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The Greek financial crisis, extreme co-movements and contagion effects in the EMU: A copula approach

Boubaker Adel, Jaghoubbi Salma (Corresponding author)

Department of finance, University of Tunis el Manar, Tunis, B.P 248 El Manar II 2092 Tunisia

E-mail: salmajaghoubi@hotmail.com

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Abstract

This paper examines the extent of the current financial Greek crisis and the contagion effects it concludes toward the euro zone by conducting an empirical investigation of the dependence structure between seventeen European stock markets during the period 2007-2011. In particular, several copula functions are used to model the degree of cross-market linkages. The model is implemented with a GARCH model for the marginal distributions and the student-t copula for the joint distribution which allows capturing nonlinear relationships and offers significant advantages over econometric techniques in analyzing the co-movement of financial time-series. Our empirical results show that there is strong evidence of market dependence in the euro area. However, the dependence remains significant but weaker, for the major of stock markets, after the occurrence of the Greek crisis.

Keywords: financial crisis, Copula Approach, Euro zone, Extreme co-movements

1. Introduction

The integration and dependence of financial markets has long been an issue of interest to financial economists in academic and investment practice alike, as it has consequences for the identification of opportunities for and barriers to international portfolio investment with important implications for portfolio allocation and asset pricing (Bartram and Dufey, 2001).

In Europe, European Monetary Union (EMU) has encouraged integration among the still fairly fragmented European financial markets both directly and indirectly. This is reflected by the introduction of the Euro, on 1st January 1999. Thus, the European Monetary Union area started with 11 countries which are: Belgium, Germany, Spain, France, Ireland, Italy, Luxembourg, the Netherlands, Austria, Portugal and Finland. On January 1, 2001, Greece became the twelfth member of the euro area. Then, five countries have joined the euro area after Greece's entry, bringing the total number of members in 2011 to seventeen: Slovenia in 2007, Cyprus and Malta in 2008, Slovakia in 2009 and Estonia in 2011.

The adoption of the euro conferred several benefits on its members. These benefits were especially important for countries, such as Greece, with histories of high inflation and inflation variability[1].Moreover, currency union means the elimination of exchange rate risk within the Euro area. Indeed, the absence of exchange rate risk allows corporations to raise funds across countries with fewer constraints and costs. In addition, the prices of assets in European markets are determined to a larger degree by common factors due to the reduction of exchange rate risk, so that country stock market returns should be more proportionally explained by their covariance with the regional stock market returns (Bekaert and Harvey, 1995; Bekaert et al., 2002; Baele, 2005; Bekaert et al., 2005).

Recent waves in Europe, particularly the Greek financial crisis, have stimulated researchers to reinvestigate the merits and problems of monetary unions. Few of their papers explicitly analyze the impact of common currencies on financial markets and its effects.

This paper highlights this aspect of monetary union in the context of the recently economic crisis in Greece and the euro-area and its impact on European markets, especially that EMU is in its tenth year.

What happens in Greece and in the rest of the euro area? The debt crisis in the euro area is largely due to difficulties faced by the Greek state to finance its budget deficit and deal with a large public debt. This Greek debt has several origins, first, the financial crisis of 2007 and the bank bailout in 2008. Then, states have debt out of proportion to rescue banks and revive the economy, unconditionally, that is to say, without putting the financial sector under public control. As a result, after 2008, there has been a surge in public debt of many countries in the economic climate. The decline in activity resulted in lower tax revenues on the one hand, and rising unemployment on the other.

In addition, there is a more distant origin: application to the European level, neoliberal policies particularly significant since the adoption of the Maastricht Treaty. In Greece, as in other European countries, these policies over the past two decades have resulted in a

[1]Garganas and Tavlas (2001) provide data on inflation and inflation variability in Greece during the period 1975-2000.

continued decline in taxation. To provide for lower tax revenues, states cannot borrow from the ECB on behalf of monetary orthodoxy prevailing in the euro area: they have to fund the capital markets at rates uncertain, who participated in the increased debt burden. Finally, in the absence of fiscal adjustment (that is to say a real "economic government" of the euro area); the inequalities between the economies of the euro area do not tend to go away, however: inflation - higher in Greece than in the rest of the euro area - has contributed to the price of Greek too high to be competitive. As a result, Greece imports more than it exports: the trade deficit of Greece has contributed to the swelling of his public and private external debt.

Failure Greek may trigger a panic on other highly indebted European countries like Italy, Ireland and Portugal, triggering further deterioration of the agencies. To assess this impact of the Greek crisis, this paper provides a comprehensive analysis of the financial market co-movement of 17 European countries during the period 2007-2011.

The purpose of this paper is to investigate the nature of the dependence between daily returns of seventeen European stock market indices, after the occurrence of the current financial Greek crisis, and the contagion effects it concludes toward the euro zone. More precisely, our main research questions are: 1) Are there any volatility spillovers between European monetary stock markets after the Greek crisis? 2) What is the dependence structure between European stock market indices? 3) Is the dependence symmetric or asymmetric? 4) Is there any extreme value dependence?

While previous works have studied market dependence and integration based on asset pricing models (; Bekaert and Harvey, 1995; Dumas and Solnik, 1995; Hardouvelis et al., 2001; Bekaert et al., 2002; Bekaert et al., 2005) or volatility spillovers (Eun and Shim, 1989;Kasa, 1992; Koutmos and Booth, 1995; Richards, 1995; Booth et al., 1997; Baele, 2005), we directly investigate the dependence of stock market indices across countries using copula approach, which allow capturing nonlinear relationships and offers significant advantages over econometric techniques in analyzing the co-movement of financial time-series. Thus, we consider that there is contagion when there is an increase in the copulas parameters after the crisis. We use this methodology to investigate the impact of certain joint stock return realizations on the subsequent dependency of European markets. As a preliminary step; we estimate the univariate distributions. Then, we provide evidence that the Student-t copula fits very well the joining behavior of the data and is able to capture the dependency structure between market returns.

This present study contributes to the related literature in that we provide a framework for addressing the extent of extreme interdependences and contagion effects between emerging and developed European markets, in the context of the recent financial Greek crisis. This is important since knowing only the degree of time-varying co movement is actually not sufficient to make international investment decisions because stock market returns might exhibit common extreme variations.

The remainder of the paper is organized as follows. In Section 2, we discuss the literature review. In section 3, we introduce the univariate model, the copula functions and we describe the copulas used in the empirical application. In Section 4, we present the data and discuss our empirical results. Finally, section 5 summarizes our results and concludes.

2. Literature review:

Studying the co-movements across financial markets is an important issue for risk management and portfolio management. There is a great deal of research focusing on the co-movements of international equity markets.

In this context, Login and Solnik (2001) showed in their work that stock returns have a dependence structure which is not consistent with multivariate normality. They used a method based on extreme value theory and found that the correlation generally increases in periods of market high volatility in the United States.

In an alternative approach, Rachmand and Susmel (1998) and Ang and Bekaert (2002) used a Markov switching model and tested the assumption of a constant international conditional correlation between stock markets. They noticed that the correlation is generally higher in a regime of high volatility that in a regime of low volatility.

Chakrabarti and Roll (2002) find that the correlations increased from the pre-crisis to the crisis period in both Asian and European stock markets. They also find that the diversification potential was bigger in Asia than in Europe in the pre-crisis period, but this was reversed during the crisis. Other examples of research on the co-movements of equity markets can be found in Longin and Solnik (2001), Forbes and Rigobon (2002), while the methodology used is along the line of correlations and conditional correlations.

Boyer et al. (2006) used both the Markov switching model and the extreme value theory. They identified a bigger co-movement during periods of high volatility and suggest that the crises deviate because of international investors' asset possession rather than by any changes in the fundamental principles.

Since the limitations of correlation-based models as identified in Embrechts et al. (2002) and Corsetti and al. (2002), research has started to use copulas to directly model the dependence structure across financial markets. Works along this line include Hu (2006) and Chollete et al. (2006), who report asymmetric extreme dependence between equity returns, the stock markets crash together but do not boom together.

Patton (2006a) employs copulas to model the asymmetric exchange rate dependence and finds that the mark and yen exchange rates are more correlated when they are depreciating against the US dollar than when they are appreciating.

Bartram et al. (2007) use the model GJR-GARCH-t for the marginal distributions and they have recourse to the Gaussian copula to model the time dependence of the 17 European stock indexes. Their results suggest that the dependence of European markets rise after the adoption of the euro as common currency only for the major stock markets such as France, Germany, Italy, Netherlands and Spain, while transaction costs remain significant barriers to investment. The increasing dependence of financial markets began in early 1998 when the relevant information was announced.

Rodriquez (2007) proposes to use copulas to change parameters to model the dependence structure and thus to study the phenomenon of financial contagion. He provides evidence of asymmetric dependence during the Asian crisis and the Mexican crisis.

In a more recent paper, Ning (2011) examine the extreme co-movements between the stock and the exchange rate European markets by directly modeling their dependence structure viacopulas approach. They found significant symmetric tail dependence in all pairs of stock currency returns, analyzed in this study, for both the two sub-periods: pre-euro and post-euro.

Boubaker, A., and Jaghoubi, S., (2011) test the hypothesis of contagion in the subprime mortgage crisis by applying the theory of copulas to measure the contagion among emerging and developed markets. Results showed that there was an increase in the copula Student parameters between markets after the subprime crisis except in the Malaysian and Chinese markets which seemed less dependent on the US market during the crisis. Consequently, they confirmed the contagious nature of the crisis between emerging and developed markets.

In this paper, several copula functions are used to model the degree of cross-market linkages after the Geek crisis. This new theory has many advantages for both statisticians and for financial analysts and provides answers to the multivariate model, non-linearity and asymptotic tail dependence.

3. Methodology:

For our purpose, we can use an ARCH family copula model to examine the extent of the current financial Greek crisis and the contagion effects it concludes toward the euro zone. Thus, marginal distributions are modeled as univariate ARCH family model and the dependence parameters are specified by the copula function choice.

3.1. A model for the marginal distributions:

As noted above, the tests in this study are based on the ARCH family of models[2] developed by Engle (1982) and generalized by Bollerslev (1986). These models have been shown empirically to provide a good fit for many financial return series and remain able to describe the short run dynamics of European stock market returns. Returns and conditional variances of financial assets are modeled to reflect the stylized facts observed on financial markets (presence of asymmetry, long memory, non-linearity and thick tails of the distributions, etc.).

3.1.1. ARCH model:

The ARCH (q) is the basic model of the ARCH process proposed by ENGLE (1982) during a study on the variance of the inflation in Great Britain. The model is based on a quadratic parameterization of the conditional variance.

A process ARCH (q) is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 = \alpha_0 + \alpha(L)\varepsilon_t^2 \quad ;\alpha_0 > 0 \text{ and } \alpha_i \geq 0 \ \ \forall i \qquad (3.1)$$

[2]We referred to these three models because the software that we three models. However, we can use other more developed extension of ARCH-GARCH process.

3.1.2. GARCH model:

Bollerslev (1986) generalized the initial model of Engle by establishing the model GARCH (p, q) (Generalized ARCH). This extension consists of the introduction of lagged values of the variance in its equation. It allows a more parsimonious description of the structure of the lag structure.

A GARCH process is defined by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 = \alpha_0 + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2$$

(3.2)

Where $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, $\forall i, \forall j$

3.1.3. EGARCH model:

The control of asymmetry is introduced through a process EGARCH. The process EGARCH contains equations describing the returns, the variances and the conditional correlations. In particular, the equation of the variance allows a differentiation between the positive effects and those of the negative shocks (effects of asymmetry). According to Nelson (1991), the positivity's constraints on the coefficients of GARCH (p, q), were often violated in practice on one hand, and, on the other hand, will eliminate all the possibility of cyclic behavior. This criticism is not valid in the case of the Exponential GARCH because the coefficients can be positive or negative.

The model is then given by:

$$\text{Ln } \sigma_t^2 = C + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \ln \sigma_{t-1}^2 \quad \textbf{(3.3)}$$

Where:

α, γ and β : The coefficients of the variance's equation of the EGARCH (1, 1);

σ_t^2:The returns and the innovations' conditional variance

In the general case, the model GARCH (p, q) is defined by the following equations:

$$y_t = f(y_{t-1}, \cdots y_{t-k} / \Omega_{t-1}) + u_t$$

$$\sigma^2_t = \omega + \sum_i^p \alpha_i u_{t-i}^2 + \sum_j^q \beta_j \sigma_{t-j}^2 \quad \textbf{(3.4)}$$

$u_t / \Omega_{t-1} \rightarrow D(0, \sigma_t^2)$

Where y_t : The asset market return;

U_t : Errors (Residuals or innovations);

D ( ): The conditional distribution of innovations

Ω_{t-1} : The informational set at time (t-1)

σ_t^2 : The conditional variance of returns and innovations.

3.2. The Copula concept:

Dependence between random variables can be modeled by copulas. A copula returns the joint probability of events as a function of the marginal probabilities of each event. This makes copulas attractive, as the univariate marginal behavior of random variables can be modeled separately from their dependence.

Copulas are multivariate distribution functions with standard uniform marginal distributions. Anm-dimensional copula is represented as follows:

C (u) = C(u_1, …, u_m)(3.5)

Where $u_1, \dots, u_m$ are standard uniform marginal distributions. In such a context, copulas can be used to link margins into a multivariate distribution function. The copula function extends the concept of multivariate distribution for random variables which are defined over [0,1]. This is possible due to the Sklar (1959) theorem which states that copulas may be constructed in conjunction with univariate distribution functions to build multivariate distribution functions.

Sklar's Theorem: Let F_{XY} be a joint distribution function with margins F_X and F_Y. Then there exists a copula C such that for all x, y in R,

$$C(u_x, u_y) = C(F_x(x), F_y(y))$$

$$= F(F_x^{-1}(u_x), F_y^{-1}(u_y))$$

(3.6)

$$C(u_x, u_y) = F(x, y)$$

If F_X and F_Y are continuous, then C is unique; otherwise, C is uniquely determined on Ran F_X×Ran F_Y and C is invariant under strictly increasing transformations of the random variables.

The density of a bivariate law can be written also in terms of the density of the copula associated and marginal densities f_x and f_y :

$$f(x,y) = c\,(F_X(x), F_y(y)) \times f_x(x)\, f_y(y) \quad \textbf{(3.7)}$$

That is, the density of F has been expressed as the product of the copula density and the univariate marginal densities. It is in this sense that we say that the copula contains all the information given by the joint distribution of a pair of random variables outside of the marginal.

The concept of tail dependence provides a description of the dependence in the tails of distribution, very interesting to study the simultaneous occurrence of extreme values. In other words, it tells us about the amount of dependence in the tails of distribution. This is in contrast to a local measure Kendall's tau and Spearman's rho, which measures the dependence of the overall distribution.

The lower tail dependence coefficient of the two random variables *X* And*y*, with distribution functions related F_x and F_y , is defined by λ_L (X, Y) = $\lim_{\alpha \to 0^+} Pr[X \le F_X^{-1}(\alpha) / Y \le F_Y^{-1}(\alpha)]$.

The upper tail dependence coefficient of random variables *X* and*Y*, with distribution functions related $F_x$etF_y, is defined byλ_U (X, Y) = $\lim_{\alpha \to 1^-} Pr[X > F_X^{-1}(\alpha) / Y > F_Y^{-1}(\alpha)]$.

We now describe the copula functions used in our empirical application. To model the dependence structure between the marginal return distributions, we need to select among various models or families of possible copulas. These copulas involve different types of dependence structures. We classify copulas into two groups: elliptic and Archimedean copulas. For all the copulas presented in this section,$(u_1, \ldots, u_m)$ represent standard uniform marginals.

3.2.1. Elliptical copula :

Elliptical copulas are easy to simulate, they are symmetrical. The two most commonly used classes of elliptical copulas are Gaussiancopula and Student copula.

- **The multivariate Gaussian copula :**

The multivariate Gaussian copula applied to a joint distribution function with correlation matrix R, is defined by:

$$C_R(u_1, \dots \dots u_m) = \emptyset_R\left(\emptyset^{-1}(u_1), \dots \dots \dots, \emptyset^{-1}(u_m)\right) \quad \textbf{(3.8)}$$

WhereC_R is the distribution function of joint variables, these variables are normal, standardized and have a correlation matrix R.

Since the majority of models in finance use this dependence structure, managers must adapt their model by modifying the structure of dependence if they consider the extreme risks. The use of copulas consistent with the extreme value theory is a modeling technique that allows analysis of rare events without being rigid methods based on the extension to several dimensions of a univariate distribution.

This copula has no tail dependence and does not correlate extreme values.
Model the dependence structure of a sample by a Gaussian copula is consistent with the extent of this dependence by the linear correlation coefficient.

- **The multivariate Student –t- copula:**

Similarly, the Student-t copula is defined by:

$$C_T(u_1, \dots, u_m) = T_{v,m,\Sigma}\left(T_v^{-1}(u_1), \dots, T_v^{-1}(u_m)\right) \quad \textbf{(3.9)}$$

Where $T_{v,m,\Sigma}$ the multivariate student distribution function with a degree of freedom v and variance-covariance matrix Σ

3.2.2. Archimedean copula:

The Gaussian and Student copulas are called elliptic. They apply to the pattern of symmetric distributions. However, the Clayton, Gumbel and Frank copulas are called Archimedean copulas. They have the great advantage of being able to describe a variety of dependence v structures including the asymmetric dependencies, where the coefficients of the lower tail and upper tailare different.

The following table shows the characteristics of the best known models where the variables u and v are cumulative distribution functions. The parameter θ measures the degree of dependence between risks.

Table 1: Models of Archimedeans bivariate copulas

Noun	Parameters	Bivariate Copula
Clayton	$\theta > 0$	C (u, v,θ) = ($u^{-\theta} + v^{-\theta} - 1)^{\frac{-1}{\theta}}$
Gumbel	$\theta \geq 1$	C (u, v,θ) = exp $[-[(-\text{Ln (u)})^{\theta} + (-\text{Ln (v)})^{\theta}]]^{\frac{1}{\theta}}$
Frank	$\theta \neq 0$	C (u, v,θ) = - $\frac{1}{\theta}$ Ln [1+ $\frac{(\exp(-\theta_u)^{-1})(\exp(-\theta_v)^{-1})}{\exp(-\theta)-1}$]

4. Empirical Study:

The model here is constructed by adopting marginal specifications that conform to the asymmetrical and leptokurtic aspects of observed densities. The theory of copulas functions is used to link the different marginal distributions and to fully specify the dependence structure between the index returns.

The sample includes daily returns of seventeen European stock market indices. The study was conducted on the period from February1, 2007 to December 21, 2011,giving 1253 observations. This period was decomposed into two sub-periods[3] to characterize the impact of the contagious effect of the financial Greek crisis: the pre-crisis from February 1, 2007 till October 15, 2009 with 691observations for each country and post-crisis from the October 16, 2009 and ending on December 21, 2011 with 562 observations for each country. Data were in local currency.

4.1. Estimation and results of the ARCH/GARCH process:

Since the copula function used to separate margins of the dependency structure corresponding to a joint distribution, it comes to choosing, initially, which of the ARCH-type process (ARCH, GARCH, EGARCH) is the greatest to model the returns and variances of European stock market returns to estimate the parameters of marginal functions, then we estimate those

[3]We define two distinct periods: a "tranquil" period which is characterized by lower volatility and significantly positive stock returns and a "crisis" period which is characterized by higher volatility and sharply negative stock returns.

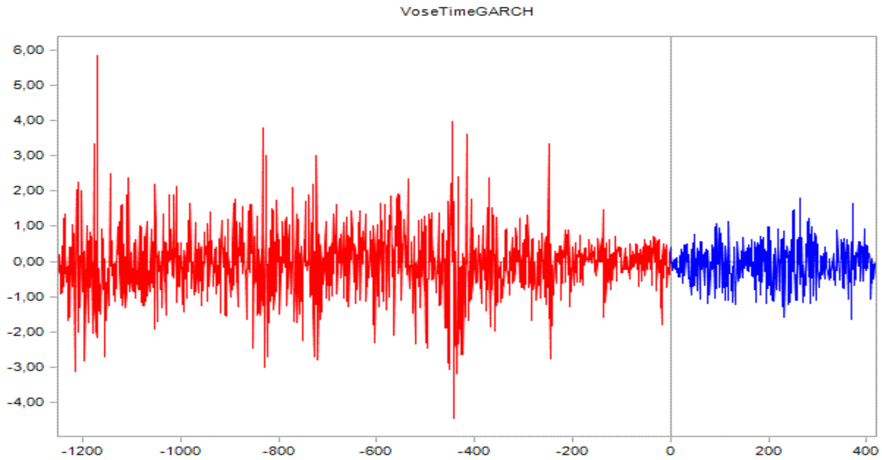
of the dependence structure. For that, a time series fit model is used.

Results in table 2, show that, for all monetary stock returns, the process GARCH minimize the information criteria and remains the best model to our data.

Table 2: Time series fit model for ATHENS INDEX COMPOS

Name	**-SIC**	**-AIC**	**-HQIC**
ARCH	-3296 .19	-3253.81	-3259.58
EGARCH	-19406.45	-19380.83	-19390.43
GARCH	**-3074.80**	**-3054.30**	**-3061.99**

Fig 2: Log returns ATHENS INDEX COMPOS (2007-2011)



The Figure 2 showing the evolution of the returns of 17 European stock indices throughout the period indicates that these series are highly volatile. We further observe clusters of volatility: the sharp fluctuations tend to be followed by large variations, and also slight variations tend to be followed by slight variations. Volatility evolves over time. This observation justifies our choice of GARCH model.

Table 3: Descriptive statistics

(a)

	AEX	ATHEN	ATX	BEL_20	CAC40	CYSE	DAX	FTSE_MIB	IGBM
Mean	-0.017572	-0.068151	1.152728	-0.035671	-0.021238	0.018518	-0.005244	-0.038663	-0.022659
Std. Dev.	0.754795	0.901909	24.24244	0.687435	0.779427	0.974732	0.746523	0.819882	0.785953
Skewness	-0.093630	0.168730	20.33048	0.237688	0.139538	-0.021023	0.118501	0.042126	0.240945
Kurtosis	9.094251	6.378040	415.0361	9.611653	7.969773	7.124780	8.201018	7.258653	8.821721
Jarque-Bera	1940.843	601.7026	8949922.	2294.031	1293.541	888.3548	1414.069	947.2274	1781.591

(b)

	MSE	OMX_H_25	OMXT	PSI_20	SAX	SBI_TOP	LUX	ISEQ_20
Mean	-0.017356	-0.016295	-0.022058	-0.027363	0.023580	0.046487	0.001546	-0.041144
Std. Dev.	0.305635	0.793113	0.657041	0.643563	0.595649	0.378522	0.000965	0.905208
Skewness	0.065548	0.101068	0.165734	-0.013060	1.592428	-0.170289	1.588051	-0.400758
Kurtosis	9.336490	5.686303	8.714507	9.880040	42.12614	10.76016	4.654095	8.079340
Jarque-Bera	2097.120	378.8802	1710.630	2471.314	80452.95	3150.042	669.5015	1380.499

In table 3, we present some illustrative statistics for each of these seventeenth indices separately. From the daily standard deviation, we see that the ATX is the most volatile and LUX the least volatile of the indices. All the indices show evidence of fat tails, since the kurtosis exceeds 3, which is the normal value, and evidence of negative and positive skewness, which means that both the left and the right tails are extreme.

The stock market indices shows substantial evidence of ARCH effects as judged by the autocorrelations of the squared residuals in Table 4. The first order autocorrelation is 0.210, and they gradually decline to 0.043 after 15 lags. These autocorrelations are not large, but they are very significant. They are also all positive, which is uncommon in most economic time series and yet is an implication of the GARCH model. Standard software allows a test of the hypothesis that there is no autocorrelation (and hence no ARCH). The test p-values shown in the last column are all zero to all market returns, resoundingly rejecting the “no ARCH” hypothesis.

Table 4: Autocorrelations of Squared indices Returns

		AC		Q-St		Prob
1		0.210		55.420		0.000
2		0.177		94.828		0.000
3		0.036		96.500		0.000
4		0.063		101.48		0.000
5		0.136		124.85		0.000
6		0.127		145.05		0.000
7		0.136		168.35		0.000
8		0.106		182.66		0.000
9		0.049		185.64		0.000
10		0.043		188.02		0.000
11		0.058		192.31		0.000
12		0.064		197.57		0.000
13		0.044		200.01		0.000
14		0.030		201.13		0.000
15		0.043		203.43		0.000

Sample: February 1, 2007 to December 21, 2011

The basic GARCH (1,1) results for European monetary stock markets before and after the Greek crisis are given in Table 7. Under this table it lists the dependent variable, Athens index Compos, and the sample period. All the variable coefficients in the equation showed a variance significantly different from zero. Therefore, there was the phenomenon of asymmetry which cannot be highlighted through the usual ARCH models. The contagion effect was investigated by adopting a conditional t-student distribution for the errors to allow for the leptokurtic distribution of stock returns. To evaluate the variation of the conditional variances, we consider two sub-periods: the quiet period then the crisis period.

Table 5 (a; b): Results of the GARCH (1, 1) model estimations for the European stock market returns for the two sub-periods

(a) Pre-crisis period

Variable	Coefficient	Std. Error	Prob.
Variance Equation			
C	0.001815	0.022776	0.9365
α	0.096175***	0.019653	0.0000
β	0.888199***	0.019556	0.0000

(b) Post-crisis period

Variable	Coefficient	Std. Error	Prob.
Variance Equation			
C	0.150802***	0.049780	0.0025
α	0.001155	0.012353	0.9255
β	0.955138***	0.017849	0.0000

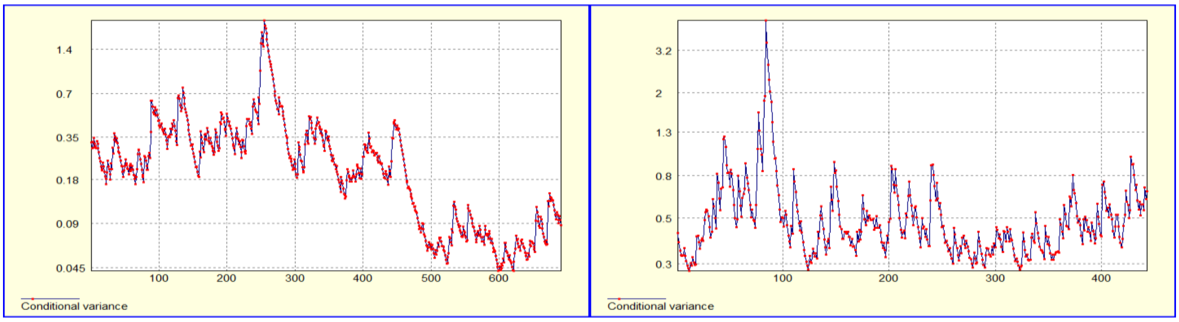
Notes: Regression with GARCH error. Gaussian's distribution

*** denote significance level at the1%.

The three coefficients in the variance equation are listed as α_0, the intercept; α, the first lag of the squared return; and β, the first lag of the conditional variance. Notice that the coefficients sum up to a number less than one, which is required to have a mean reverting variance process. Since the sum is very close to one, this process only mean reverts slowly. Standard errors and t- statistic complete the table. The results provide clear evidence for the increase in the coefficients in the equation of variance during the Greek crisis, from the pre-crisis to the crisis period, suggesting the transmission of the volatility from the Greek to the rest of euro zone financial markets. This result supports the contagion hypothesis.

The estimates of the conditional variance obtained in our sample are reproduced in Figure 3 below and well aware of clusters of volatility, that is to say, the succession of periods of turbulence and calm on the relevant market.

Fig 3: Plot of non-constant conditional variance for the two sub-periods



<u>Pre-crisis</u>: From February 1, 2007 till October 15, 2009**<u>Post-crisis</u>:** From the October 16, 2009 and till December 21, 2011.

4.2. Selecting the appropriate copula:

The choice of the best copula to model the dependence between the best random variables is of great importance. The question that arises is: what is the best dependency structure can be adapted to the phenomenon studied? However, fit tests for copulas are relatively new. It should be noted that we found few articles on the subject, but the area is under constant development.

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A test of adequacy was done to validate copula choice for a couple of variables. In our case, the dependence between European stock returns is modeled by the copula Student after running the test of adequacy on copulas Student, Clayton, Gumbel, Frank and Normal.

A graphic example of the 17th European returns adequacy to multivariate copulas Clayton, Student, Frank, Gumbel and Normal is presented below for the period under study.

Copules	-SIC	-AIC	-HQIC
Clayton	2014.04	2019.37	2017.38
Frank	1501.96	1507.29	1505.31
Gumbel	1722.75	1728.07	1726.09
Normal	13770.14	14314.32	14121.61
Student	**14465.98**	**15015.17**	**14820.79**

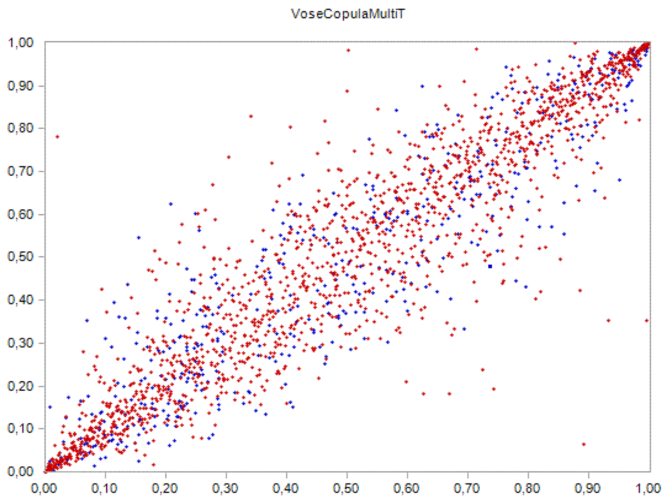

Fig 4: The 17th returns adequacy to multivariate copulas Clayton, Frank, Gumbel, Normal and Student

4.3. Estimation and results of the copula parameters :

To estimate the parameters of the copula, we used the parametric estimation method Inference Functions for Margins (IFM) or method of inference functions of marginal which is proposed by Shih and Louis (1995). First, we estimate the marginal parameters of the method of maximum likelihood estimators; either $\hat{\theta}_i =$ argmax $\theta_i \sum_{k=1}^{n} f_i(x_i^k, \theta_i))$ and then we introduce in the copula log-likelihood function to determine the parameters of the copula which leads to $\theta_C =$ argmax $\theta_C \sum_{k=1}^{n} ln\left(c\left(F_1(x_1^k, \hat{\theta}_1), \ldots, F_n(x_n^k, \hat{\theta}_n), \theta_C\right)\right)$.

Table 6 present the main results of this paper: the estimation results for Student copulas parameters, for the Greek index with the rest of European stock markets, for the two sub-periods.

Table 6: Copula parameters

	Pre-crisis	Post-crisis
	ATHENS INDEX COMPOS.	
CAC 40	0.64	0.43
DAX	0.63	0.39
MSE	0.075	-0.056
BEL-20	0.0069	0.071
ISEQ-20	0.54	0.4
ATX	0.64	0.045
FTSE-MIB	0.00077	0.16
IGBM	0.59	0.45
SBI-TOP	-0.0062	0.017
CYSE	0.077	-0.0035
OMXT	0.24	0.04
AEX	0.63	0.41
OMXH 25	0.63	0.4
LUX	-0.0073	-0.023
PSI 20	-0.015	0.26
SAX	-0.00054	-0.021

During the pre-crisis, the dependence parameters are positive and strongly significant for almost of the returns expect for the following indices: SBI-TOP (Slovenia), LUX (Luxemburg), PSI 20 (Portugal) and SAX (Slovakia) where the dependence were negative.

Comparing the dependence before and after the occurrence of Greek crisis, we find that the degrees of dependence vary. Indeed, the dependence between the ATHEN INDEX COMPOS and CAC 40, DAX, MSE, ISEQ-20, ATX, IGBM, CYSE, OMXT, AEX, OMXH 25, LUX and SAX decreased after the crisis and become smaller. Moreover, we show that the dependence between the Greek index and Malta and Cyprus indices become negative during the post-period. This can be interpreted by the fact that these stock markets seemed less dependent with the Greek after the crisis.

Dependence is also observed between the ATHEN INDEX COMPOS and the SBI-TOP index and PSI 20. These indices show a negative dependence with the ATHEN INDEX COMPOS before the crisis but a positive dependence after it. Indicating that the higher the parameter, the greater the dependence meaning that these countries are more and more dependent on the occurrence of the Greek crisis.

Furthermore, the dependence parameters have highly increased between ATHEN INDEX COMPOS and FTSE-MIB index, BEL-20, SBI-TOP and PSI 20 when the Greek crisis occurred reflecting some financial contagion.

5. Conclusion:

Studying the transmission of return and volatility shocks from one market to another as well as examining the dependence structure between financial markets is essential in finance, because it has many implications for international asset pricing and portfolio allocation. Indeed, the existence of extreme co-movement (tail dependence) between markets would reduce the diversification benefits.

In this paper we propose a copula methodology to model the extreme co-movement between seventeenth European stock markets after the occurrence of the Greek financial crisis during the 2007–2011 period. We first provide evidence of the superiority of a GARCH (1,1) model which seems able to capture the conditional heteroscedasticity of daily returns on stock market indices. Then, a test of adequacy was done to validate copula choice for the studied indices. In our case, the dependence between European stock returns is modeled by the copula Student which retains the correlation dependence and also has symmetric non-zero tail dependence. This Implies that both markets boom and crash together.

Our main finding is the existence of the financial contagion effect between Greek and these European countries: Italy, Portugal, Belgium and Slovenia, when the Greek financial crisis occurred. Indeed, their degree of dependence with the Greek market has considerably changed after the crisis.

This finding is important for global investors in their risk management during extreme market events.

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