figure 2. Conditional volatility of stock indices returns estimated by the EWMA, GARCH, and GJR GARCH models. The sample period is from 6 January 2004 to 22 October 2020 for Europe and from 11 December 2007 to 22 October 2020 for the US. The vertical lines mark the beginning of the different sub-periods: pre-crisis, global financial crisis, sovereign debt crisis, post-crisis, and COVID-19 periods.

5.2. Dynamic Unconditional Correlations

Once the volatility series of the stock indices returns have been calculated, as a preliminary step, we analyze the dynamic unconditional correlation between these series and the returns of sovereign CDS spreads (Figure 3). One would expect that, as they are both measures of risk, the a priori correlation between them would be positive. Indeed, this is the behavior observed in the four geographical areas during the global financial crisis and, to a greater extent, during the COVID-19 crisis. It is precisely during the health crisis and, more specifically, during the first wave of the pandemic (March 2020), that the highest positive correlations are observed in the whole sample, especially for Europe. Furthermore, we note that the highest correlation values associated with the crisis periods are obtained by the EGARCH and GJR GARCH models. This fact once again suggests that this asymmetric model seems better able to capture the greater impact of negative shocks produced in crisis periods on volatility. These preliminary results suggest that there is a dynamic connection between the two series, which varies with the business cycle. The question that now arises is whether or not this relationship translates into causality, which explains the causality analysis that follows.

Panel A: US CDS returns-SPX volatility

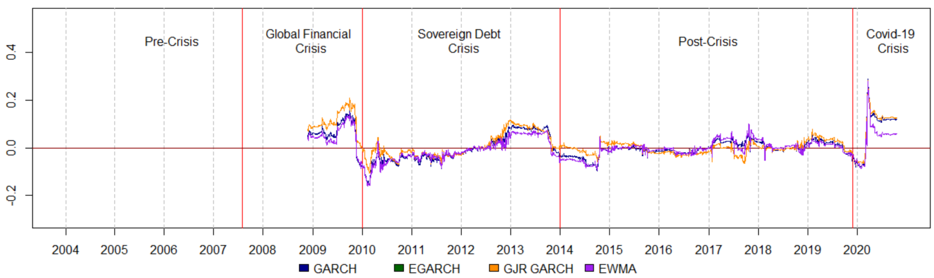
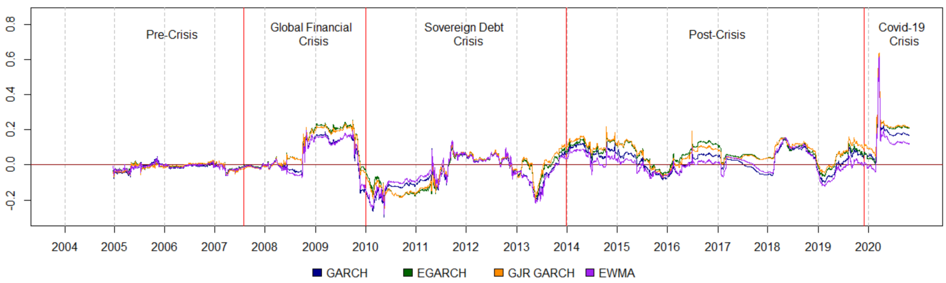
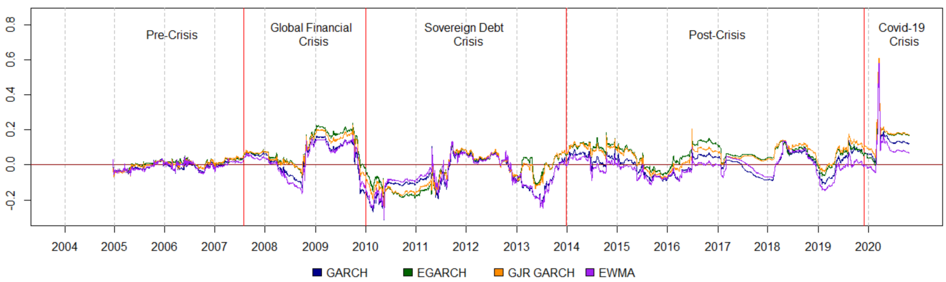


Figure 3. *Cont.*

Panel B: Europe CDS returns-STOXX volatility



Panel C: Eurozone CDS returns-Euro-STOXX volatility



Panel D: Non-Eurozone CDS returns-Non-Euro-STOXX volatility

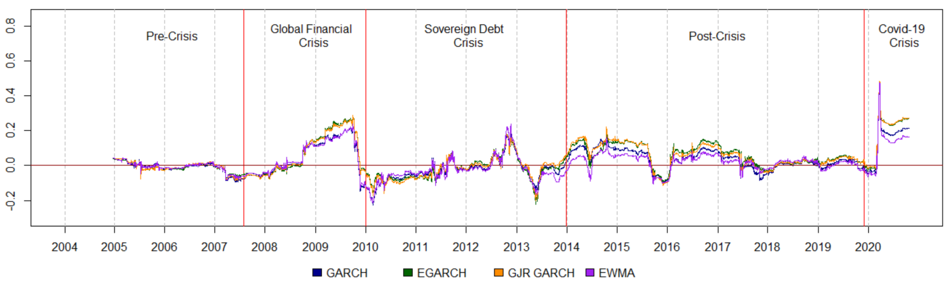


Figure 3. Daily time evolution of the unconditional correlation coefficients of the sovereign CDS returns and the stock indices returns conditional volatility using 250-day rolling windows. The sample period is from 6 January 2004 to 22 October 2020 for Europe and from 11 December 2007 to 22 October 2020 for the US. The vertical lines mark the beginning of the different sub-periods: pre-crisis, global financial crisis, sovereign debt crisis, post-crisis, and COVID-19 periods.

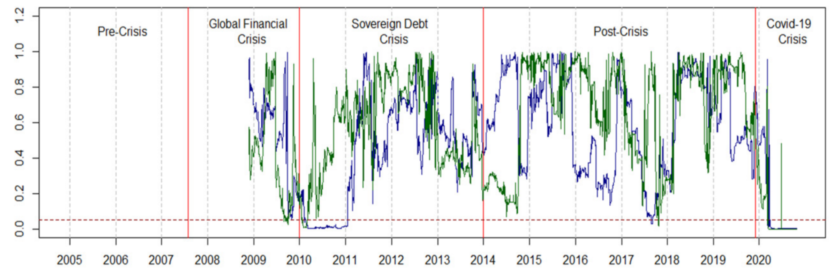
5.3. Granger Causality Test Results

In this section, we analyze, in the Granger sense, the causality relationships that exist between the volatilities of the stock indices and the returns of sovereign CDS spreads. Prior to the estimation of the VAR model, a stationarity test is performed for these series using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to verify that the series are trendless. The results confirm that the series are stationary.

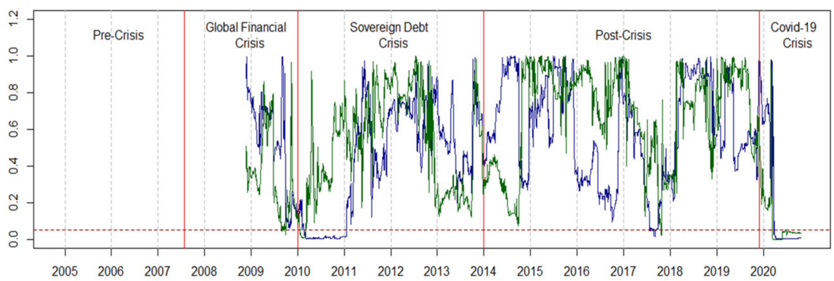
Figure 4 shows the temporal evolution of the causality contrasts for each of the four regions considered. Specifically, the figures indicate the two series of *p*-values obtained by testing the null hypothesis that sovereign CDS returns do not Granger-cause index return volatilities (blue line) and the null hypothesis that index return volatilities do not Granger-cause CDS returns (green line), together with a dashed red line, indicating a significance level of 5%. Accordingly, there will be a significant causal relationship whenever the series of p-values are below the said dashed red line. Additionally, with the aim of quantifying the causality results, Table 3 presents the results in percentage terms for both the full sample period and the different sub-periods.

Panel A: US

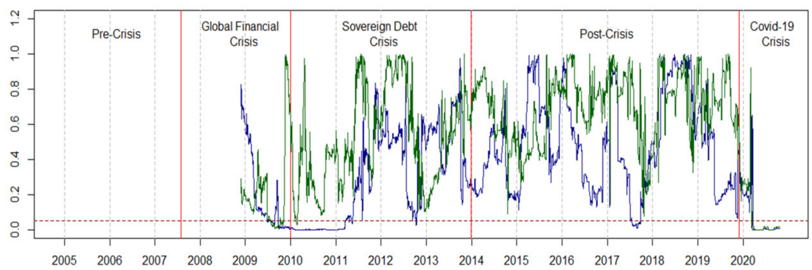
Panel A.1. EWMA model



Panel A.2. GARCH model



Panel A.3. EGARCH model

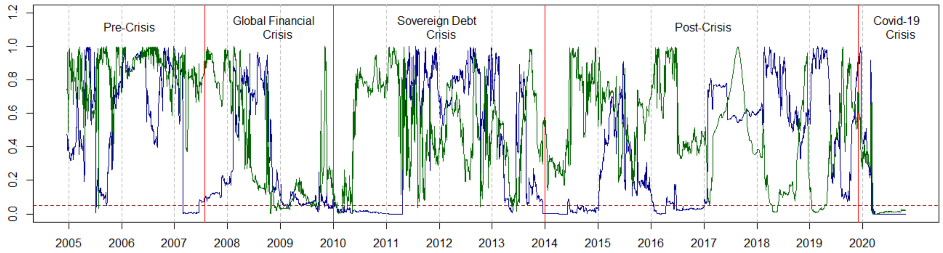


Panel A.4. GJR GARCH model

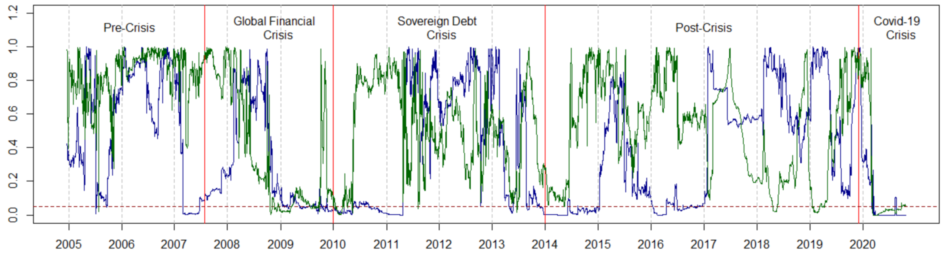
Figure 4. *Cont.*

Panel B: Europe

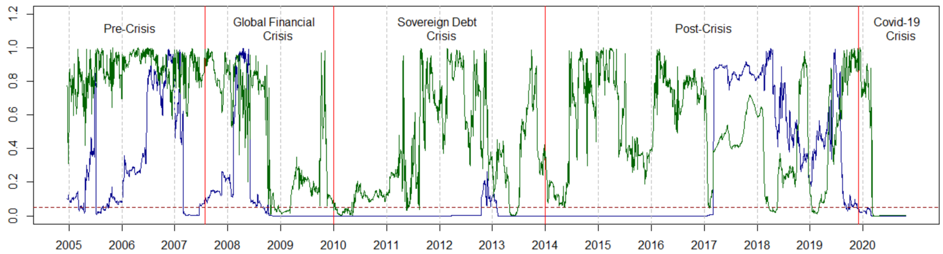
Panel B.1: EWMA model



Panel B.2: GARCH model



Panel B.3: EGARCH model



Panel B.4: GJR GARCH model

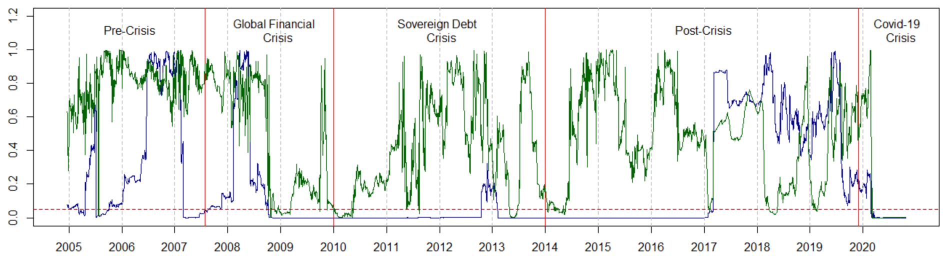
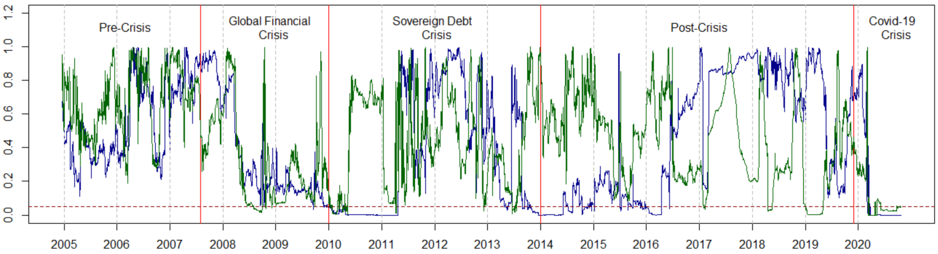


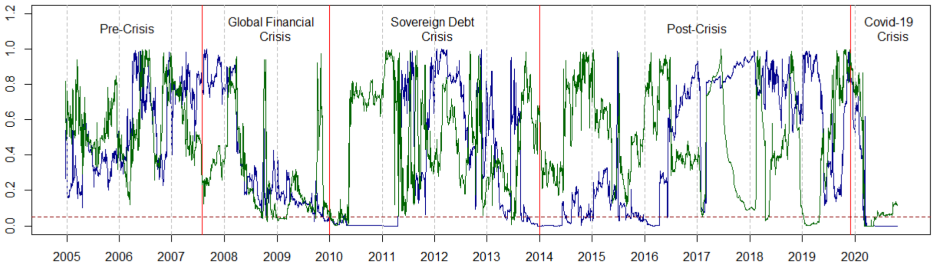
Figure 4. *Cont.*

Panel C: Eurozone

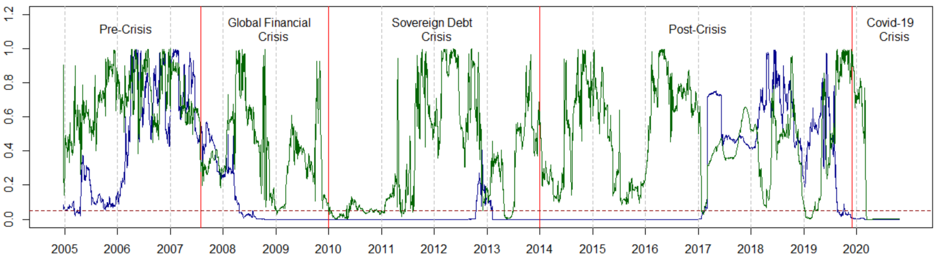
Panel C.1: EWMA model



Panel C.2: GARCH model



Panel C.3: EGARCH model



Panel C.4: GJR GARCH model

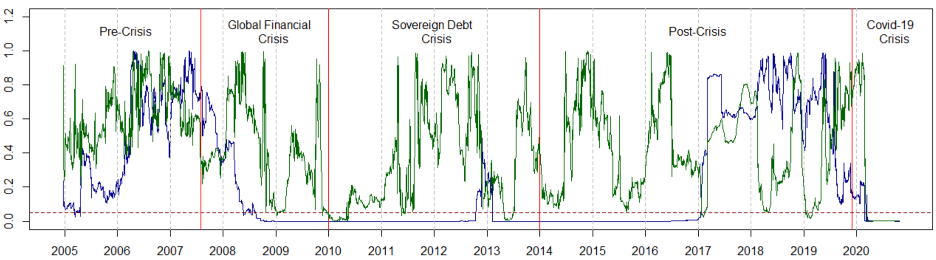
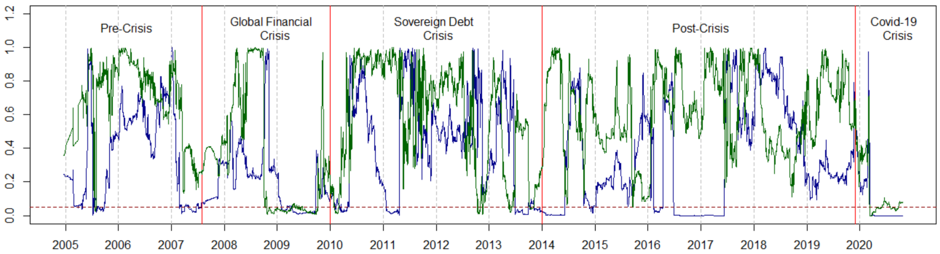


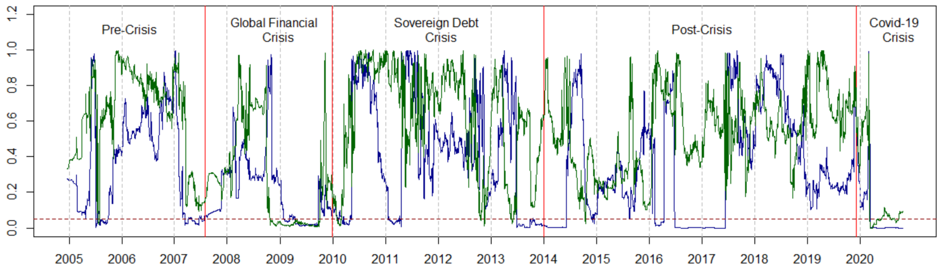
Figure 4. *Cont.*

Panel D: Non-Eurozone

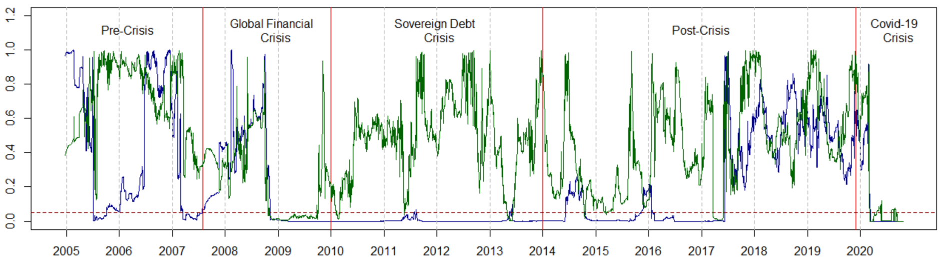
Panel D.1: EWMA model



Panel D.2: GARCH model



Panel D.3: EGARCH model



Panel D.4: GJR GARCH model

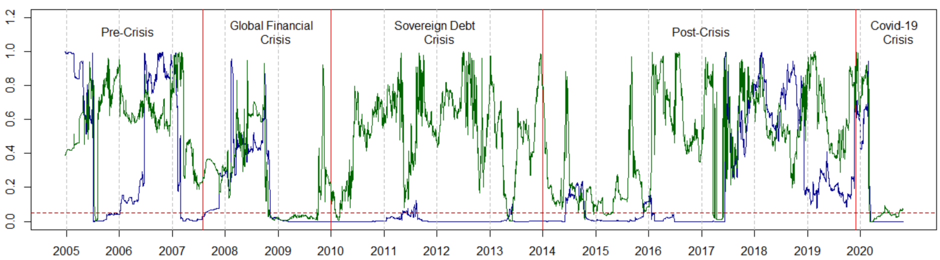


Figure 4. Rolling vector autoregressive (VAR) model estimation results. The figure shows the *p*-values of the rolling test statistic testing the null hypothesis that CDS returns do not Granger-cause index return volatilities (blue line) and the null hypothesis that index return volatilities do not Granger-cause CDS returns (green line). Panels A, B, C, and D show the test for the US, Europe, Eurozone, and Non-Eurozone. The sample period is from 6 January 2004 to 22 October 2020 for Europe and from 11 December 2007 to 22 October 2020 for the US. The significance level indicated on the graphs is equal to 0.05 (dashed red line). The vertical lines mark the beginning of the different sub-periods: pre-crisis, global financial crisis, sovereign debt crisis, post-crisis, and COVID-19 periods.

Table 3. Granger causality test results for sovereign CDS returns and the conditional volatility of stock indices returns [3].

Zone	Complete Sample Period (2004–2020)			Pre-Financial Crisis (2004–2007)			Global Financial Crisis (2007–2009)			Sovereign Debt Crisis (2010–2013)			Post-Financial Crisis (2014–2019)			COVID Crisis (2019–2020)		
	→	←	↔	→	←	↔	→	←	↔	→	←	↔	→	←	↔	→	←	↔
EWMA model																		
US	7.72%	1.16%	5.53%	-	-	-	0.00%	3.47%	0.00%	22.05%	1.63%	1.34%	0.52%	0.26%	0.00%	0.85%	2.14%	67.52%
Europe	21.92%	4.33%	5.37%	12.59%	0.15%	0.00%	5.50%	11.77%	3.21%	31.35%	0.48%	3.64%	29.55%	6.09%	0.00%	1.71%	0.85%	69.66%
Eurozone	16.60%	4.67%	4.48%	0.00%	0.00%	0.00%	1.99%	7.03%	0.00%	33.75%	2.59%	5.08%	18.66%	7.52%	0.00%	14.10%	1.71%	56.41%
Non-Eurozone	20.11%	4.21%	5.64%	14.87%	1.06%	0.00%	5.50%	14.68%	19.72%	20.13%	6.71%	0.58%	27.35%	0.00%	0.00%	27.78%	0.43%	41.88%
GARCH model																		
US	8.20%	1.32%	5.08%	-	-	-	0.00%	1.39%	0.00%	22.05%	2.30%	0.86%	1.36%	0.26%	0.00%	1.71%	3.85%	63.68%
Europe	22.24%	4.14%	4.86%	12.75%	0.15%	0.00%	15.14%	13.30%	4.28%	28.09%	0.29%	3.93%	27.03%	4.47%	0.00%	11.11%	4.70%	56.41%
Eurozone	18.78%	4.14%	2.88%	0.00%	0.00%	0.00%	5.20%	9.02%	0.00%	33.94%	1.63%	5.66%	18.28%	5.96%	0.00%	45.30%	1.28%	25.64%
Non-Eurozone	20.37%	3.66%	5.62%	15.78%	1.06%	0.00%	2.14%	16.36%	21.56%	22.15%	3.07%	0.38%	27.03%	0.26%	0.00%	32.48%	0.43%	37.18%
EGARCH model																		
US	13.80%	0.84%	6.92%	-	-	-	19.10%	6.60%	18.06%	31.16%	0.00%	0.77%	3.11%	0.00%	0.00%	0.43%	2.99%	66.24%
Europe	51.87%	1.77%	9.37%	22.76%	0.00%	0.00%	41.44%	0.00%	11.93%	79.39%	0.00%	13.33%	53.70%	4.73%	0.07%	28.63%	0.00%	70.51%
Eurozone	47.25%	1.09%	9.63%	5.01%	0.00%	0.00%	66.36%	0.00%	1.22%	70.08%	0.00%	20.26%	47.52%	2.92%	0.85%	29.49%	0.00%	70.51%
Non-Eurozone	46.94%	0.36%	11.04%	21.55%	0.00%	0.00%	12.69%	0.46%	36.09%	94.82%	0.77%	4.03%	44.46%	0.06%	3.95%	17.09%	1.30%	50.85%
GJR-GARCH model																		
US	14.70%	0.77%	7.24%	-	-	-	24.31%	6.25%	16.32%	31.54%	0.00%	2.11%	3.69%	0.00%	0.00%	0.43%	2.56%	66.67%
Europe	49.80%	1.16%	10.60%	27.77%	0.00%	0.61%	42.66%	0.00%	12.23%	79.10%	0.00%	13.14%	49.74%	3.11%	2.98%	1.71%	0.00%	72.22%
Eurozone	46.76%	1.11%	8.19%	1.37%	0.00%	0.00%	56.57%	0.00%	1.99%	77.66%	0.00%	14.57%	47.76%	2.92%	0.00%	3.42%	0.43%	70.09%
Non-Eurozone	47.88%	0.46%	11.98%	30.80%	0.00%	2.28%	15.44%	0.61%	36.24%	91.08%	1.05%	3.93%	43.81%	0.06%	5.70%	20.94%	1.28%	48.72%

[3] This table shows the Granger causality test results by sub-period for sovereign CDS returns and the conditional volatility of stock indices during the period from 6 January 2004 to 22 October 2020 for Europe and from 11 December 2007 to 22 October 2020 for the US. For each region, we show the number of times (in percentage) that the null hypothesis of Granger causality is rejected. → indicates a unidirectional relationship and that the CDS returns cause the volatility. ← indicates a unidirectional relationship and that the volatility causes the CDS returns. ↔ indicates that both the CDS returns and the volatility cause each other, reciprocally, in a given estimation window.

Overall, it is evident that, to a greater extent, sovereign CDS spread returns cause a Granger-like volatility of stock index returns. This finding is in line with the studies in [14] and [11] for US corporate and European and US sovereign data, respectively. Moreover, this causality is intensified if the conditional volatility of stock returns has been obtained by employing the asymmetric EGARCH or GJR GARCH models, and it is more notable in Europe. For example, it is observed that, for the full sample, CDSs anticipate volatility by about 8% (22%) for US (Europe) with the EWMA and GARCH models, while for EGARCH and GJR GARCH, they do so by 14% (50%). This result is not surprising, given that it was already observed preliminarily that higher correlations were obtained with these models. These differences are not so evident during the COVID crisis period, where at the peak of the pandemic, similar correlations are seen for all four models. This is a significant finding of this study, since we observe that the way the conditional volatility of index returns is modeled directly affects the results on market anticipation. Models that do not account for the asymmetry of the volatility response capture lower causal relationships. In view of this finding, and given that the general relationships hold when estimating conditional volatility with any of the models analyzed, the results discussed will be those of the EGARCH and GJR GARCH models.

In the specific case of the US, we observe a unidirectional causal relationship between sovereign CDS spreads and SPX index volatility of around 20% during the global financial crisis period and 30% during the sovereign debt crisis. However, in the COVID-19 crisis period, there is a bidirectionality relationship of around 67%, which is the highest in the whole sample for the US. In the case of Europe, sovereign CDS returns cause a conditional volatility of STOXX index returns of around 42% in the period of the global financial crisis, 79% in the sovereign debt crisis, and 50% in the post-crisis period. These high percentages mean that European CDSs anticipate stock volatility information for about 50% of the full sample. On the other hand, it is worth noting that for the COVID-19 crisis, there is a bidirectionality ratio of over 70%, which is the highest in this crisis for the four regions analyzed.

Examining the results within Europe and distinguishing between the eurozone and non-eurozone countries, it can be seen how the unidirectional causality relationship of sovereign CDS to the conditional volatility of the Euro-STOXX and Non-Euro-STOXX indices, respectively, predominates. In terms of the full sample, it could be said that both currency zones follow the results obtained for Europe, with a result of around 47% for the CDS market anticipation of stock index volatility. The analysis of the sub-periods reveals more particular results in terms of market anticipation in both zones. The eurozone exhibits an evident unidirectional relationship in the period of the global financial crisis of between 57% and 66% (depending on the model), while during the sovereign debt crisis, both zones show high levels of causality in the same direction, this being more notable in the case of the non-eurozone (between 70% and 77%, compared to 91% to 94%, respectively). It is worth noting that, as was the case for Europe, this relationship is still maintained during the post-crisis period, with the eurozone showing similar levels of causality to those in the period of the global financial crisis. The bidirectionality between CDSs and volatility observed in the COVID-19 period is maintained for both currency zones, with a greater impact in the eurozone (70%, compared to 50%).

The conclusion can be drawn that US and European sovereign CDS spreads anticipate the volatility of their respective stock market indices. Europe has a much higher level of CDS spread leadership than the US (50%, compared to 13% for the full sample). Analyzing the results for the different sub-periods, it can be seen that regardless of the model and for Europe in the pre-crisis period, the causal relationships are lower than those obtained for the other sub-periods. The greatest anticipation of the CDS market on volatility occurs during the sovereign debt crisis in Europe (with a larger impact in the non-eurozone) and, to a lesser extent, in the US, where for this period and the period of the global financial crisis, very similar causality percentages are obtained. It is worth noting that, similarly to the findings in [14] with respect to US corporate data, this unidirectionality between CDSs and stock volatility for the US takes place during the post-Lehman crisis period.

Another interesting result is obtained for the post-crisis period, where Europe shows causality percentages that are relatively high for a period theoretically defined as stable. While the causality is very low for the US, the CDS anticipation of volatility for Europe reaches quite significant levels (similar to those found for the global financial crisis). In this period, there are still countries in Europe with high levels of credit risk during 2014 and early 2015, as noted in [11]. It is worth noting the virtual absence of bidirectional relationships between CDSs and index volatility until the COVID-19 crisis. While the trend of the results was a unidirectional relationship, in this last subperiod, we observe that bidirectional relationships do exist. It should be mentioned that this relationship is the one found in [16,17] at the general level between corporate CDSs and stock volatility; however, we note that these authors include in their analyses the volatility of CDSs and not their returns. In our study, these two-way relationships are of great magnitude. In the case of the US, this represents the highest percentage of causality in the entire sample, while for Europe, it is only slightly lower than that obtained in the sovereign debt crisis. It seems that the presence of a health crisis spills over in terms of causality differently from what was observed in previous financial crises. The high values reached for this relationship may be due to the great uncertainty existing in the economies of all countries, as a result of the management and progression of the pandemic.

To test the robustness of our results, we follow the studies in [34] and [12] and select three exogenous variables to be included in the dynamic VAR analysis to control for possible influences. In particular, we include the changes in the T-bill rate, the changes in the slope of the term structure, and the changes in the implied volatility of the equity market. Note that this additional analysis is carried out only for the US and Europe, since given the characteristics of the control variables, the analysis is not feasible for the European sub-currency zones. For the US model, we include the changes in the 10-year Benchmark Treasury rates. The second variable is the changes in the slope of the term structure of interest rates, calculated as the difference between the 10-year and 2-year Benchmark Treasury rates. This variable captures the expectations of future short rates and is an indicator of overall economic health. For the case of Europe, analog variables are utilized, but using the interest rate of German bonds. The third control variable considered in the US analysis is the changes in the implied volatility of the Chicago Board Options Exchange (CBOE) volatility index (VIX). This index is a very popular measure for capturing market expectations in terms of volatility and is considered a barometer of investor sentiment and market volatility [12]. For the analysis of Europe, we consider the STOXX 50 Volatility VSTOXX EUR (V2TX index), which is the analogous index to the VIX for Europe, since it measures the implied volatility of near-term STOXX Europe Total Market index options that are traded on the Eurex exchange. Both volatility indices reflect the financial uncertainty in the US and the European stock markets, so that a higher value of these indices would be accompanied by higher sovereign CDS spreads.

The results indicate that for both the US and Europe, the earlier causality relationships still hold for the dynamic VAR model with exogenous variables. Only in the case of Europe and for the COVID-19 period are differences observed. The particular bidirectionality previously obtained for this period is no longer relevant when the exogenous variables are included in the analysis. By contrast, the results are in line with the rest of the periods, that is, that CDS returns also cause the volatility of equity markets during the COVID-19 period. It seems clear that the inclusion of exogenous variables is decisive during the COVID-19 period, at least in the case of Europe. When analyzing the results of the VAR estimation, we observe that this is the only period in which the three control variables considered come out significant with a high percentage of rolling windows in the volatility equation. Consequently, the causal relationships are better captured in this period, a fact that also highlights the particularities of the health crisis, compared to previous periods. It should be noted that it is also during this entire COVID-19 period that Europe has negative interest rates, which may be affecting the causality results.

6. Conclusions

The recent financial crises have intensified the interest in analyzing in depth the risk transmission channels between markets. High levels of credit risk and international financial integration have led to contrasting cross-market contagion. In this regard, this study analyzes the Granger causality between the CDS market and stock market volatility. The lack of adequate literature is evident, and the results of the few existing references are ambiguous. Specifically, we analyze the existence of dynamic relationships between sovereign CDS spread returns and stock index volatility for the US and Europe during the period 2004–2020. The conditional volatility of the stock market is estimated with four models from the GARCH family, two of which are asymmetric, which allows us to capture a larger effect on volatility in the presence of negative shocks. To analyze the transmission relationships between markets, a dynamic VAR model with moving windows was used, which enabled us to see the progression of this market anticipation over time.

The results show how US and European sovereign CDS spreads anticipate the volatility of their respective stock market indices, with a greater leadership impact in Europe. Moreover, this causality is intensified if the volatility of index returns is obtained using the asymmetric model. We can conclude that the way conditional volatility is modeled directly affects the results of lead–lag relationships. The greatest anticipation of the CDS market on volatility in both zones occurs during the sovereign debt crisis in Europe and, to a lesser extent, in the US. Analyzing the European currency zones, we find that while there are only high causal relationships for the eurozone during the global financial crisis, it is during the sovereign debt crisis that the greatest impact on the non-eurozone is observed. In addition, for Europe, a significant number of relationships are observed during the post-crisis period, which demonstrates that credit risk levels were still elevated in Europe. During the COVID-19 period, a change in the trend of the causality relationship is observed, with the emergence of a bidirectional relationship between CDS returns and conditional volatility, with the highest percentages observed in the whole sample. It seems that this new crisis has altered the existing dynamics of causality between the two markets.

This study yields important and novel results in the field of information transmission between the CDS and equity markets. Understanding the impact and directionality of the contagion mechanisms is crucial for identifying future crises and can help market policymakers to limit the financial instability inherent in financial crises. In this regard, it would be interesting to analyze cross-border transmission relationships in order to deepen our understanding of cross-market relationships.

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