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Financial Contagion from the Subprime Crisis: A Copula Approach

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Abstract

The magnitude of the subprime crisis effects caused recessions in several economies, giving rise to the global financial crisis. The scale of this major shock and the different recovery profiles of European economies motivated this paper. The main objective is to look for evidence of contagion between the North American financial market (S&P500) and the financial markets of Portugal (PSI20), Spain (IBEX35), Greece (ATHEX) and Italy (FTSEMIB), in the South of Europe, and the financial markets of Sweden (OMXS30), Denmark (OMX2C0), Finland (OMXH25) and Norway (OsloOBX), in the North of Europe. Considering the period from January 1, 2003 to December 31, 2013, the ARMA-GARCH models were estimated to remove the autoregressive and conditional heteroscedastic effects from the time series of the daily returns. Then, the copula models were used to estimate the dependence relationships between the European stock indexes and the North American stock index, from the pre-crisis subperiod to the crisis subperiod. The results indicate financial contagion of the subprime crisis for all analyzed European countries. The North European markets intensified the relations of financial integration (both in negative and positive shocks) with the North American market, apart from the Danish against the Portuguese. In addition to the contribution made by the joint application of the ARMA-GARCH models, the findings are useful to identify channels of financial contagion between markets and to warn about the effects of possible new crisis, which will require different levels of adaptation by the companies' financial managers and intervention by the authorities.

Keywords: financial contagion; financial markets; subprime crisis; Copulas; ARMA-GARCH.

JEL classification: G01; G15; C13.

1. INTRODUCTION

The subprime crisis started in 2007 in the North American real estate market, having spread to the financial market and generated serious difficulties in several institutions. This crisis was motivated by the unbridled granting of real estate credit and by the failures in the regulation of the financial system that allowed the transfer of the mortgage credit in series,

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and consequently, of the risk to other counterparties. Therefore, the magnitude and speed with which the effects spread caused recessions in several economies, originating the global financial crisis.

The effects of the subprime crisis quickly reached the European continent, though with different intensities. In general, Southern European countries faced severe economic recessions from which they have not yet fully recovered, while Northern European countries, which represent small economies, showed a better capacity to face and recover from the financial crisis.

Given the strong worldwide spread, the subprime crisis has been a protagonist in studies of the financial contagion effect in several countries (Horta *et al.*, 2010; Zorgati *et al.*, 2019). However, divergences continue to be found among the international empirical evidence, justifying additional approaches. Furthermore, the concept of financial contagion is not unanimous along the literature. This paper uses the approach of Forbes and Rigobon (2002), who define financial contagion as a significant increase in the correlation between markets after a shock occurs.

The purpose of this work is to look for evidence of financial contagion from the subprime crisis over Southern and Northern European countries. More specifically, it is intended to study whether this crisis has resulted in a significant increase in the correlation, or in the dependence relationships, between the North American financial market (S&P500) and the financial markets of Portugal (PSI20), Spain (IBEX35), Greece (ATHEX) and Italy (FTSEMIB), in Southern Europe, and the financial markets of Sweden (OMXS30), Denmark (OMXC20), Finland (OMXH25) and Norway (OsloOBX), in Northern Europe. Subsequently, a global period of eleven years was considered, from January 1, 2003 to December 31, 2013. On one hand, the scale and time proximity of the subprime crisis, and on the other hand, the different recovery profiles of European countries, justify the motivation of this manuscript. The results of the study are useful because they contribute to assess the form and intensity with which severe events can spread among economies, according to their size, or whether they are more or less prepared to counter them. The research findings are also timely given the concerns of political leaders with the consequences of the long Covid-19 pandemic and the Russia-Ukraine crisis, still in progress.

The procedure to analyze the financial contagion effect of the crisis on the sample of European markets uses the ARMA-GARCH model and the copula models. The joint estimation of the AutoRegressive Moving Average (ARMA) model and the Generalized AutoRegressive Conditional Heteroscedasticity (GARCH) model allows this study to obtain series of filtered returns removed from autoregressive and conditional heteroscedasticity effects, providing greater reliability to the results. This step constitutes an important contribution of this paper. The copula models have been used to estimate the dependence relationships between the series of the financial indexes (Costinot *et al.*, 2000; Embrechts *et al.*, 2003; Hu, 2006; Horta *et al.*, 2010; Zorgati *et al.*, 2019).

This study is organized into five sections, starting with this introduction. Then, a literature review is developed, where the subprime crisis is contextualized, the financial contagion effect is defined and empirical evidence is presented. The 3rd Section details the methodology, sample data and procedures of the empirical study. In the 4th Section, the estimation results are presented and discussed. The last section summarizes the conclusions.

2. LITERATURE REVIEW

2.1 The North American Subprime Crisis

The subprime crisis began in August 2007 in the United States and it was known for triggering the global financial crisis, considered one of the most serious crisis since the Great Depression (Brunnermeier, 2009). During the pre-crisis period, the US economy was going through a stability phase with low long-term interest rates (Mizen, 2008). Nevertheless, the excess of global savings based on low interest rates from emerging industrialized economies and the development of financial products, such as mortgage-backed securities (MBS), with greater complexity, higher leverage and weaker underlying assets based on subprime mortgages gave rise to the beginning of the crisis (Mizen, 2008).

The traditional banking model, in which banks held loans until they were repaid, was replaced by the "originate and distribute" model, in which loans are resold by securitization (Brunnermeier, 2009). Meanwhile, the unexpected fall in prices in the real estate market, where some mortgages exceeded the value of the house itself, caused an increase in the default of these mortgages (Levitin *et al.*, 2009). Simultaneously, investors who held MBS began to reassess the risks associated with these financial assets (Mizen, 2008).

In addition to the problems in the American real estate market, the ratings given by the rating agencies also contributed to the collapse of the financial system. The structured products market evolved as an agency "rated" market, in which several types of risks were regrouped in order to create multiple "AAA"-rated securities with competitive yields. However, some agencies based their risk models on unrealistic assumptions, ignoring the possibility of falling prices in the real estate market (Coval *et al.*, 2009).

As the market crashed, banks suffered heavy losses and the ratings of several structured products were downgraded. Uncertainty about the value of structured products and the potential associated losses induced banks to restrict credit lines and accumulate funds (Brunnermeier, 2009; Acharya & Merrouche, 2013).

2.2 The Financial Crisis in the European Countries of the Sample

The effects of the subprime crisis were quickly felt in European markets, given the strong involvement of institutions in American MBS financial products (McCauley, 2018; Hardie & Thompson, 2021). For example, McCauley (2018, p. 40) states that "*European banks not only bought risky US mortgage bonds but also manned the production line through their US securities subsidiaries, which were active in packaging and selling such bonds*".

Southern Europe

The shocks felt in the financial sector severely affected the dynamics of sovereign spreads in the euro area, especially in countries with high public debt-to-GDP ratios (Mody & Sandri, 2011). In 2007, the public debt of Greece and Italy was high (Acharya *et al.*, 2012). Although Portugal and Spain had lower ratios, there was a tendency for growth in the Portuguese case (Lane, 2012). According to Zamora-Kapoor and Coller (2014), these southern European countries suffered, simultaneously, an economic crisis and a political crisis that should not be considered separately. The impact of adversities, such as domestic recession, instability in the banking sector, lack of liquidity and risk aversion from international investors, created the conditions for a sovereign debt crisis (Lane, 2012). As of 2009, the governments of these countries had to resort to financial aid in exchange of austerity policies with consequences in terms of the reduction of the State role in the economy, the reduction of economic activity and the rise of unemployment. According to Zamora-Kapoor and Coller (2014, p. 1511) *"the South of Europe, in particular, is one of the regions in the world where the consequences of the crisis have become most salient"*.

Northern Europe

Finland, Sweden, Iceland, Denmark and Norway are considered countries with small export-dependent economies and are therefore more vulnerable to external fluctuations (Gylfason *et al.*, 2010). Consequently, it would be expected that these countries would be severely affected by international crisis. However, the Nordic countries (specifically Finland, Sweden and Norway) had the experience of having faced, in the early 1990s, one of the biggest crisis in developed economies (Gylfason *et al.*, 2010; Honkapohja, 2012). According to Berglund and Mäkinen (2019), banks of these three countries were less exposed to the instability caused by the global financial crisis, performing better than other European banks.

The impact of the recession that hit Europe and the measures to counter it were different among the Nordic countries, mainly because, with the exception of Finland, they do not belong to the eurozone, having independent currencies and central banks (Østrup *et al.*, 2009).

2.3 The Financial Contagion Effect

The literature suggests that the subprime crisis quickly spread at the global level, becoming the global financial crisis and severely affecting a variety of countries through the phenomenon of financial contagion. According to Constâncio (2012, p. 109) "c*ontagion is one of the mechanisms by which financial instability becomes so widespread that a crisis reaches systemic dimensions*". Despite being frequently studied, the effect still does not have a consensual definition in the scientific literature.

King and Wadhwani (1990) define financial contagion as a significant increase in the correlation coefficients of international financial markets. However, this approach based on linear correlation coefficients can induce incorrect dependence measures, due to heteroscedastic financial returns and to the simultaneous nature of financial interactions (Forbes & Rigobon, 2002; Horta *et al.*, 2010).

Eichengreen *et al.* (1996) define the effect as the increase in the probability of a crisis occurring in one correlated country with the incidence of a crisis in another country, after the effects of political and economic fundamentals being controlled.

Forbes and Rigobon (2002, p. 2223) define contagion as *"a significant increase in cross-market linkages after a shock to one country (or group of countries)"*. This means that the maintenance of correlation levels between two markets, after a shock, suggests the evidence of interdependence between the economies, but not of financial contagion. In this paper, this perspective will be adopted. In addition to being usual in recent literature, it has empirical advantages: it simplifies the way of testing evidence of contagion, avoids the difficulties in identifying transmission mechanisms and distinguishing between them (Horta *et al.*, 2010).

Pericoli and Sbracia (2003) suggest the existence of financial contagion when: (i) the probability of a crisis occurring in one country increases due to the existence of a crisis in another country; (ii) the asset price volatility extends from the country in crisis to the other countries; (iii) the correlation of asset prices is not driven in a reasoned manner; (iv) increases the correlation of financial assets between countries; (v) the transmission mechanism between countries changes due to a crisis in one of the countries, implying changes in the correlations of asset prices in these countries.

2.3.1 Empirical Evidence of Financial Contagion

Forbes and Rigobon (2002) tested the evidence of financial contagion with the 1997 Asian crisis, the 1994 Mexican crisis and the 1987 crash in the U.S. stock market. Using heteroscedasticity biased tests based on correlation coefficients, the authors only detected interdependence in all analyzed situations.

Trying to control for three levels of bias (heteroscedasticity, endogeneity, and omitted variables), Caporale *et al.* (2005) performed a conditional correlation analysis, finding financial contagion in East Asian during the 1997 crisis.

Rodriguez (2007) analyzed the daily returns of five East Asian financial indexes during the Asian crisis and four Latin American indexes during the Mexican crisis. Applying the Markow Switching model to study dependence structures through copulas, the results suggest financial contagion effects in the periods of crisis. Horta *et al.* (2010) also resorted to copula models to investigate the effects of contagion from the subprime crisis on the financial markets of the NYSE Euronext group, which included the French, Dutch, Belgian and Portuguese indexes. The results support the existence of contagion with the same intensity in most of those financial markets.

W. S. Kao *et al.* (2018) adopted the method proposed by Forbes and Rigobon (2002) to test the contagion effect in 31 financial markets (East Asian, Emerging, Western and Latin American) during the subprime crisis. The results show evidence of financial contagion in East Asian and Emerging markets. Later, Y. S. Kao *et al.* (2019) used the Engle and Granger (1987) symmetric cointegration test between the American S&P500 index and 23 stock indexes from Asia, Europe and America, but did not detect evidence of contagion. Since the traditional procedure of this test does not consider the asymmetry characteristics of financial markets, the authors also applied the Momentum Threshold AutoRegression model and the Logistic Smooth Transition Regression. The study found contagion effects across markets, except for China, especially after the bankruptcy of Lehman Brothers in 2008.

Zorgati *et al.* (2019) used the copula method to study the financial contagion of the subprime crisis in five American countries (Brazil, Argentina, Mexico, Canada and the USA) and in nine Asian countries (Japan, Hong Kong, India, Australia, Indonesia, Malaysia, Korea, China and Singapore). The authors found contagion effects in countries on the American continent, as well as in Australia, Indonesia, Malaysia, China and Singapore.

More recently, Ayadi and Said (2020) compared the effects of subprime crisis on the developed markets of France, Germany, U.K. and Japan. Using the vector error correction model and Johansen's cointegration approach, the authors found that all the markets are cointegrated in the long run and there is long run equilibrium.

Zorgati and Lakhal (2020) investigated the influence of the spatial dimension on financial contagion in the subprime crisis based on adjusted and local correlation measures. The first sample group includes the U.S and countries that are geographically close: Brazil, Argentina, Mexico, and Canada; the second group includes countries that are geographically distant: Hong Kong, India, Australia, Indonesia, Malaysia, South Korea, China, and

Singapore. Using local correlations and polynomial regressions, the authors found spatial contagion between the U.S. and all countries in the American region, but only between the U.S. and some distant countries (India, Australia, Indonesia, Malaysia and China).

3. METHODOLOGICAL PROCEDURES

3.1 ARCH Effect and ARMA-GARCH Model

Time series of financial data often exhibit a “volatility clustering” behavior characterized by periods of low/high volatility, meaning the presence of autoregressive and conditional heteroscedasticity effects. In this context, Engle (1982) proposed the AutoRegressive Conditional Heteroscedasticity (ARCH) model, which models the squared variation of volatility as a moving average of past observations of the time series.

Before estimating the heteroscedastic models, it is important to confirm the presence of those effects through the Ljung and Box (1978), under the null hypothesis of no autocorrelation in the time series, and the Engle test (1982), under the null of no ARCH effect.

To circumvent the limitations of the ARCH model, Bollerslev (1986) proposed the GARCH model as an extension, allowing the use of fewer parameters and greater stability in the estimation. The GARCH (p, q) model considers the conditional variance of the error process:

$$\sigma_t^2 = w + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2 \tag{1}$$

where $w > 0$, $\alpha_i \geq 0$ $(i = 1, \cdots, p)$ and $\beta_j \geq 0$ $(j = 1, \cdots, q)$. When $q = 0$ the model reduces to an ARCH model of order p.

This paper uses an extension of the GARCH model, the ARMA-GARCH model resulting from the combination with the ARMA model, which makes possible the modeling of a linear time series with the GARCH model, allowing the non-linearity of the series residuals to be modeled.

The ARMA (m, n) model consists of a combination of m autocorrelation terms, which are lags of the time series y_t, with n moving average terms, which are lags of errors ε_t:

$$y_t = \mu + \sum_{i=1}^{m} \phi_i y_{t-i} + \sum_{j=1}^{n} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{2}$$

where μ is a constant term, ϕ_i are the parameters of the autoregressive terms, θ_j are the parameters of the moving average terms, m and n are non-negative integers values (the orders of the model) with $E(\varepsilon_t) = 0$ and $V(\varepsilon_t) = \sigma^2$.

In order to correct autoregressive and conditional heteroscedasticity effects associated with the volatility of financial time series, we use the ARMA-GARCH model as follows:

i) the conditional mean equation follows the ARMA (m, n) model expressed as in Equation (2);

ii) the conditional variance equation follows the GARCH (p, q) model expressed as in Equation (1).

After estimating the ARMA-GARCH candidate models, the selection of the most appropriated structure can be made through the minimum value obtained by the Akaike Information Criterion (AIC):

$$\mathrm{AIC} = 2k - 2\ln(L) \tag{3}$$

where L is the value of the likelihood function obtained through the parameters estimation and k is the number of estimated parameters.

3.2 Copula Models

The copula method has been pointed out as the most suitable for studying the phenomenon of contagion or financial dependence (Costinot *et al.*, 2000; Embrechts *et al.*, 2003; Hu, 2006; Horta *et al.*, 2010), since *"copulas provide a natural way to study and measure dependence between random variables"* (Embrechts *et al.*, 2003, p. 9). A copula can be defined as a multivariate distribution function on $[0\,,1]^n$ with uniform marginal distributions (Embrechts *et al.*, 2003; Boubaker & Salma, 2011). These models allow connecting the marginal distributions of two variables in order to obtain their joint distribution, being an ideal tool to study the level and structure of financial contagion (Hu, 2006). Let X and Y be random variables with a copula C. For Y to be a function of X, C needs to be between the two Fréchet-Hoeffding bounds:

$$W(u\,,v) = \max(0, u+v-1) \;\text{ and }\; M(u\,,v) = \min(u,v),\;\; (u\,,v) \in [0,1]. \tag{4}$$

Thus, a copula C represents a model of the dependence structure between X and Y that lies between these two limits:

$$W(u\,,v) \leq C(u\,,v) \leq M(u\,,v) \tag{5}$$

The tail dependence coefficients λ_u and λ_l allow measuring the probability of a variable to reach an extreme value when the other variable has already reached it. For instance, can be used to evaluate the probability of a market crash, assessing the lower asymptotic tail λ_l, or of a market boom, assessing the upper asymptotic tail λ_u (Horta *et al.*, 2010). The tail dependence coefficients can be defined as a function of a copula C as follows:

$$\lambda_u = \lim_{u \to 1} \frac{1 - 2u + C(u\,,u)}{1-u}, \;\; \lambda_l = \lim_{u \to 0} \frac{C(u\,,u)}{u} \tag{6}$$

The **Gaussian copula** is given by:

$$C(u_1\,,u_2\,;\,\rho) = \Phi_2(\Phi^{-1}(u_1), \Phi^{-1}(u_2)\,;\,\rho) \tag{7}$$

where Φ^{-1} represents the inverse of the distribution function $N(0\,,1)$ and Φ_2 represents the bivariate normal distribution function with mean 0, variance 1 and correlation coefficient ρ (Czado, 2019).

The **t-Student copula** is given by:

$$C_{v,R}^{t}(u) = t_{v,R}^{n}(t_{v}^{-1}(u_1), \cdots, t_{v}^{-1}(u_n)) \quad (8)$$

where $t_{v,R}^{n}$ represents the multivariate distribution t_{v}-Student, t_{v}^{-1} represents the inverse of the t-Student distribution with v degrees of freedom and $R_{ij} = \Sigma_{ij}/\sqrt{\Sigma_{ii}\Sigma_{ij}}$.

The **Clayton copula** is given by:

$$C_{\theta}(u\,,v) = \max(\left[u^{-\theta} + v^{-\theta} - 1\right]^{-1/\theta}, 0) \quad (9)$$

where $\varphi(t) = (t^{-\theta} - 1)\,/\theta$ and $\theta \in [-1\,,\infty) \setminus \{0\}$.

The **Gumbel Copula** given by:

$$C_{\theta}(u\,,v) = \varphi^{-1}\big(\varphi(u) + \varphi(v)\big) = \exp(-\left[(-\ln u)^{\theta} + (-\ln v)^{\theta}\right]^{1/\theta}) \quad (10)$$

The **Frank Copula** is given by:

$$C_{\theta}(u, v) = -\frac{1}{\theta}\ln(1 + \frac{\left(e^{-\theta u} - 1\right)\left(e^{-\theta v} - 1\right)}{e^{-\theta} - 1}) \quad (11)$$

where $\varphi(t) = -\ln\frac{e^{-\theta t} - 1}{e^{-\theta} - 1}$ and $\theta \in \mathbb{R} \setminus \{0\}$.

The **Survival Gumbel copula** is given by:

$$\bar{C}_{\alpha}(u\,,v) = u + v - 1 + \exp\left\{-((-\log(1-u))^{\alpha} + (-\log(1-v))^{\alpha})^{\frac{1}{\alpha}}\right\} \quad \text{with } \alpha \geq 1 \quad (12)$$

and the **Survival Clayton copula** is given by:

$$\bar{C}_{\alpha}(u\,,v) = u + v + ((1-u)^{-\alpha} + (1-v)^{-\alpha} - 1)^{-\frac{1}{\alpha}} \quad \text{with } \alpha > 0 \quad (13)$$

Given that the distribution functions of bivariate copula models operate in a space $[0\,,1]^2$ it is important to transform the series of filtered returns into uniform margins. If $\hat{u}_{i,j}$ are the uniform margins of the filtered return series, then it is possible to obtain them through the empirical distribution function $\hat{F}_{j,n}(x_{i,j})$, as follows:

$$\hat{u}_{i,j} = \hat{F}_{j,n}(x_{i,j}) \quad \text{and} \quad \hat{F}_{j,n}\left(x_{i,j}\right) = \frac{1}{n+1}\sum_{i=1}^{n} I_{[x_{ij} \leq x]} \quad (14)$$

The interdependence between the marginal distributions is estimated using a parametric family of copulas (Kim *et al.*, 2007). Considering the copula $C(u_1, u_2, \ldots u_m\,;\,\theta)$ and its respective density function $c(u_1, u_2, \ldots u_m\,;\,\theta)$, θ corresponds to the vector of parameters to be estimated by the Maximum Likelihood (ML) method, in what:

$$\hat{\theta} = arg \max_{\theta \in \Theta} \sum_{i=1}^{n} \log c(\hat{u}_{i1}, \dots, \hat{u}_{im}; \theta) \quad (15)$$

3.3 Sample, Data and Procedure

The sample consists of nine stock indexes divided into three groups: the S&P500 index quoted in the United States, where the subprime crisis originated, the Southern European indexes – PSI20 (Portugal), IBEX35 (Spain), ATHEX (Greece) and FTSEMIB (Italy) – and the Northern European indexes – OMXS30 (Sweden), OMXC20 (Denmark), OMXH25 (Finland) and OsloOBX (Norway) – where the intention is to investigate the financial contagion effect. The data consists of the returns of each index, calculated from the respective daily closing prices:

$$return_t = \frac{price_t - price_{t-1}}{price_{t-1}} \quad (16)$$

Following the proposal by Horta *et al.* (2010), this study assumed the beginning of the subprime crisis on August 1, 2007. Thus, the eleven-year time horizon is divided into the pre-crisis subperiod, from January 1, 2003 to July 31, 2007, and into the crisis subperiod, from August 1, 2007 to December 31, 2013.

The methodological procedure to investigate the financial contagion effect of the subprime crisis on Southern and Northern European countries consists of the following phases:

1) define the time series of the financial index returns and remove autoregressive and conditional heteroscedastic effects through the ARMA-GARCH models in order to obtain the filtered returns. The selection of the most appropriate model for each index is done by the AIC criterion;
2) divide each series of filtered returns into the pre-crisis subperiod and the crisis subperiod. For each subperiod, filtered returns of each stock index are transformed into uniform margins;
3) obtain the empirical values of Kendall's *tau* coefficient and estimate the copulas for the two subperiods of each index through the uniform distributions;
4) select the most appropriate model to conclude on the hypothesis of financial contagion from the subprime crisis, using the AIC criterion.

Figure no. 1 shows the daily closing prices and the respective returns for the stock indexes:

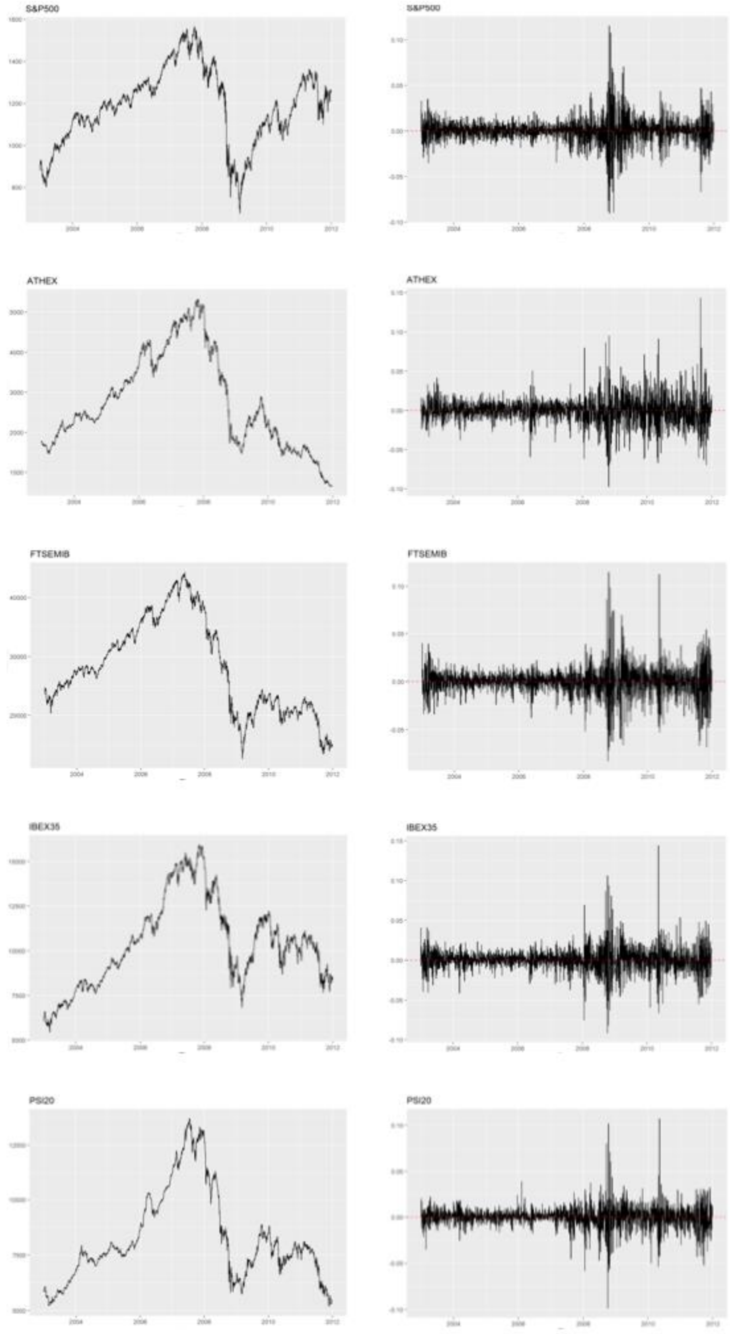

Figure no. 1A – Daily prices (to the left) and daily returns (to the right) for US and Southern European indexes

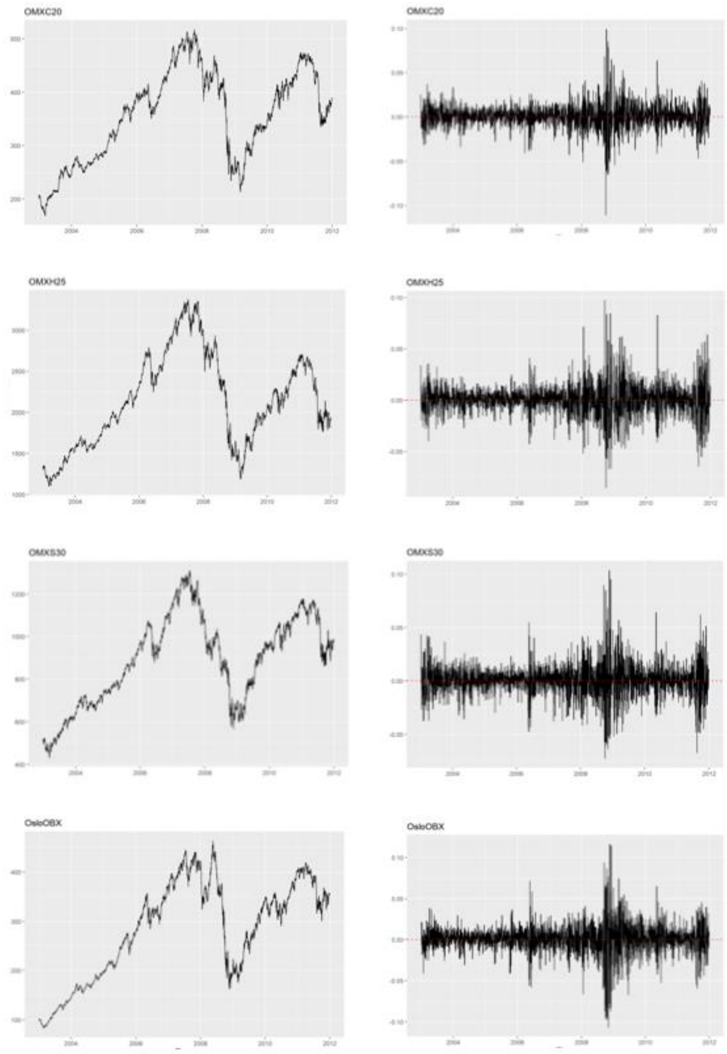

Figure no. 1B – Daily prices (to the left) and daily returns (to the right) for Northern European indexes

4. PRESENTATION AND ANALYSIS OF RESULTS

4.1 Elimination of Autoregressive Effects and Conditional Heteroscedasticity

The first step is to investigate the existence of volatility in the series of daily returns for each index. Table no. 1 shows the results of the Ljung-Box test (for lags 10, 15 and 20) and of Engle's ARCH test for the S&P500 index:

Table no. 1 – Ljung-Box test and ARCH test about the daily returns of S&P500 index

Lag	Ljung-Box test	*p-value*	ARCH test	*p-value*
10	62,644	1,141E-09	650,590	<2,2E-16
15	76,478	3,059E-10	763,440	<2,2E-16
20	100,640	9,658E-13	767,260	<2,2E-16

The *p*-value is extremely low in both tests, rejecting their null hypothesis and concluding that there are autoregressive and heteroscedastic effects in the S&P500 index. The results of these statistical tests for the European countries indexes suggest the same conclusion.

To remove such effects, ARMA-GARCH models were estimated for the series of daily returns of each stock index and the residuals, denominated as filtered returns, were obtained:

Table no. 2 – Estimation of ARMA-GARCH models for stock indexes returns

Countries	Index	Model	Persistence	AIC
US	S&P500	ARMA (5,5) – GARCH	0,9800	-6,4066
Southern Europe				
Greece	ATHEX	ARMA (5,5) – GARCH	0,9991	-5,7161
Italy	FTSEMIB	ARMA (5,4) – GARCH	0,9922	-6,1199
Spain	IBEX35	ARMA (5,4) – GARCH	0,9930	-6,0584
Portugal	PSI20	ARMA (5,4) – GARCH	0,9956	-6,6144
Northern Europe				
Denmark	OMXC20	ARMA (4,2) – GARCH	0,9857	-6,1509
Finland	OMXH25	ARMA (3,4) – GARCH	0,9916	-5,9846
Sweden	OMXS30	ARMA (5,4) – GARCH	0,9887	-5,9177
Norway	OsloOBX	ARMA (4,5) – GARCH	0,9871	-5,6986

Note: ARMA-GARCH models were estimated with autoregressive parameters *m* e *n*, between values 0 and 5, and with parameters *p* e *q*, between values 1 and 2. The choice of the most appropriate model used the AIC criterion.

The values of the persistence measure are relatively close to 1 across all financial indexes, meaning that the shock will persist in the long run (Zorgati *et al.*, 2019).

The Ljung-Box test and the Engle's ARCH test were repeated (for lags 10, 15 and 20) on the filtered returns of the S&P500 index:

Table no. 3 - Ljung-Box test and ARCH test on the filtered returns of the S&P500 index

Lag	Ljung-Box test	*p-value*	ARCH test	*p-value*
10	4,777	0,9056	12,799	0,2351
15	12,893	0,6106	15,590	0,4098
20	17,620	0,6125	19,309	0,5018

The results of both tests present *p*-values with a significance level above 5%, suggesting that the autoregressive and conditional heteroscedastic problems were removed. The results of these statistical tests for the European countries indexes suggest the same conclusion.

4.2 Estimation of Copula Models

The study proceeds with the estimation of bivariate copula models to analyze the dependence structure between each pair of indexes, including the North American index.

Firstly, the time series of each financial index were divided in the pre-crisis subperiod and the crisis subperiod. For each pair of stock indexes the empirical value of Kendall's *tau* (τ) correlation coefficient (Kendall, 1938) corresponding to the subperiods under study was obtained:

Table no. 4 – Kendall's tau coefficient for the stock index pairs in the pre-crisis and crisis subperiods

Subperiods	S&P500/ ATHEX	S&P500/ FTSEMIB	S&P500/ IBEX35	S&P500/ PSI20
Pre-crisis	0,1112	0,2938	0,2922	0,1668
Crisis	0,2074	0,4205	0,3976	0,3162
	S&P500/ OMXC20	**S&P500/ OMXH25**	**S&P500/ OMXS30**	**S&P500/ OsloOBX**
Pre-crisis	0,1882	0,2240	0,2390	0,1762
Crisis	0,3268	0,3938	0,3963	0,3622

The increased correlation between the pre-crisis subperiod and the crisis subperiod in all pairs of financial indexes reveals signs of financial contagion from the American subprime crisis in the Southern and Northern European countries analyzed.

Then, the filtered returns were transformed into 18 uniform margins to estimate copula models through Canonical Maximum Likelihood (CML) method. For the same pairs of indices, the Gaussian, t-Student, Clayton, Gumbel, Frank, Survival Clayton and Survival Gumbel copula models were estimated, including the dependence parameter, Kendall's tau coefficient and the tail dependence.

Table no. 5A – Estimation of copula models for Southern European index pairs

Index Pairs	Copulas	Dependence Parameter	Freedom Degrees	Kendall's *tau* Coefficient	Upper Tail Dependence	Lower Tail Dependence	AIC
S&P500/ATHEX	**Gaussian**	0,1882	-	0,1205	-	-	-40,2599
		0,3270	**-**	**0,2121**	**-**	**-**	**-125,9343**
	t-student	0,1821	11,8295	0,1166	0,0108	0,0108	-44,6240
		0,3260	30,0000	0,2114	0,0004	0,0004	-124,5542
	Clayton	0,2282	-	0,1024	-	0,0480	-42,0301
		0,3566	-	0,1513	-	0,1432	-83,5970
	Gumbel	1,1109	-	0,0999	0,1338	-	-31,4029
		1,2356	-	0,1907	0,2476	-	-114,9177
	Frank	1,0380	-	0,1139	-	-	-31,9861
		1,9566	-	0,2041	-	-	-111,7173
	Survival Clayton	0,1783	-	0,0819	0,0205	-	-25,1489
		0,3991	-	0,1664	0,1761	-	-105,9844
	Survival Gumbel	**1,1253**	**-**	**0,1113**	**-**	**0,1486**	**-46,0613**
		1,2237	-	0,1828	-	0,2380	-101,2952
S&P500/FTSEMIB	Gaussian	0,4619	-	0,3057	-	-	-280,4462
		0,6169	-	0,4232	-	-	-542,9721
	t-student	**0,4562**	**8,4760**	**0,3016**	**0,0910**	**0,0910**	**-292,2445**
		0,6184	**7,9998**	**0,4244**	**0,1791**	**0,1791**	**-557,4551**
	Clayton	0,6301	-	0,2396	-	0,3329	-226,3116
		0,9708	-	0,3268	-	0,4897	-404,2427
	Gumbel	1,3928	-	0,2820	0,3551	-	-264,3143
		1,6771	-	0,4031	0,4882	-	-529,1902
	Frank	2,8921	-	0,2960	-	-	-240,3289

Index Pairs	Copulas	Dependence Parameter	Freedom Degrees	Kendall's *tau* Coefficient	Upper Tail Dependence	Lower Tail Dependence	AIC
		4,5126	-	0,4196	-	-	-496,6665
	Survival	0,6226	-	0,2374	0,3285	-	-222,1476
	Clayton	1,0340	-	0,3408	0,5115	-	-446,1171
	Survival	1,3936	-	0,2824	-	0,3556	-269,5961
	Gumbel	1,6608	-	0,3979	-	0,4820	-503,7886
S&P500/IBEX35	Gaussian	0,4565	-	0,3018	-	-	-273,0353
		0,5947	-	0,4055	-	-	-494,4667
	t-student	**0,4520**	**8,3469**	**0,2986**	**0,0918**	**0,0918**	**-283,4983**
		0,5945	**10,7438**	**0,4053**	**0,1101**	**0,1101**	**-501,8404**
	Clayton	0,6641	-	0,2493	-	0,3521	-244,5626
		0,9055	-	0,3117	-	0,4651	-371,5894
	Gumbel	1,3773	-	0,2739	0,3459	-	-244,8283
		1,6160	-	0,3812	0,4644	-	-472,0261
	Frank	2,8566	-	0,2925	-	-	-235,8619
		4,1540	-	0,3931	-	-	-438,8419
	Survival	0,5801	-	0,2248	0,3027	-	-193,8233
	Clayton	0,9487	-	0,3217	0,4816	-	-397,5917
	Survival	1,4017	-	0,2866	-	0,3603	-280,3917
	Gumbel	1,6043	-	0,3767	-	0,4596	-454,7545
S&P500/PSI20	Gaussian	0,2466	-	0,1587	-	-	-71,5877
		0,4781	-	0,3175	-	-	-292,4677
	t-student	**0,2553**	**10,6213**	**0,1643**	**0,0227**	**0,0227**	**-79,4567**
		0,4802	**10,2909**	**0,3189**	**0,0712**	**0,0712**	**-299,9753**
	Clayton	0,3086	-	0,1337	-	0,1058	-67,1706
		0,6357	-	0,2412	-	0,3361	-219,8728
	Gumbel	1,1662	-	0,1425	0,1881	-	-59,5742
		1,4275	-	0,2995	0,3749	-	-282,8947
	Frank	1,5552	-	0,1647	-	-	-73,7764
		3,1490	-	0,3190	-	-	-269,8398
	Survival	0,2626	-	0,1160	0,0714	-	-46,8616
	Clayton	0,6748	-	0,2523	0,3580	-	-235,8228
	Survival	1,1800	-	0,1525	-	0,2006	-79,2800
	Gumbel	1,4139	-	0,2927	-	0,3673	-265,6000

Note: The selection of the most appropriate copula model (in "bold") for each subperiod used the (lowest) value of AIC.

The pre-crisis subperiod is on the top row and the crisis subperiod is on the bottom row.

Table no. 5B – Estimation of copula models for Northern European index pairs

Index Pairs	Copulas	Dependence Parameters	Freedom Degrees	Kendall's *tau* Coefficient	Upper Tail Dependence	Lower Tail Dependence	AIC
S&P500/OMXC20	**Gaussian**	0,2958	-	0,1912	-	-	-105,4468
		0,4970	-	**0,3311**	-	-	**-319,9391**
	t-student	0,2956	13,6765	0,1911	0,0130	0,0130	-108,8944
		0,4970	30,0000	0,3312	0,0029	0,0029	-319,1339
	Clayton	0,3996	-	0,1665	-	0,1764	-109,1404
		0,6935	-	0,2575	-	0,3681	-256,3827
	Gumbel	1,1928	-	0,1616	0,2120	-	-77,6241
		1,4237	-	0,2976	0,3728	-	-276,4324
	Frank	1,7670	-	0,1849	-	-	-94,5522
		3,2658	-	0,3276	-	-	-290,2656
	Survival Clayton	0,2929	-	0,1278	0,0938	-	-59,9752
		0,6450	-	0,2438	0,3414	-	-225,1076
	Survival Gumbel	**1,2230**	**-**	**0,1823**	**-**	**0,2375**	**-119,2003**
		1,4400	-	0,3056	-	0,3817	-294,6781

Index Pairs	Copulas	Dependence Parameters	Freedom Degrees	Kendall's *tau* Coefficient	Upper Tail Dependence	Lower Tail Dependence	AIC
S&P500/OMXH25	Gaussian	0,3537	-	0,2302	-	-	-155,0110
		0,5791	-	0,3932	-	-	-462,5299
	t-student	0,3511	7,6977	0,2284	0,0724	0,0724	-168,0389
		0,5817	**7,9999**	**0,3952**	**0,1573**	**0,1573**	**-476,2003**
	Clayton	0,4852	-	0,1952	-	0,2397	-148,7603
		0,8995	-	0,3102	-	0,4627	-364,3670
	Gumbel	1,2600	-	0,2063	0,2665	-	-137,1578
		1,5951	-	0,3731	0,4557	-	-441,2744
	Frank	2,1407	-	0,2222	-	-	-136,1222
		4,1379	-	0,3920	-	-	-430,3224
	Survival Clayton	0,4036	-	0,1679	0,1795	-	-105,0852
		0,8981	-	0,3099	0,4622	-	-360,7484
	Survival Gumbel	**1,2849**	**-**	**0,2218**	**-**	**0,2850**	**-170,1752**
		1,5935	-	0,3725	-	0,4551	-441,0126
S&P500/OMXS30	Gaussian	0,3826	-	0,2500	-	-	-184,0225
		0,5850	-	0,3978	-	-	-474,3089
	t-student	**0,3742**	**7,8461**	**0,2442**	**0,0762**	**0,0762**	**-196,8723**
		0,5868	**8,7318**	**0,3992**	**0,1433**	**0,1433**	**-486,0273**
	Clayton	0,5096	-	0,2030	-	0,2566	-161,2668
		0,8847	-	0,3067	-	0,4568	-358,1865
	Gumbel	1,2918	-	0,2258	0,2898	-	-169,2907
		1,6077	-	0,3780	0,4610	-	-458,0184
	Frank	2,2809	-	0,2360	-	-	-154,6864
		4,1802	-	0,3951	-	-	-437,7205
	Survival Clayton	0,4670	-	0,1893	0,2267	-	-139,1025
		0,9293	-	0,3172	0,4743	-	-382,0464
	Survival Gumbel	1,3036	-	0,2329	-	0,2982	-190,0873
		1,5931	-	0,3723	-	0,4549	-439,3181
S&P500/OsloOBX	Gaussian	0,2867	-	0,1851	-	-	-98,6435
		0,5303	-	0,3558	-	-	-372,9936
	t-student	0,2832	11,0016	0,1828	0,0237	0,0237	-103,9584
		0,5377	**6,6730**	**0,3614**	**0,1689**	**0,1689**	**-398,4971**
	Clayton	0,3759	-	0,1582	-	0,1582	-99,5365
		0,7977	-	0,2851	-	0,4194	-305,3361
	Gumbel	1,1904	-	0,1600	0,2099	-	-79,1327
		1,5114	-	0,3384	0,4181	-	-356,1184
	Frank	1,6588	-	0,1749	-	-	-83,3943
		3,7430	-	0,3628	-	-	-360,2644
	Survival Clayton	0,2920	-	0,1274	0,0931	-	-59,8256
		0,7706	-	0,2781	0,4068	-	-289,3627
	Survival Gumbel	**1,2125**	**-**	**0,1752**	**-**	**0,2288**	**-110,4718**
		1,5176	-	0,3410	-	0,4211	-366,4902

Note: the same as in table 5A.

The t-Student copula is the most suitable for most of the pairs of financial indexes and subperiods analyzed. Regarding to the indexes of Italy, Spain and Portugal, in Southern Europe, the dependence structures show a symmetrical relationship under that copula with S&P500. This suggests strong dependence when the US market goes up or down (booms or crashes).

Concerning the indexes of Finland and Norway, in Northern Europe, the Survival Gumbel is the most appropriate copula for the pre-crisis subperiod and the t-Student copula for the crisis subperiod. This suggests that these markets have shifted from a strong dependence relationship when the S&P500 goes down (lower tail dependence), before the crisis, to a symmetrical dependence relationship in the face of either crashes or booms, in the crisis subperiod.

In the case of Greek and Danish indexes, the most suitable copula for the pre-crisis subperiod is the Survival Gumbel and for the crisis period is the Gaussian copula, suggesting a change from a strong dependence relationship in the lower tail to a symmetrical weak dependence relationship on both limits of the distribution.

Since different copula models were selected, the estimated dependence parameters are not comparable. Therefore, we resort to a variation of estimations of Kendall's *tau* coefficient (from Tables no. 5A and 5B) between the pre-crisis subperiod and the crisis subperiod for each pair of indexes studied:

Table no. 6 – Financial contagion effect of the subprime crisis on Southern and Northern European stock indexes

Region	Countries	Indexes	$\Delta\tau$
Southern Europe	Greece	S&P500 / ATHEX	+0,1008
	Spain	S&P500 / IBEX35	+0,1067
	Italy	S&P500 / FTSEMIB	+0,1228
	Portugal	S&P500 / PSI20	+0,1546
Northern Europe	Denmark	S&P500 / OMXC20	+0,1488
	Sweden	S&P500 / OMXS30	+0,1550
	Finland	S&P500 / OMXH25	+0,1734
	Norway	S&P500 / OsloOBX	+0,1862

The increase in Kendall's *tau* coefficient reveals that the dependence relationships between European financial markets and the North American financial market were intensified from the pre-crisis subperiod to the crisis subperiod. This denotes the existence of financial contagion from the subprime crisis on those countries in Southern and Northern Europe. More specifically, the variation of the coefficient was higher for the Northern countries, with the exception of Denmark compared to Portugal. The financial markets of Finland and Norway recorded the largest increases of the coefficient, meaning that their increase in the dependence with the North American market was more pronounced.

Following the perspective of Zorgati *et al.* (2019), if the financial contagion effect is more intense in Northern markets than in Southern markets, then the increase in the dependence – measured by the variation of the Kendall's *tau* coefficient – will be higher between the Northern European markets and the North American market. Table no. 7 presents the variation of estimates of Kendall's *tau* coefficient (from Table no. 6) between the stock indexes studied in Southern and Northern Europe:

The positive results confirm that the increase in the dependence with the North American market after the subprime financial crisis was bigger for the Northern European countries, with the exception of Denmark compared to Portugal. This corroborates the evidence of recovery of the financial indexes of these countries in line with the S&P500 index until the first quarter of 2011 (cfr. Figure no. 1). The Southern European markets did not recover from the subprime crisis in the same way (cfr. Figure no. 1), although the t-Student copula was selected for the crisis subperiod, except in the case of Greece.

Table no. 7 – Intensity of the financial contagion effect of the subprime crisis on Southern and Northern European indexes

	$\Delta\tau(North - South)$	Southern European Indexes **ATHEX** Greece	**FTSEMIB** Italy	**IBEX35** Spain	**PSI20** Portugal
Northern European Indexes	**OMXC20** Denmark	+0,0480	+0,0260	+0,0421	-0,0058
	OMXH25 Finland	+0,0726	+0,0506	+0,0667	+0,0188
	OMXS30 Sweden	+0,0542	+0,0322	+0,0483	+0,0004
	OsloOBX **Norway**	+0,0854	+0,0634	+0,0795	+0,0316

5. CONCLUSION

The financial contagion effect is a phenomenon of relevance in financial research, especially when marked by severe events. From the perspective of a significant increase in correlation relationships between markets after a shock occurs (Forbes & Rigobon, 2002), this paper aimed to identify the effect of the subprime crisis over the dependence structures between the US stock index (S&P500) and some Southern European indexes (PSI20, IBEX35, ATHEX and FTSEMIB) and some Northern European indexes (OMXS30, OMXC20, OMXH25 and OsloOBX).

The increase in the Kendall's *tau* coefficient for all pairs of indexes, between the pre-crisis subperiod (from January 1, 2003 to July 31, 2007) and the crisis subperiod (From August 1, 2007 to December 31, 2013), suggests that the dependence relationships between the European markets analyzed and the North American market intensified, justifying the existence of financial contagion of the subprime crisis.

The t-Student copula was selected in the pre-crisis subperiod for most of the stock index pairs, except for the Greek and Danish, in which the Gaussian copula was selected. Although this copula model does not consider strong dependence at the tail of the distribution, both copulas are elliptical, denoting symmetrical dependence relationships between the European indexes and the North American index. This sustains a financial contagion effect between the S&P500 index and these European indexes in the face of negative and positive shocks.

Northern European markets intensified more their relations of financial integration with the North American market after the subprime crisis, except for Denmark compared to Portugal. This was to be expected, given that the Nordic countries represent small economies that are heavily dependent on exports, thus reacting more sensitively to external fluctuations. For instance, these markets followed the recovery line of the North American financial market.

The markets in Southern Europe were also affected by the subprime crisis, but they did not follow the recovery of the North American market in same way as the Northern European markets. The several structural problems that these countries were facing contributed to this inability to recover, especially due to their sovereign debts, which were aggravated by the subprime crisis.

The conclusions of this paper allow to identify channels of financial contagion between markets and alert to the effects of possible new crises. In addition, the intensity of the contagion is also important to the definition of levels of intervention by the authorities in the face of shocks. Finally, when economies are more prepared to face crises arising from financial contagion, their recovery is easier to implement.

Considering the cyclicality of extreme events, it is expected that decision makers will strengthen policies to mitigate their effects on international markets. In addition to rules requiring well-capitalized and transparent banks under sound governance and accounting standards, improvements in micro-prudential regulations are needed to reduce the procyclicality of financial markets (Claessens *et al.*, 2010). In this context, it is important to make progress in the way of assessing vulnerabilities in asset and credit markets and incorporate them into macroeconomic and regulatory policies.

For future research, we suggest the study of other crises with international relevance and the expansion of the sample in order to cross the contagion effects through the level of development of the economies and the distinctive characteristics of different geographical areas.

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