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ORIGINAL ARTICLE

Contagion effects of the subprime crisis in the European NYSE Euronext markets

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Abstract This paper presents three tests of contagion of the US subprime crisis to the European stock markets of the NYSE Euronext group. Copula models are used to analyse dependence structures between the US and the other stock markets in the sample, in the pre-crisis and in the subprime crisis periods. The first test assesses the existence of contagion on the relevant stock markets' indices, the second checks the homogeneity of contagion intensities, and the third compares contagion in financial and in industrial sectors' indices. Results suggest that contagion exists, and is equally felt, in most stock markets and that investors anticipated a spreading of the financial crisis to the indices of industrial sectors, long before such dissemination was observable in the real economy.

Keywords Financial contagion · Subprime crisis · Stock markets · Copula theory

JEL Classification F30 · G14 · G15

The views expressed in this paper are those of the authors and do not necessarily represent those of the hosting institutions. Comments from three anonymous referees are much appreciated.

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1 Introduction

In the last two decades, localised episodes of financial disorder, quickly spreading across borders, sometimes without apparent fundamental justification, caught the attention of financial researchers. With colourful media designations such as the Tequila crisis, the Asian flu, or the Russian virus, each crisis propagated like a contagious disease, quickly affecting not only neighbouring but also distant markets. As these events became the object of an increasing number of theoretical and applied analyses, the word *contagion* began to frequently appear in the financial literature.

In spite of its popularity in the financial context, there is no consensus on the definition of financial contagion and the different versions identified in the literature vary with the specific nature of each analysis. In this study, we test for the existence of contagion from the US subprime crisis to the European stock markets in the NYSE Euronext group,[1] adopting Forbes and Rigobon's (2002, p. 2223) definition of financial contagion: "a significant increase in cross-market linkages after a shock to one country (or group of countries)". According to the authors, this definition presents two operational advantages, which are relevant in the context of the empirical analysis developed ahead. It provides a straightforward framework to test for the existence of contagion, simply by checking whether there were significant increases in such linkages after a crisis, and avoids the difficult measurements of, and distinctions amongst, mechanisms of transmission.

From such perspective, testing for the existence of financial contagion requires an analysis of dependence structures between markets. To this end, early empirical assessments mostly relied in comparisons of Pearson's linear correlation coefficients in stable and in crisis periods. Evidence of contagion was reported when statistically significant increases in correlation occurred in periods of crisis. Later studies identified a number of methodological problems in correlation based assessments and proposed alternative testing procedures. One option, by Costinot et al. (2000), adopted, *inter alia*, by Chan-Lau et al. (2004), Hu (2006) and Rodriguez (2007), is the use of copulas. We follow this suggestion and adopt the copula methodology to examine the dependence structures between the US and each European market in the sample, using data on global and on sectoral indices, representing the financial and industrial firms listed in those markets, from January 2005 until April 2008.

Three tests of contagion are performed. The first assesses whether the representative indices of the analysed markets exhibit evidence of contagion from the US. The homogeneity of contagion intensity across markets is evaluated in a second test. The third test checks the existence of contagion in financial and in industrial sector indices. The first two tests are useful to analyse the

[1] NYSE Euronext is a US holding company, created in 2007 by the combination of NYSE Group, Inc. and Euronext N.V. It operates six stock exchanges in seven countries and eight derivatives exchanges. In Europe, NYSE Euronext comprises the stock exchanges of Paris, Amsterdam, Brussels and Lisbon.

potential benefits of international diversification. If some markets or sectors are not affected, or if some are distinctly or more severely affected than others, diversification could still be beneficial.[2] The information provided by the third test is also useful in this respect.

While the sample of data does not cover the time when it became more obvious that the financial crisis had spread to the real sectors of the economy, i.e. the summer of 2008, the results show that all stock markets are equally affected and contagion intensity appears to be identical across global and sectoral indices. However, the empirical analysis also suggests that, in spite of the generalised effects of the crisis, dependence structures vary across pairs of indices and thus, different markets, though equally affected, display distinct reactions to the same stimulus, a fact that may be of interest for investment decisions.

Although the international impact of the subprime crisis is non-negligible, formal assessments and discussion of its contagious effects are still scarce.[3] Dungey et al. (2008), Fry et al. (2008) and Idier (2008) are examples of studies that, though adding to the overall discussion on the financial contagion literature, focus directly on this latest crisis. Dungey et al. (2008) proposed a model capable of fitting a series of crisis episodes occurred in the 1998–2007 period, uncovering evidence of contagion in all cases, with signs of serious contagion in the Russian and in the US subprime crises, only. Fry et al. (2008) and Idier (2008) adopted alternative approaches to test contagion, respectively focusing on higher order co-moments and utilising Markov switching multi-fractal models. Both confirmed the existence of contagion in the context of the US subprime crisis.

The empirical evidence gathered so far suggests that contagion from the US subprime crisis existed and some monetary authorities have shared this view from an early stage. For instance, Ben Bernanke, the chairman of the US Federal Reserve, stated in a speech delivered on 15 October 2007, that the developments of the relatively small US subprime market were having a large impact upon the global financial system. In fact, the first losses associated with the subprime crisis were then reported in the media by a number of institutions, including the Citigroup, in the US, the Crédit Agricole, in France, the HSBC, in the United Kingdom, the CIBC, in Canada, or the Deutsche Bank, in Germany. At the time, few would have anticipated the dimension of the collapses that would soon occur, such as the bankruptcy of Lehman

[2]Forbes and Rigobon (2001, p. 43) refer that analyses of financial contagion are of ‘critical importance in: portfolio investment strategy; justifying multilateral intervention; and understanding how shocks are propagated internationally’. From this perspective, assessing whether contagion exists and if contagion homogeneity varies across countries may also be of interest to justify distinct levels of intervention and attention on the part of the relevant authorities, following the subprime crisis.

[3]One of the first initiatives to discuss research on this subject was a workshop on Contagion and Financial Stability, organised by the Banque de France, in Paris, on 30 May 2008, were the work by Dungey et al. (2008), Fry et al. (2008) and Idier (2008), referred ahead, were presented.

Brothers, the fourth-largest US investment bank, announced in September 2008.

There is, apparently, consensus over the fact that contagion is present in the case of the current US subprime crisis. However, the extent and intensity of contagion across markets, as well as the nature of the changes suffered by dependence structures between the US and other markets are empirical issues that have not been addressed, yet. In this study these problems are assessed with the instruments provided by the copula theory. Specifically, dependence structures between the US and each European stock market in the NYSE Euronext group are compared in a tranquil and in a crisis period.

Following these introductory remarks, the remainder of the paper is organised as follows: Section 2 briefly surveys some relevant empirical studies of contagion and presents the data utilised in the analysis; Section 3 describes the use of copula theory in assessments of financial contagion; Section 4 presents the results and Section 5 concludes and discusses the implications of the study.

2 Empirical tests of financial contagion

Increasing international financial integration and the occurrence of various banking, currency and stock market crises, with noticeable cross-border impacts, have attracted the interest of academics to the phenomenon of financial contagion. Many have addressed this subject from a variety of distinct perspectives.[4] However, given the nature of the analysis developed in Section 4, our attention is mainly focused on empirical studies where contagion is defined as an intensification of cross-market linkages following a shock. Contrary to what is done elsewhere, for instance by Favero and Giavazzi (2002), who tested for nonlinearities in the propagation of financial shocks and considered the possibility of "flight to quality", we are only interested in assessing increases in the response of the four markets in our sample to the shock originated in the US.

As previously referred, early assessments relied on linear correlation coefficients to measure dependence and reported evidence of contagion when statistically significant increases in correlation occurred after a crisis. Examples are Calvo and Reinhart (1996) or Baig and Goldfajn (1998), who concluded that contagion existed in the cases of the 1994 Mexican and the 1997 Asian crises, respectively.

Later, methodological problems in correlation based tests of contagion were identified and corrections, or alternative approaches, were proposed. Embrechts et al. (2003, p. 342) classified linear correlation coefficients as "very misleading" measures of dependence, only valid for elliptical distributions,

[4] A thorough survey of such theoretical and empirical literature is provided by Pericoli and Sbracia (2003).

which are rare in financial data. Rodriguez (2007) added to this view, stating that multivariate distributions with identical correlations may display distinct dependence structures.

Forbes and Rigobon (2002) used a numerical example to show that linear correlation coefficients are conditional on volatility and are biased upwards in periods of crisis. As a consequence, assessments that do not take such bias into account may mistakenly report evidence of contagion in cases where correlation coefficients simply pick up the high levels of co-movement, or interdependence, existing between the analysed countries in moments of financial turmoil, but also in calm periods. Using a heteroskedasticity corrected version of correlation, the authors found "virtually no evidence" of contagion in the cases of the Asian, the Mexican and the 1987 US crises, thus contradicting some previous assessments.

The mixed results obtained in empirical analyses of common crisis episodes, motivated further research, not only on the broad issue of financial contagion, but also on the more specific question of distinct transmission of large and small shocks across markets and its consequences for portfolio diversification (Chan-Lau et al. 2004). For instance, Ramchand and Susmel (1998), Longin and Solnik (2001) and Ang and Bekaert (2002) analysed the asymmetry of correlations using distinct methodologies (switching ARCH models, extreme value theory and regime switching models, respectively) and coincided in concluding that correlations tend to increase in bear, but not in bull, markets.[5]

Bae et al. (2003), on the other hand, provided mixed evidence that contagion is stronger for extreme negative returns. They estimated multinomial logistic regressions to model the occurrence of large returns, designated as "exceedances", in various crisis episodes from 1992 to 2000 and concluded that contagion from Latin America to other regions was more important than from Asia, with the US appearing relatively shielded against contagious effects, especially from Asia.

According to Hu (2006), in contagion analyses attention should not be focused on linear correlations, even if these are corrected as in Forbes and Rigobon (2002), for they only allow the study of the degree of dependence between markets. Correlations cannot model dependence structures, thus failing to describe the manner in which markets are related. Also recognising the importance of fully understanding financial dependence, Costinot et al. (2000) proposed the use of copulas, in line with Embrechts et al. (2003, p.341), who considered them as the "natural way to study and measure dependence between random variables". These authors also acknowledged the fact that copulas are useful for allowing the analysis of situations that go beyond normal dependence or involve series of data that are not elliptically distributed. In fact,

[5]This asymmetry compromises the advantages of diversification when they are most needed, a phenomenon that became known as the 'breakdown of correlations', after studies by Longin and Solnik (1995, 2001).

if these issues are not taken into account, as often was the case in previous analyses, biased results may be obtained, namely the underestimation of the downward risk of simultaneously investing in markets affected by financial contagion (Hu 2006).

To overcome such problems, authors such as Chan-Lau et al. (2004), Hu (2006) or Rodriguez (2007) followed Costinot et al. (2000) suggestion and utilised copulas in evaluations of financial contagion. Chan-Lau et al. (2004) analysed various worldwide episodes of financial disorder, between 1987 and 2001, and concluded that there was an increase in contagion during this period. Comparisons of their results with those produced with linear correlation based assessments suggest that the latter can be misleading, producing coincidental outcomes only in the case of crises initiated in Latin America. Hu (2006) confirms this result in an analysis of dependence structures between pairs of stock indices from the US, UK, Japan and Hong Kong, from 1970 to 2003.

Table 1 Sensitivity analysis to the dating of the crisis (global indices)

		Our date (1 Aug 2007)	Krugman (2009) (9 Aug 2007)	Dungey et al. (2008) (26 Jul 2007)
Pre-crisis period				
US/Belgium	Selected copula	*t*-Student	*t*-Student	*t*-Student
	Kendall τ	0.2653	0.2642	0.2649
	Spearman ρ	0.3893	0.3876	0.3886
US/France	Selected copula	*t*-Student	*t*-Student	*t*-Student
	Kendall τ	0.3189	0.3178	0.3198
	Spearman ρ	0.4631	0.4616	0.4643
US/ The Netherlands	Selected copula	*t*-Student	*t*-Student	*t*-Student
	Kendall τ	0.2993	0.2991	0.2996
	Spearman ρ	0.4364	0.4361	0.4368
US/Portugal	Selected copula	*t*-Student	*t*-Student	*t*-Student
	Kendall τ	0.1540	0.1537	0.1502
	Spearman ρ	0.2293	0.2289	0.2238
Crisis period				
US/Belgium	Selected copula	Gumbel	Gumbel	Gumbel
	Kendall τ	0.3702	0.3779	0.3709
	Spearman ρ	0.5248	0.5347	0.5257
US/France	Selected copula	Clayton–Gumbel	Clayton–Gumbel	Clayton–Gumbel
	Kendall τ	0.4099	0.4288	0.4157
	Spearman ρ	0.5536	0.5751	0.5551
US/ The Netherlands	Selected copula	Gumbel	Gumbel	Gumbel
	Kendall τ	0.3789	0,3862	0.3814
	Spearman ρ	0.5360	0,5452	0.5391
US/Portugal	Selected copula	Frank	Frank	Gaussian
	Kendall τ	0.2242	0.2288	0.2192
	Spearman ρ	0.3317	0.3382	0.3239

The sensitivity analysis shows that the selection of copulas is robust to the crisis dating choice. Only for the pair US/POR (crisis period), a distinct copula is selected when the date proposed by Dungey et al. (2008) is chosen. However, even in this case, the Kendall' τ and the Spearman's ρ do not differ substantially from those computed using our dating. Furthermore, the new selected copula (the Gaussian copula) displays the same behaviour as the Frank copula in terms of asymptotic tails. The λ_L and the λ_U are zero in both copulas

She finds that the level of correlation is almost irrelevant for the probability of joint crashes. Focusing solely in the 1997 Asian and the 1994 Mexican crises, Rodriguez (2007) uncovered evidence of contagion in the sense of Forbes and Rigobon (2002) in most analysed markets.

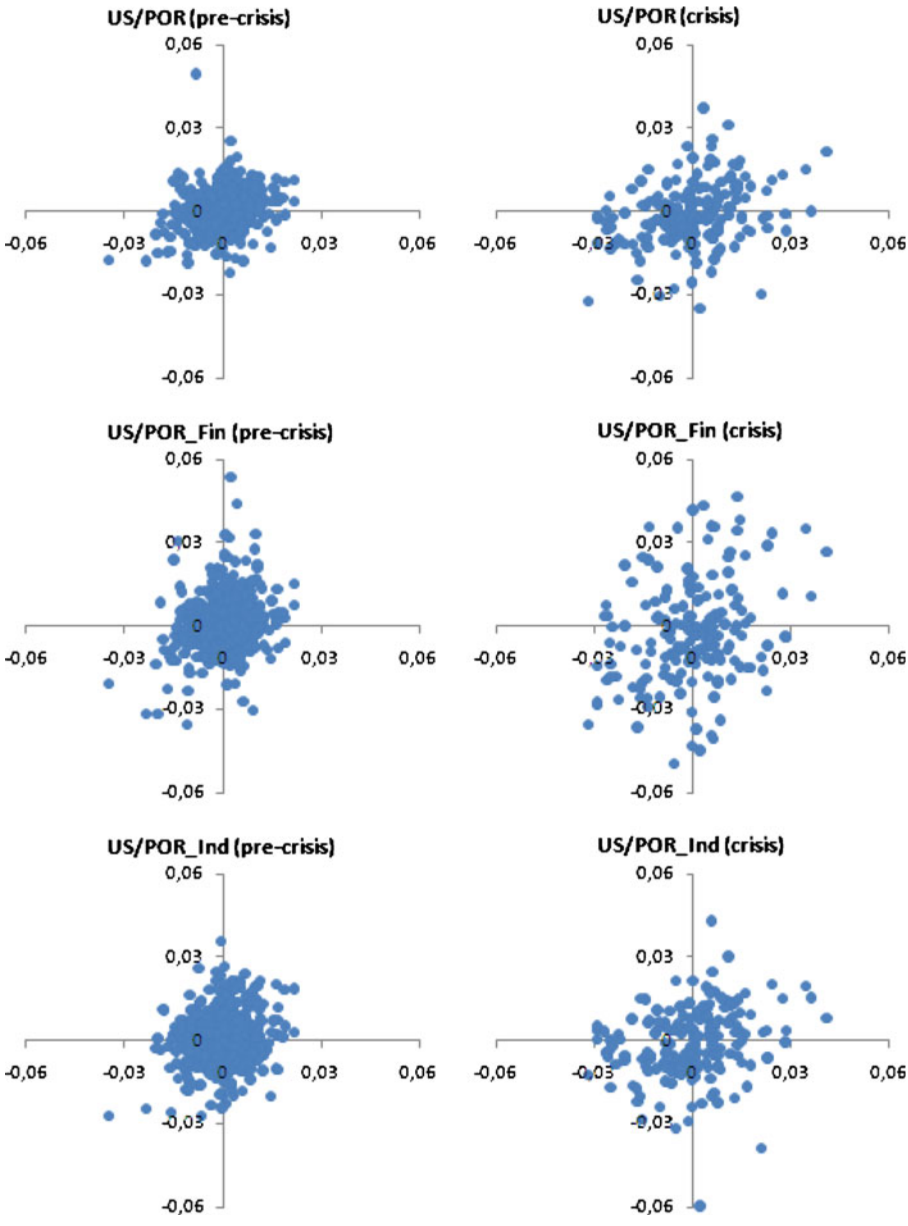


Fig. 1 Raw data scatter plots

We follow this strategy and adopt the copula methodology to assess financial contagion from the US subprime crisis to the four European stock markets in the NYSE Euronext group. The analysed time frame is comprised between

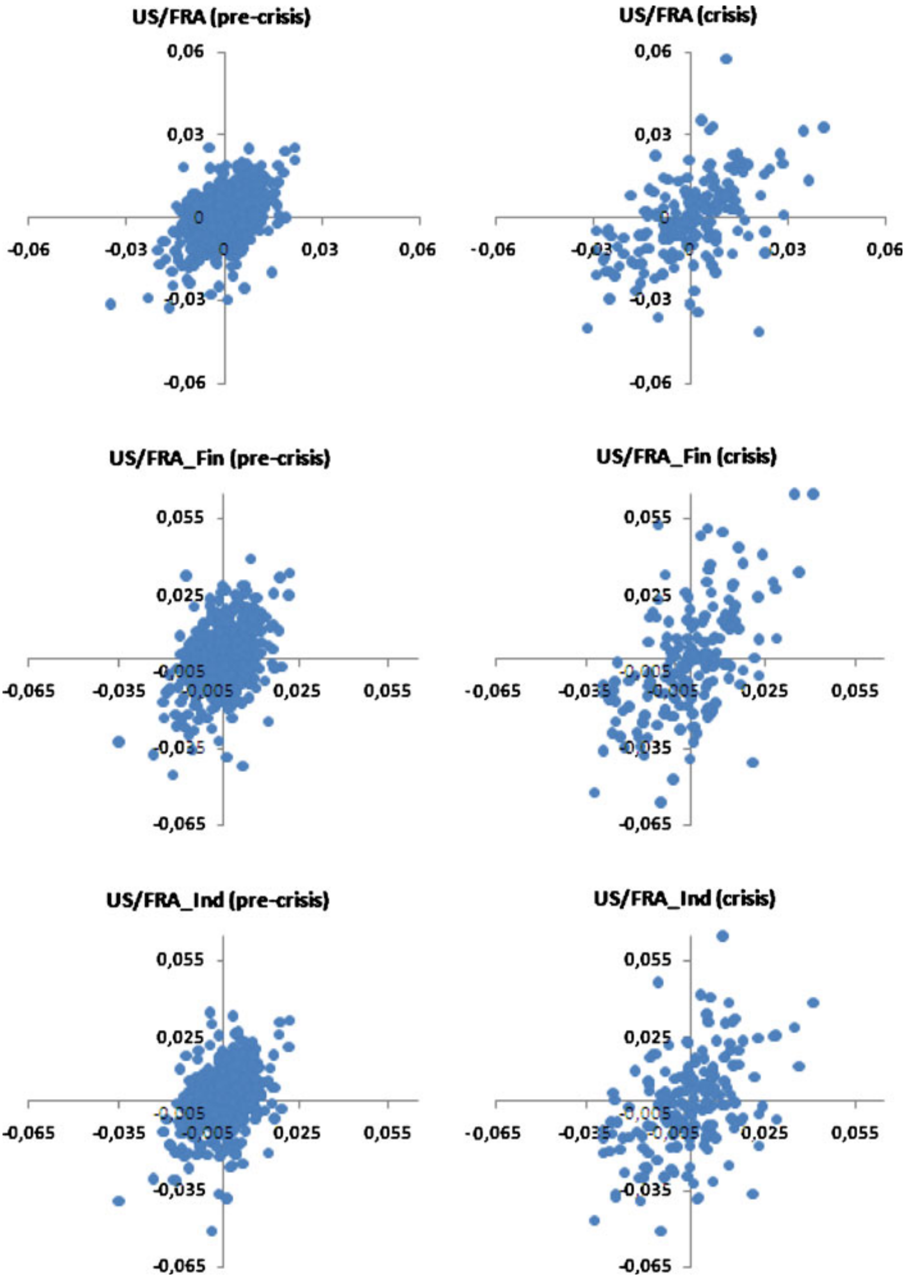


Fig. 1 (continued)

1 January 2005 and 21 April 2008, and the pre-crisis and crisis periods are divided by the burst of the mortgage bubble, assumed to have occurred on 1 August 2007. Given that the choice of the crisis dating can qualitatively

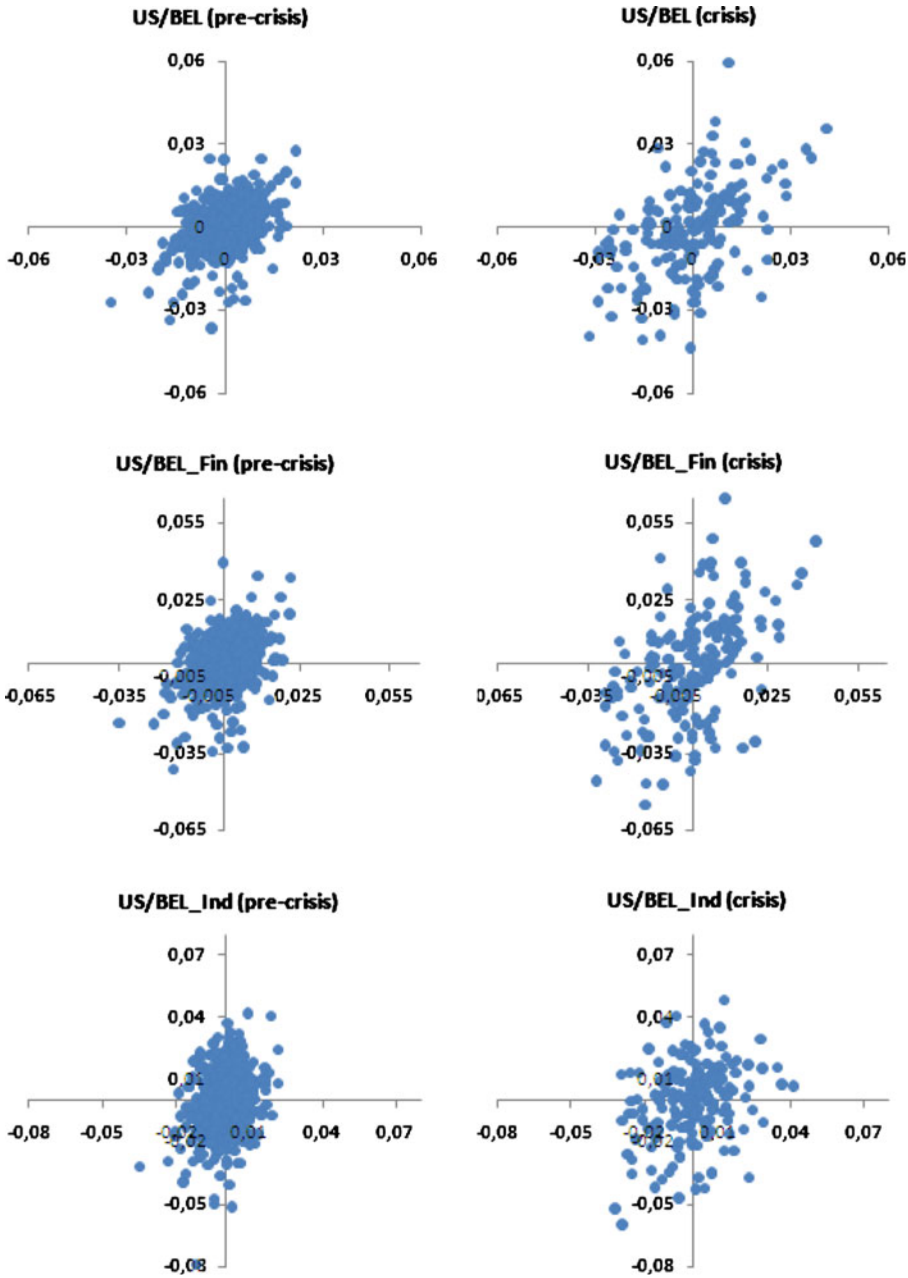


Fig. 1 (continued)

affect the outcome of the study, a sensitivity analysis was performed. The dates proposed by Dungey et al. (2008) and Krugman (2009) (26 July 2007 and 9 August 2007, respectively) were also considered and the results, displayed in Table 1, confirmed the robustness of our choice.

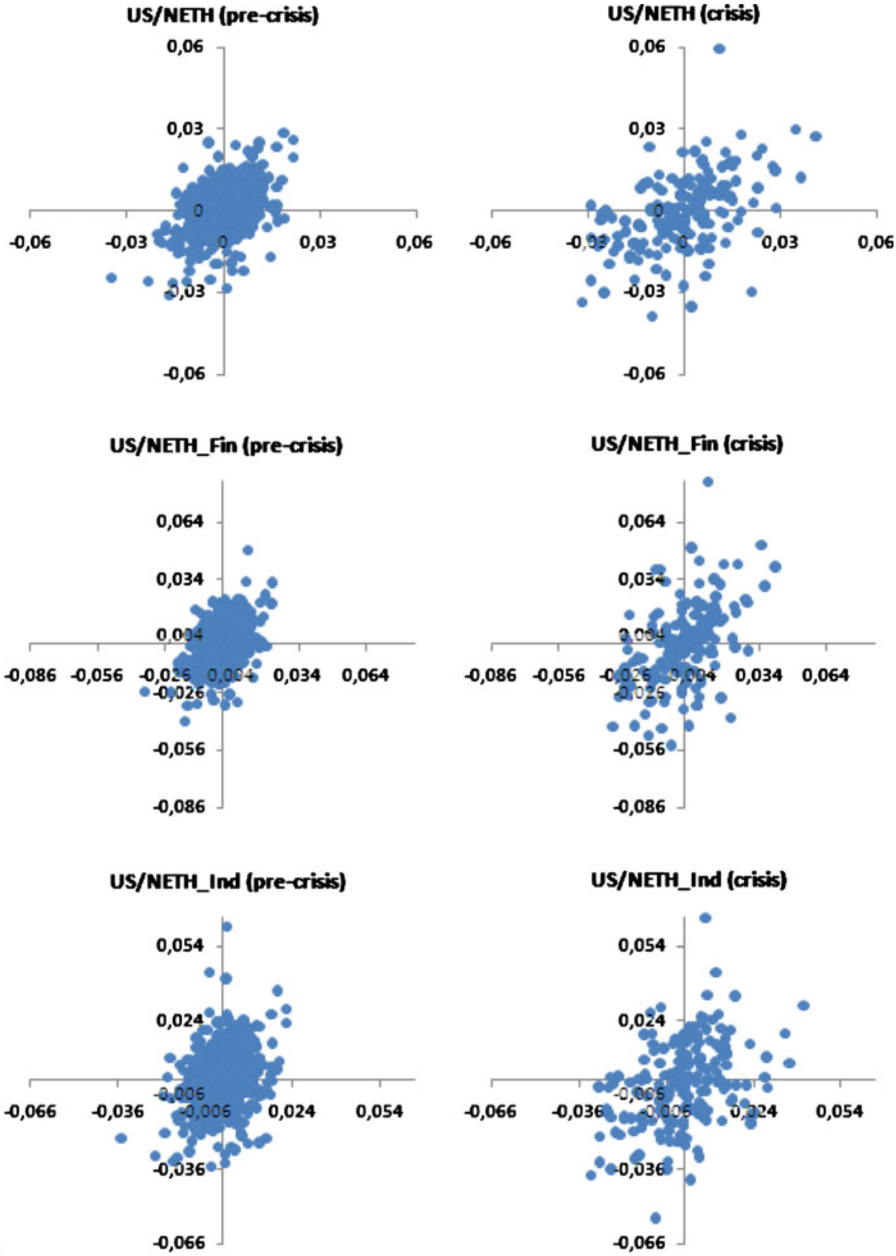


Fig. 1 (continued)

Changes in the logarithms of closing daily values of Morgan Stanley Capital International (MSCI) indices, denominated in local currency, are used to represent daily returns from stock markets in Belgium, France, The Netherlands, Portugal and the US. Global and sectoral indices, representing the financial and the industrial sectors, in each market are analysed. The assessed pairs of indices are the following: US–Belgium, US–France, US–The Netherlands, US–Portugal, US–Belgium/Financial, US–France/Financial, US–The Netherlands/Financial, US–Portugal/Financial, US–Belgium/Industrial, US–France/Industrial, US–The Netherlands/Industrial and US–Portugal/Industrial. Each series contains 642 observations for the pre-crisis period and 180 for the crisis period, summing up 822 observations for the whole sample. Scatter plots of the data are provided in Fig. 1.

3 The use of copulas in analyses of financial contagion

Copulas are functions used to model dependence between random variables. According to Trivedi and Zimmer (2005), they are very useful in applied analyses where researchers know more about the individual characteristics of related variables than about their joint distributions. In such cases, the copula allows establishing a stable connection between the joint distributions and their margins, even when these are non-normal and come from different distribution families. In this section, only an intuitive description of the copula theory and estimation processes, based on the work of Trivedi and Zimmer (2005), is provided. Comprehensive analyses may be found there, but also in Joe (1997), or in Nelsen (2006).

One of the most important results in the theory of copulas is the Sklar theorem (Sklar 1959) stating that any d-dimensional distribution function F, with univariate marginal distribution functions $F_1,\ldots,F_d$, may be written as:

$$F\left(x_1, \ldots, x_d\right) = C\left(F_1\left(x_1\right), \ldots, F_d\left(x_d\right); \theta\right) \tag{1}$$

with $X = (X_1,\ldots,X_d)$ representing a vector of random variables, C representing the copula (a distribution function in the space $[0, 1]^d \to [0, 1]$), and θ representing the copula's dependence vector.

Since $F_i(X_i) = U_t$, with $U_i \sim Unif\,[0,1]$, Eq. 1 may be written as:

$$C\left(u_1, \ldots, u_d; \theta\right) = F\left(F_1^{-1}\left(u_1\right), \ldots, F_d^{-1}\left(u_d\right)\right) \tag{2}$$

where F_i^{-1} represents the inverse of the distribution function of X_i.[6]

An important aspect in the Sklar's theorem is that it allows a great level of flexibility in multidimensional modelling. For example, knowing the marginal distribution functions and knowing the copula function (which can be chosen independently from the marginal distributions), the joint distribution function may be obtained by directly applying the theorem. In this study,

[6] See the development in Nelsen (2006).

only bivariate copula models are considered, mainly for two reasons. Firstly, since the subprime crisis originated in the US, we are interested in assessing the dynamics of dependence structures connecting the US index and each of the other countries' indices. Secondly, not only is the building of higher dimensional copulas very difficult, as acknowledged *inter alia* by Aas et al. (2009) or Sarabia and Gómez-Déniz (2008), but also the number of parametric bivariate copulas available is large, whereas that of higher-dimensional copulas is rather limited.

A variety of copulas is found in the literature. The most commonly used in financial analyses are the Gaussian copula, proposed by Lee (1983), the *t*-Student copula and some copulas of the Archimedean family, such as the Gumbel copula (Gumbel 1960), the Clayton copula (Clayton 1978) or the Frank copula (Frank 1979).[7] Kole et al. (2007), for example, proposed the use of *t*-Student copulas in the context of risk management. The Gaussian and the *t*-Student copulas can be used to model symmetric dependence structures, the Clayton copula is more adequate when left tail dependence exists, and the Gumbel copula is better to model right tail dependence (Trivedi and Zimmer 2005). The Frank copula is symmetric but has a number of advantages in relation to the Gaussian and the *t*-Student copulas, namely allowing a simpler estimation of the dependence parameter. This copula is also appropriated to model variables with weak tail dependence structures.

Besides pure copulas, it is also possible to use mixed versions (see, *inter alia*, Hu 2006). The mixture of a Gumbel and a Clayton copula, for instance, is useful to model dependence in cases where symmetry is almost perfect, but also for different forms of asymmetry and even independence.

The dependence structure between variables may be characterised by a copula, but may also be expressed using scalar synthetic measures derived from the same copula. Examples of such measures are rank correlation coefficients, as the Kendall's τ or the Spearman's ρ (Schmidt 2006). For two-dimensional variables, the τ and the ρ may be directly obtained from the copulas' functions, as shown by Nelsen (2006):

$$\rho_{Spearman}\left(X_1, X_2\right) = 12 \int_0^1 \int_0^1 \left(C\left(u_1, u_2\right) - u_1 u_2\right) du_1 du_2 \tag{3}$$

$$\tau_{Kendall}\left(X_1, X_2\right) = 1 - 4 \int_0^1 \int_0^1 \frac{\partial C\left(u_1, u_2\right)}{\partial u_1} \frac{\partial C\left(u_1, u_2\right)}{\partial u_2} du_1 du_2 \tag{4}$$

Rank correlation measures are very useful, because they allow comparative analyses of global dependence structures when copulas are different and, consequently, the copulas' dependence parameters (θ) are non-comparable. Rank

[7] The specific functional forms of these copulas may be found in Trivedi and Zimmer (2005).

correlations always vary between −1 and 1, and are invariant to non-linear transformations, as long as they are monotonic, as is the case of probability integral transforms of marginal variables in the context of the copula theory. In this study, the Kendall's τ and the Spearman's ρ are used to assess global dependence structures, and the τ is the basis of the developed contagion tests.

Other than rank correlations, the lower and upper asymptotic tail coefficients associated to the copulas can also be used as measures of local dependence between variables. These coefficients measure the probability of one variable reaching one extreme value, given that another variable has already attained it, and may thus be used to assess the probability of markets crashing or booming together. In the first case, the assessment is based on the lower asymptotic tail coefficient (λ_L). In the second, the upper asymptotic tail coefficient (λ_U) is used. Different copulas exhibit distinct asymptotic tail coefficients. For example, whereas the Clayton copula exhibits lower and no upper asymptotic tail coefficients, the Gumbel copula displays upper and no lower asymptotic tail coefficients. The *t*-Student copula exhibits both lower and upper asymptotic tail coefficients, which are identical, due to the copula's symmetric shape. The Gaussian and Frank copulas are also symmetric but do not exhibit asymptotic tail coefficients.

λ_L and λ_U are formally defined as (Schmidt 2006):

$$\lambda_L = \lim_{q \to 0} P\left(X_2 \leq F_2^{-1}(q)\,|X_1 \leq F_1^{-1}(q)\right) \tag{5}$$

$$\lambda_U = \lim_{q \to 1} P\left(X_2 > F_2^{-1}(q)\,|X_1 > F_1^{-1}(q)\right) \tag{6}$$

Following Hu (2006), two main processes may be followed in copula estimation. The copula and the marginal distributions are jointly estimated or, alternatively, the margins are estimated first, assuming that they are independent, and then plugged into the copula, to be used in the estimation of the copula's parameters. The second method, denominated by McLeish and Small (1988) as inference functions for margins (IFM), is less complex, has been adopted in most empirical studies dealing with copulas and is also chosen here. It has the advantage of permitting an evaluation of the marginal distributions' goodness of fit before estimating the copulas, and thus avoiding the possibility of estimating low quality copulas, as would be the case if copulas and margins were simultaneously estimated and the margins were misspecified.

The assessment of financial contagion developed below follows a four step approach, briefly described as follows:

Step 1: With the purpose of removing autoregressive and heteroskedastic effects from the series of indices, ARMA–GARCH models are estimated. The standardised residuals, here denominated as filtered returns, are recuperated and the respective means and variances are checked for time independence.

Step 2: The series of the filtered returns are divided into two periods, one of calm and another of crisis. Assuming that the series are iid, the parametric distribution functions for both periods are estimated by maximum likelihood. Gaussian, t-Student, logistic and Gumbel (extreme values) functions are estimated and the Akaike information criterion (AIC) is used to select the most appropriate.

Step 3: The marginal distributions selected in step 2 are used to estimate the copulas by maximum likelihood and the AIC is again used to select the most adequate copula. Pure and mixed copulas are estimated. The former are Clayton, Gumbel, Frank, Gaussian and t-Student and the mixed copulas are the Clayton–Gumbel, Gumbel–Survival Gumbel and Clayton–Gumbel–Frank.

Step 4: The measures λ_U, λ_L, ρ and τ are computed using the estimated copulas.

Step 5: Implementation of the bootstrap technique referred by Trivedi and Zimmer (2005, p. 59) to calculate the variance–covariance matrix V of the parameters and other indicators associated to the copulas selected in step 3. The bootstrap technique consists of:

a) Obtaining the marginal distributions' vector of parameters ($\widehat{\beta}_1$ and $\widehat{\beta}_2$) and the vector of the copulas' dependence parameters ($\widehat{\theta}$), by IFM methodology. The global parameters' vector is defined as $\widehat{\Omega} = \left(\widehat{\beta}_1, \widehat{\beta}_2, \widehat{\theta}\right)^T$;
b) Randomly drawing a sample of observations (with replacement) from the original data;
c) Using the randomly drawn sample to re-estimate β_1, β_2 and θ, by IFM, and storing the values;
d) Repeating b) and c) R times and denoting each estimated parameter as $\widehat{\beta}_1(r)$, $\widehat{\beta}_2(r)$ and $\widehat{\theta}(r)$ for the rth re-estimation. The global parameters' vector is identified as $\widehat{\Omega}(r) = \left(\widehat{\beta}_1(r), \widehat{\beta}_2(r), \widehat{\theta}(r)\right)^T$;
e) The standard errors for the estimated parameters are the squared roots of the elements in the main diagonal of matrix V, estimated as follows: $\widehat{V} = R^{-1} \sum_{r=1}^{R} \left(\widehat{\Omega}(r) - \widehat{\Omega}\right)\left(\widehat{\Omega}(r) - \widehat{\Omega}\right)^T$.

The Kendall's τ, estimated in step 3, is the basis for the three tests of contagion developed here. The same bootstrap procedure, used to obtain standard errors of the dependence parameters, is used to obtain standard errors for the various test statistics. The first of such tests assesses the existence of contagion by checking whether dependence between the global indices increases from the pre-crisis to the crisis period. This test's null hypothesis is the absence of contagion:

$$\begin{cases} H_0 : \Delta\tau(i) = \tau_{crisis}(i) - \tau_{pre-crisis}(i) \leq 0 \\ H_1 : \Delta\tau(i) = \tau_{crisis}(i) - \tau_{pre-crisis}(i) > 0 \\ i = \text{Belgium, France,Netherlands,Portugal} \end{cases} \tag{7}$$

Note that $\tau^{(i)}_{crisis}$ is the global dependence measure between the US global index and the global index of market i, for the crisis period and $\tau^{(i)}_{pre-crisis}$ has the same meaning, but refers to the pre-crisis period; $\Delta\tau(i)$ represents the increase in the global dependence measure between the US global index and the global index of market i, from the pre-crisis to the crisis period.

Test 2 investigates if contagion is more intense in index i than in index j. If this is the case, the increase in dependence from the pre-crisis to the crisis period, between the US global index and global index of country i is higher than the increase in dependence between the US global index and global index of country j, in the same periods. This test is defined as:

$$\begin{cases} H_0 : \Delta\tau\,(i, j) = \left(\tau_{crisis}\,(i) - \tau_{pre-crisis}\,(i)\right) - \left(\tau_{crisis}\,(j) - \tau_{pre-crisis}\,(j)\right) \leq 0 \\ H_1 : \Delta\tau\,(i, j) = \left(\tau_{crisis}\,(i) - \tau_{pre-crisis}\,(i)\right) - \left(\tau_{crisis}\,(j) - \tau_{pre-crisis}\,(j)\right) > 0 \\ i, j = \text{Belgium, France,Netherlands,Portugal} \\ i \neq j \end{cases} \tag{8}$$

Note:$\Delta\tau\,(i, j) = \Delta\tau\,(i) - \Delta\tau\,(j)$.

The third test evaluates whether the stock markets anticipated the spreading of financial contagion to the industrial indices by comparing the intensity of contagion in indices representing financial firms and in indices representing the industrial firms listed in the analysed European stock markets. Accordingly, if the stock markets data reflect the fact that the crisis is mainly financial, the increase in dependence between the US market global index and each European financial indices should be stronger than the increase in dependence between the US market global index and each European industrial sector indices, from the pre-crisis to the crisis period.

$$\begin{cases} H_0 : \Delta\tau_{Fin-Ind}\,(i) = \left(\tau^{Fin}_{crisis}\,(i) - \tau^{Fin}_{pre-crisis}\,(i)\right) - \left(\tau^{Ind}_{crisis}\,(i) - \tau^{Ind}_{pre-crisis}\,(i)\right) \leq 0 \\ H_1 : \Delta\tau_{Fin-Ind}(i) = \left(\tau^{Fin}_{crisis}\,(i) - \tau^{Fin}_{pre-crisis}\,(i)\right) - \left(\tau^{Ind}_{crisis}\,(i) - \tau^{Ind}_{pre-crisis}\,(i)\right) > 0 \\ i = \text{Belgium,France,Netherlands,Portugal} \end{cases} \tag{9}$$

$\tau^{Fin}_{crisis}(i)$ is the global dependence measure between the US global index and the financial index of market i, for the crisis period, and $\tau^{Fin}_{pre-crisis}(i)$ has the same meaning, but refers to the pre-crisis period. The superscripts "Fin" and "Ind" represent the financial and industrial sectoral indices, respectively.

The results of the estimation process described in steps 1 to 4 and of the three tests of contagion depicted above are presented in the following section.

4 Estimation results

After confirming, with Ljung–Box–Pierce and ARCH of Engle tests, that the series of indices' returns display evidence of time dependence, both in mean and in variance, ARMA models are selected for the average return of each index, subsequently estimated by maximum likelihood, along with GARCH models for the respective variances. The trend of the conditional volatility of filtered returns, for the pre-crisis and the crisis periods, obtained with the Hodrick–Prescott's filter with a smoothing parameter of 1.000.000, is displayed in Fig. 2.[8]

The notorious increase in volatility, following the burst of the mortgage bubble, reflects the turbulence experienced by the different markets. Not surprisingly, for a crisis of financial origin, the highest increases are experienced by the stock indices representing the financial sector. The Portuguese and Belgian financial indices appear to be relatively less affected, with volatilities inverting the growth trend by the end of the analysed period.

Following the procedure described in step 2, the marginal distributions are estimated by maximum likelihood and the most adequate, within a set of Gumbel, Gaussian, logistic and *t*-Student distributions, is selected with the AIC. Table 2 contains the selected functions.

The logistic distribution is chosen for the majority of indices. Although the values of the likelihood functions for the logistic and the *t*-Student distributions are similar, the AIC selects the former, for efficiency reasons, as it involves the estimation of one parameter less. The shape of both distributions is akin and the fact that they are both chosen in most cases suggests the existence of heavy tails in the series of filtered returns, especially in the pre-crisis period, but no asymmetry, since the Gumbel distribution is never selected.

The univariate distributions are used to estimate the copula models for the pairs of indices under observation in this study, following the procedures described in step 3. In the sake of brevity, not all the estimated results are shown, but are available upon request. The selected copulas for the global and sectoral indices, in the pre-crisis and in the crisis periods, are displayed in Tables 3 and 4.

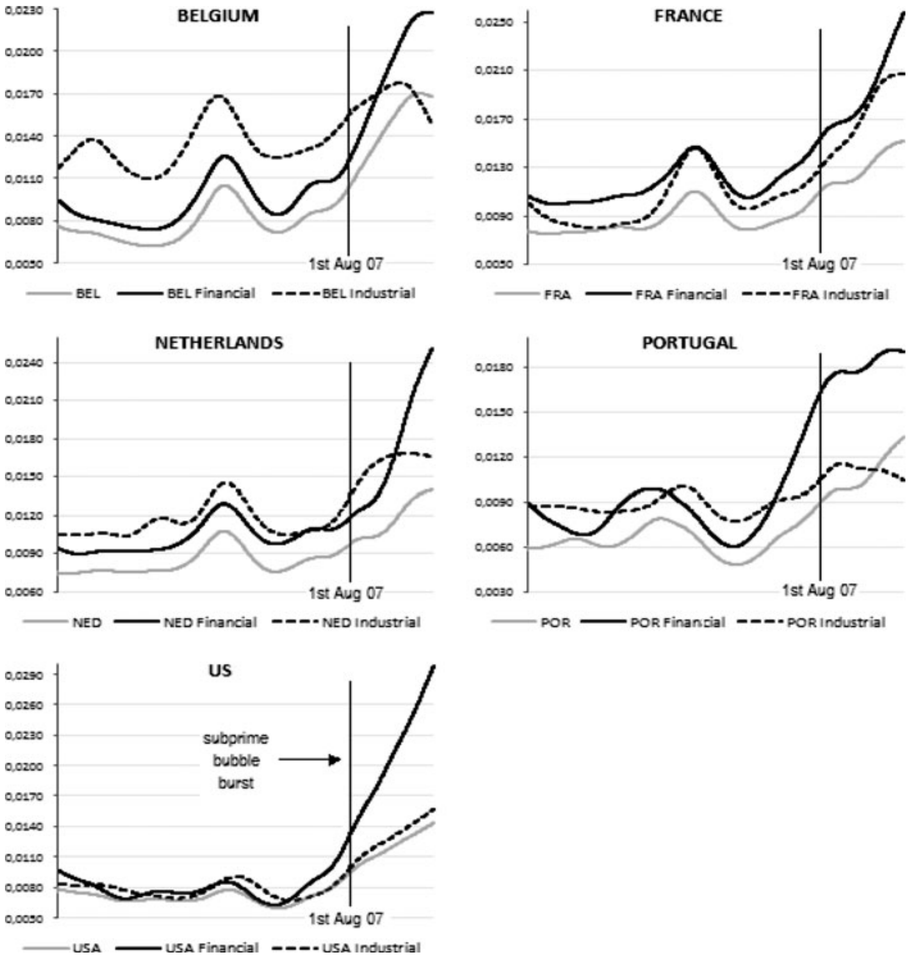
The copulas' parameters (θ, ν and w), along with rank correlations (τ and ρ) and asymptotic tail coefficients (λ_U and λ_L) are shown in Table 3.

Table 4 contains the copulas selected to model the dependence structures between the US global stock market index and the indices representing the financial and industrial sectors of European stock markets in the NYSE Euronext group. The comparative analysis of the information displayed in

[8] Ravn and Uhlig (2002) suggested the use of the following equation to adjust the Hodrick–Prescott's parameter (λ) to the frequency of the data: $\lambda = s^n$*1,600, where s is related to the frequency of the data ($s = 1/4$ for annual data, $s = 3$ for monthly data, and $s = 90$ for daily data) and n is close to 4. Other authors have suggested alternative values for n. For instance, Backus and Kehoe (1992) used $n = 2$ and Correia et al. (1992) used $n = 1$. In our case (daily data), λ would be 104.976.000.000 if $n = 4$, 12.960.000 if $n = 2$, and 144.000 if $n = 1$. Since our objective was simply to get a good visual perception of the series' trends, we used $\lambda = 1.000.000$. However, the choice of λ has no implications for the tests performed ahead.

Tables 3 and 4 suggests that the copulas selected for the sectoral and global indices are often distinct. The Clayton copula, for instance, although never chosen for pairs of global indices, is selected for the US–Belgium/Industrial pair, in both periods, thus suggesting that the link between these two indices is more pronounced in cases of sharp decreases than in those of high returns. The US index and the Belgian industrial index are thus more prone to joint crashes than booms.

For global indices, during the crisis period, the Gumbel copula is selected in two, out of four, country pairs and, in the US–France pair, the Clayton–Gumbel mixed copula places most of the weight on the Gumbel part. This



Note: This figure graphs the conditional volatility of filtered returns' trends for global and sectoral indices of the five countries in the sample, before and after the burst of the mortgage bubble.

Fig. 2 The trend of the conditional volatility of filtered returns suggests that there is strong upper tail dependence between the US and the European markets. In order to improve our understanding of the reasons why the Gumbel copula tends to be selected, we looked for days in which the global indices from the US, France, The Netherlands and Belgium displayed simultaneous increases of more than 1.5%. Seven days were identified. Subsequently, we searched the media for news that could have influenced the behaviour of the stock markets in such days. News related to the Fed's monetary policy decisions emerged in three of them.[9] In the other three, there was unexpected news of good performance on the part of some major US banks.[10] Therefore, the existence of more pronounced upper tails in the copulas estimated for the crisis period may be related to the high sensitivity of investors towards news on monetary policy measures designed to react to the crisis and on banks performing better than anticipated.

Another relevant aspect resulting from the analysis of Table 3 is the fact that the Gaussian copula is never selected to represent the structure of dependence between pairs of indices. This supports our choice of the copula methodology in this analysis, rather than alternative techniques, such as the estimation of some form of corrected linear correlation coefficients, requiring the utilization of normally distributed data (which is definitely not the case of all assessed series of indices).

Although dependence coefficients from distinct copulas are not comparable, rank correlation measures, directly computed from the copulas, may be used to evaluate the global dependence structures between pairs of indices across the sample.[11] The values for the Kendall's τ and the Spearman's ρ

[9]On 17 August 2007, the Fed unexpectedly cut the reference interest rate in 50 b.p. which appears to have motivated a generalized increase in stock exchange indices. On 28 November 2008, the vice-chairman of the Fed made public comments which, according to the Reuters, generated expectations of future cuts of the reference rate. On 1 April 2008, the Financial Times reported that monetary policy actions to combat the financial crisis were discussed by central banks and governmental authorities at the Rome's Financial Stability Forum.

[10]The publication of quarterly reports by major financial institutions, revealing results above expectations, promoted increases in stock exchange indices (Reuters). Examples were Goldman and Sachs and Lehman Brothers, on 18 March 2008, Citigroup (though with news of negative results), on 18 April 2008, and JP Morgan Chase, on 16 April 2008.

[11]Rank correlation coefficients from distinct copulas are directly comparable and may be used to assess dependence, just like the copulas' global dependence parameters. Following Eq. 4, for the case of the Gumbel copula, the Kendall's τ is expressed as a function of that copula's global dependence parameter, $\theta: \ \tau = 1 - \frac{1}{\theta}; \theta \in [1, \infty)$. For the Clayton copula, the relation between the τ and the θ is: $\tau = \frac{\theta}{\theta+2}; \theta \geq 0$. It is possible to convert each copula's global dependence parameter into rank correlation measures, which allow direct comparisons of global dependence between variables. However, if the interest is not on global, but rather on local dependence, the copulas also allow such analysis. One possibility is to extract the asymptotic tail coefficients from each copula, using Eqs. 5 and 6, to compare asymptotic dependence between variables (this cannot be done using rank correlation coefficients). Flexibility is thus one additional advantage of using copulas in tests of financial contagion, or in other contexts where the understanding of the links between financial variables is important.

Table 2 Distribution functions for the series of the filtered returns

		Belgium	France	The Netherlands	Portugal	US
Global	Pre-crisis	Logistic	Logistic	Logistic	Logistic	Logistic
	AIC	−459.5	−478.3	−462.5	−446.7	−457.3
	Crisis	Logistic	Gaussian	Gaussian	Logistic	Logistic
	AIC	−191.3	−182.5	−189.6	−169.8	−187.9
Financial	Pre-crisis	Logistic	Logistic	Logistic	t	–
	AIC	−481.1	−478.8	−473.6	−416.0	–
	Crisis	Gaussian	Gaussian	Gaussian	Logistic	–
	AIC	−186.1	−183.3	−191.1	−179.3	–
Industrial	Pre-crisis	Logistic	Logistic	Logistic	Logistic	–
	AIC	−466.9	−474.5	−463.7	−427.2	–
	Crisis	Gaussian	Gaussian	Logistic	Logistic	–
	AIC	−188.4	−178.4	−179.8	−193.5	–

These are the selected distribution functions for the marginal

increase from the pre-crisis to the crisis period for all analysed pairs of indices and are always smaller for the pairs involving Portugal. This suggests that contagion effects from the US subprime crisis do exist, are distinct across the analysed European markets and are weaker in Portugal. Such suggestion is formally assessed below with tests 1 and 2. The spreading of the crisis across the financial and industrial sectoral indices is examined with test 3.

The existence of contagion is confirmed as the increases in dependence from the pre-crisis to the crisis period are statistically significant. This evidence is obtained with test 1, whose results are shown in Table 5. In order to build the probability function for $\Delta\tau$, 1,000 replications were performed in the bootstrapping procedure ($R = 1{,}000$). For each replica, the values of $\Delta\tau$ were collected, ordered and used to build a probability distribution function and in the calculus of the *p-values,* considering the absence of contagion as the null hypothesis (H0: $\Delta\tau \leq 0$). The$p$-values are obtained in a unilateral test, reflecting the probability mass to the left of point $\Delta\tau = 0$.

For the pairs involving Belgian, French and Dutch indices, the null of no contagion is rejected at the 5% significance level, whereas for the Portuguese case rejection occurs at the 10% significance level. As a priori expected, the indices for which rank correlation parameters are higher, and thus appear to be connected with stronger links to the US market, in both periods, are those apparently exhibiting the strongest signs of contagion.

The results of the test for sectoral indices are displayed in Table 6.

Evidence of contagion appears to be stronger in financial than in industrial indices, thus suggesting that stocks of the industrial sector are, during the period covered by our sample, relatively less exposed to the effects of the US crisis. The Belgian industrial index, for instance, displays no statistically significant signs of contagion and, in the French case, statistical significance exists only at the 10% level.

Table 3 Copula models for global indices

Global	US/Belgium	US/France	US/The Netherlands	US/Portugal
Pre-crisis period				
Selected copula	*t*-Student	*t*-Student	*t*-Student	*t*-Student
AIC	−124.8	−188.2	−164.2	−39.5
Dependence parameter (θ_1)	0.4048 (0.0371)	0.4803 (0.0346)	0.4531 (0.0349)	0.2395 (0.0390)
Degree of freedom (ν)	9.8953 (5.1463)	6.5568 (3.3933)	7.1885 (3.3669)	12.4256 (4.8465)
Kendall τ	0.2653 (0.0258)	0.3189 (0.0252)	0.2993 (0.0249)	0.1540 (0.0256)
Spearman ρ	0.3893 (0.0362)	0.4631 (0.0340)	0.4364 (0.0342)	0.2293 (0.0375)
Tail λ_U	0.0550 (0.0426)	0.1442 (0.0561)	0.1164 (0.0503)	0.0128 (0.0208)
Tail λ_L	0.0550 (0.0426)	0.1442 (0.0561)	0.1164 (0.0503)	0.0128 (0.0208)
Crisis period				
Selected copula	Gumbel	Clayton–Gumbel	Gumbel	Frank
AIC	−63.4	−73.0	−73.0	−19.0
Dependence parameter (θ_1)	1.5878 (0.0990)	26.7144 (20.1415)	1.6102 (0.1031)	2.1048 (0.4757)
Dependence parameter (θ_2)	–	1.5625 (0.4165)	–	–
Weight parameter (w_1)	–	0.0874 (0.1666)	–	–
Weight parameter (w_2)	–	0.9126 (0.1666)	–	–
Kendall τ	0.3702 (0.0386)	0.4099 (0.0451)	0.3789 (0.0393)	0.2242 (0.0463)
Spearman ρ	0.5248 (0.0496)	0.5536 (0.0557)	0.5360 (0.0502)	0.3317 (0.0637)
Tail λ_U	0.4527 (0.0414)	0.4031 (0.0680)	0.4620 (0.0419)	–
Tail λ_L	–	0.0852 (0.0728)	–	–

Standard errors in brackets. Symmetric dependence structures: *t*-Student and Frank copulas. Right-hand side dependence more intense: Gumbel copula. Left-hand side dependence more intense: Clayton copula

The assessments of contagion developed with global indices indicate that all analysed European stock markets appear to have been affected. In what follows, tests of contagion intensity are performed to ascertain whether the US crisis affected each stock market with the same intensity. The results of test 2 for global indices, with a null hypothesis of homogeneous contagion intensity, are displayed in Table 7.

Each number represents the difference between the value of τ for one pair of indices, in the pre-crisis and in the crisis periods, subtracted from the difference between the τ for another pair of indices in the same periods. For instance, the first figure in the first line (0.0139) is the difference between the τ for the pair US–Belgium, in the pre-crisis and in the crisis periods, subtracted

Table 4 Copula models for sectoral indices

	US/Belgium	US/France	US/The Netherlands	US/Portugal
Financial				
Pre-crisis period				
Selected copula	Gaussian	*t*-Student	*t*-Student	Clayton
AIC	−112.3	−152.4	−134.4	−28.5
Dependence parameter (θ_1)	0.4047	0.4434	0.4205	0.2288
Degree of freedom (ν)	–	7.1110	8.6488	–
Kendall τ	0.2652	0.2925	0.2763	0.1027
Spearman ρ	0.3891	0.4270	0.4046	0.1535
Tail λ_U	–	0.1114	0.0764	–
Tail λ_L	–	0.1114	0.0764	0.0484
Crisis period				
Selected copula	Gaussian	Gaussian	Frank	Gaussian
AIC	−56.4	−70.9	−63.6	−14.6
Dependence parameter (θ_1)	0.5266	0.5773	4.1055	0.2983
Kendall τ	0.3531	0.3918	0.3959	0.1928
Spearman ρ	0.5089	0.5593	0.5673	0.2859
Tail λ_U	–	–	–	–
Tail λ_L	–	–	–	–
Industrial				
Pre-crisis period				
Selected copula	Clayton	*t*-Student	Gaussian	Clayton
AIC	−38.6	−116.0	−60.2	−19.9
Dependence parameter (θ_1)	0.2490	0.3943	0.3032	0.1897
Degree of freedom (ν)	–	11.5813	–	–
Kendall τ	0.1107	0.2581	0.1961	0.0866
Spearman ρ	0.1654	0.3790	0.2907	0.1297
Tail λ_U	–	0.0366	–	–
Tail λ_L	0.0618	0.0366	–	0.0259
Crisis period				
Selected copula	Clayton	Frank	Gaussian	Frank
AIC	−14.9	−42.0	−36.7	−13.4
Dependence parameter (θ_1)	0.3411	3.2018	0.4419	1.7452
Kendall τ	0.1457	0.3246	0.2914	0.1883
Spearman ρ	0.2167	0.4725	0.4255	0.2797
Tail λ_U	–	–	–	–
Tail λ_L	0.1310	–	–	–

Symmetric dependence structures: Gaussian, *t*-Student and Frank copulas. Left-hand side dependence more intense: Clayton copula

Table 5 Tests of financial contagion in global indices

Global indices	$\Delta\tau$	*p* value
US/Belgium	0.1049[a]	0.0110
US/France	0.0910[a]	0.0440
US/The Netherlands	0.0796[a]	0.0440
US/Portugal	0.0702[b]	0.0860

[a]Mean significance (contagion) at 5% level
[b]Mean significance (contagion) at 10% level

Table 6 Tests of financial contagion in sectoral indices

	$\Delta\tau$	p value
Financial		
US/Belgium	0.0879[a]	0.0320
US/France	0.0993[a]	0.0260
US/The Netherlands	0.1196[a]	0.0180
US/Portugal	0.0901[a]	0.0400
Industrial		
US/Belgium	0.0350	0.2160
US/France	0.0665[b]	0.0860
US/The Netherlands	0.0953[a]	0.0180
US/Portugal	0.1017[a]	0.0210

[a]Mean significance (contagion) at 5% level
[b]Mean significance (contagion) at 10% level

from the difference between the τ for the pair US–France in the same periods: $0.0139 = (0.3702 - 0.2653) - (0.4099 - 0.3189)$. Positive numbers, as is always the case in Table 7, suggest that index i has been more seriously affected than index j. Negative numbers would suggest the opposite. However, the null hypothesis could never be rejected, thus indicating that there are no statistically significant differences in contagion intensities and all stock markets have been equally affected by the US crisis.

The final test in this analysis, whose results are displayed in Table 8, checks whether investors anticipated the spreading of the financial crisis to the industrial sector, within the analysed time period. The null hypothesis of test 3 is one of contagion homogeneity in financial and in industrial sectoral indices.

As in Table 7, positive numbers indicate that financial indices have been more seriously affected than industrial ones. This appears to be the case for all markets but the Portuguese. Notwithstanding, the null could never be rejected and thus no evidence of stronger contagion in one of the two sectors could be found for any market. This result suggests that, although the US subprime crisis is financial in nature, and in spite of the results of test 1 indicating that some industrial indices appear to be less affected than financial ones, the intensity of the crisis' impact upon the European industrial and financial indices is not statistically distinguishable.

Table 7 Tests of contagion intensity across markets

	$\Delta\tau(i,j)$	Index j			
		Belgium	France	The Netherlands	Portugal
Index i	Belgium		0.0139	0.0253	0.0347
	France			0.0114	0.0208
	The Netherlands				0.0094
	Portugal				

Table 8 Tests of contagion intensity in financial and industrial indices

	$\Delta\tau_{\text{Fin}-\text{Ind}}$	Industrial Index			
		Belgium	France	The Netherlands	Portugal
Financial Index	Belgium	0.0529			
	France		0.0328		
	The Netherlands			0.0243	
	Portugal				−0.0116

5 Conclusions

The copula theory was used to assess financial contagion from the US subprime crisis to the European stock markets in the NYSE Euronext group, with data on global, industrial and financial indices, from January 2005 to April 2008. Assuming that the crisis began with the burst of the mortgage bubble in August 2007, the dependence structures between the US and each European index, in the pre-crisis and in the crisis periods, are compared.

Maximum likelihood procedures were employed to estimate distribution functions for the individual indices, copula models and the parameters to be used in tests of contagion. In such tests, attention was focused on the Kendall's τ, and not on each copula's dependence coefficients, because it allows direct comparisons of distinct copula models. Furthermore, the Kendall's τ was chosen as a measure of global dependence over the more commonly used Pearson's linear correlation coefficient, reliable for elliptic distributions only, as it is appropriate for many types of distributions and thus ensures more robust testing.

Three empirical tests of contagion were performed. The first suggests that, with the exception of the stock index representing Belgian industrial firms, all remaining global and sectoral indices exhibit statistically significant contagion signs. Statistical significance is however weaker in the cases the US and Portugal (for global indices) and the US and France (for the industrial index). In line with the definition of contagion proposed by Forbes and Rigobon (2002), co-movements between the analysed stock markets have become more pronounced after the bursting of the mortgage bubble. Despite the differences uncovered by the first test, the second test indicates that there are no statistically significant differences in contagion intensity amongst global indices, and thus that the crisis is affecting all countries' stock markets with identical strength. Finally, the third test suggests that contagion signs are equally intense across financial and industrial indices, indicating that investors anticipated from an early stage that the financial crisis would spread to industrial sectors, long before such dissemination was observable in the real economy.

The empirical assessments developed in this study were performed with a methodology still relatively unusual in the financial context, but proofed to be robust enough to have been able to identify the seriousness and the wide potential effects of the subprime crisis, when the most mediatised episodes and the more visible signs of contagion were still to emerge. The study reveals that contagion spread in a few months after the burst of the subprime bubble, was equally felt across a variety of countries and was not circumvented to financial sector indices. In addition to the specific object of this analysis, the use of copulas to test contagion also produced evidence useful in other contexts. For instance, it may be interesting for those involved in risk evaluation or in portfolio diversification that not only the strength of the links between markets but also their nature was significantly changed following the crisis, and that the connections with the US market have become more heterogeneous.

In the pre-crisis period, all pairs of global indices were linked by a *t*-Student copula. By then, the French index appeared to be the most correlated with the US's, presenting the highest dependence coefficient, followed by the Dutch, the Belgian and, the least dependent index in this sample, the Portuguese. After the burst of the mortgage bubble, most selected copula models display a strong upper tail dependence and small or no lower tail dependence. In the pair involving the Portuguese index, on the other hand, the Frank copula, which exhibits perfect symmetry and tail independence, is chosen. These results appear to contradict the conclusions of Longin and Solnik (2001), Ang and Chen (2002), or Ang and Bekaert (2002), according to whom markets tend to be more connected in down markets and thus that diversification opportunities dwindle precisely when they are most needed. In this study, in spite of the fact that the null of no contagion is clearly rejected in all cases, most global European indices appear to be more prone to boom with the US index than to crash with it. On the other hand, the copulas selected for the industrial and financial indices are often distinct between them and from those chosen for the global indices. The links between European industrial indices and the US are more asymmetric than those of the financial sector. For instance, the Clayton copula, which is never selected for the global indices, is selected to represent the pair US–Belgium/Industrial, here showing that the relationship between the two series is more pronounced when returns fall abruptly.

The results of the three tests suggest that, with the exception of the industrial sector of the Belgian stock market, contagion from the US subprime crisis spread to all analysed stock markets. Furthermore, the fact that this is a crisis of financial origin did not prevent the anticipation, on the part of stock market investors, of a spreading to the industrial sector indices. Taking into account the implications of such contagion assessments for investors and monetary authorities, the increased dependence between indices may be a sign for portfolio managers to reconsider the geographical and sectoral allocation of assets, taking into account the specific changes in dependence structures in each case. On the other hand, and given that there appears to be no doubt about the contagious effects of the subprime crisis in these countries, the liquidity supplied by central banks, aiming at controlling the more severe effects of the crisis on the financial sector, appears to be justified.

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