


“Volatility spillovers between energy market and international financial markets”

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Volatility spillovers between energy market and international financial markets

Abstract

Purpose: This research aims to measure the dependence between energy market and international financial markets.

Design/methodology/approach: This study proposes bivariate copula models to capture non-linear relationships in energy sector and eight general indices – S&P 500 Index, DAX-30, Dow Jones, FTSE-100, Nikkei 225, Hang Seng, Shanghai Composite and MSCI World Index – during the subprime mortgage crisis. MSCI World Energy Index and S&P 500 Energy Sector Index are adopted to represent the global energy market. The authors also apply the asymmetric dynamic conditional correlation (A-DCC) model in order to investigate the correlation dynamics among the aforementioned asset classes and the presence of asymmetric responses in conditional variances and correlations to negative returns.

Findings: Findings support that there is financial contagion during the recent financial crisis, even though energy sector had lower impact than other sectors. When extreme financial crashes occur, investors need to swivel to more safe investments.

Originality/value: This study helps interested parties to form a staggered portfolio and avoid markets' turbulence by diversifying their portfolio when they invest in energy sector.

Keywords: energy, financial contagion, copulas, A-DCC model.

JEL Classification: F3, G1.

Introduction

Energy market is a quick developing market and a very interesting business industry. During the last decade, governments' policies became friendlier to the environment. Developed and emerging markets focus to new energy resources in order to avoid the "dependence" from the oil and start using "green" energy. Of course, the renewable energy investments' cost is still high and governments tend to support their development due to their long-term valuable benefits. According to Al-Mulali and Che Sab (2013), governments should increase their investment and spending on green energy projects to increase the share of green energy out of their total energy consumption. Even though the economic environment for new investments is problematic, energy is a key factor for countries' relations and a very important geopolitical subject as energy deals may change the balance between the interested parties as well as their existing economic relations.

Moreover, energy has a significant role in countries' economy and their internal market. When oil prices increase, alternative solutions are needed in order to cover consumers' demand. Since, oil is getting more expensive – as per OPEC's desires – renewable

resources become necessary. Even though energy production depends on huge investments, governments tend to create the ideal economic environment which attracts new investors. Thus, energy investors need motivation and economic and political stability.

Financial markets' stability is a fundamental factor for firms' growth and their stock prices. When markets volatility is high, the consequences are portrayed to anomalies on stock prices, hedge funds, bonds, currency exchange rates etc. Therefore, in turbulent economic periods – like the "subprime" crisis period – aforementioned financial products follow irregular curves.

Furthermore, history confirms that financial rise and economic boom follow markets' decrease soon. Sometimes markets' reaction delays and there is a "domino effect" to the other markets. Boyer et al. (2006) confirmed that crisis is transmitted from one market to another and from one country to the other. This phenomenon is called financial contagion. Many researchers studied this phenomenon, even though the limitations for heteroskedasticity and correlation exist and need further investigation.

This study investigates the dependence between eight general market indices and two energy indices. Both energy indices are widely accepted and represent the development of world energy market and its fluctuation during the period under investigation. On the other hand, the eight general indices present markets' movement on a worldwide basis. Each index represents a specific geographical area and they are used to measure the effect of the subprime crisis – which is the biggest financial shock in the new century – to the energy industry.

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Recent geopolitical developments both in Europe as well as in Middle East have a common denominator, the energy. Cyprus decision to explore natural gas reserves in its territorial waters brought them against country's neighbor, Turkey which also wants to protect its interests, while Syria tries to get back the control of its oil wells since this is very important for country's economy and a fundamental factor to develop further.

On the other hand, energy firms try to expand their operations and market presence all over the world. High competition forces energy companies to look for interesting and profitable projects but this is in positive relation with above mentioned geopolitical developments. So, apart from general ascertainments firms emphasize to further growth. This growth is portrayed in firms' stock prices and – by extension – in global energy indices. Albeit, energy market will always be a very important industry, investors – most of the times – focus on short-term profits as well as safe investments during financial crashes and periods with high volatility. Therefore, the question of this study is the level of energy's correlation with international financial markets and the answer will give the essential information regarding financial contagion.

Thus, the aim of this research is to examine whether this hypothesis exists in the energy sector by adopting copula functions (Normal, Clayton and symmetrized Joe-Clayton). The A-DCC model (Cappiello et al., 2006) is employed to examine the presence of asymmetry during the Subprime crisis.

This paper contributes to the existing literature by: i) testing the contagion hypothesis by applying the A-DCC method during the subprime crisis, ii) comparing the level of dependence among stock markets' and energy indices using copulas and iii) studying a crucial sector with high investment interest worldwide.

Results provide evidence that there is an asymmetric increase at the dependence among stock markets and energy sector during crises periods. Furthermore, the energy sector seems to be influenced less than expected mainly because of energy market's importance and this confirms that investors may create a more diversified portfolio.

The rest of this study is structured as follows. Section 1 presents the literature review while Section 2 states the data used and the methodology followed in order to investigate the financial contagion on energy market during the subprime crisis. Section 3 contains the empirical results and our study's conclusions are stated in the final section.

1. Literature review

The last years the use of the phrase "financial contagion" is rapidly increased. Before we mention

the main bibliographical references regarding the contagion phenomenon we need to state the meaning of the financial contagion. First of all, financial contagion is a small shock to a specific financial market or sector which spreads to a wider range of sectors or countries. In other words, financial contagion acts like a cell which affects the other adjoining cells. After we cite the most important research studies, we will point out our study's methodological issues and the empirical results.

There are many researchers that studied the financial contagion phenomenon both in the past (King and Wadhvani, 1990; Lee and Kim, 1993; Calvo and Reinhart, 1996) and the years that came after the subprime crisis in USA and the Eurozone debt crisis (Spyrou, 2013; Bouri and Yahchouchi, 2014). Results differ since some researchers confirmed the increased correlation after the financial crash and some others opposed to this conclusion.

Lately, the methodologies used to investigate the financial contagion's presence are based – as often as not – on dynamic models. Engle and Sheppard (2001) and Engle (2001) were the first who proposed and used a dynamic conditional correlation GARCH model to surpass previous studies' restrictions regarding the financial contagion. Their main issue was the heteroskedasticity problem when they were trying to estimate the time-varying conditional correlations. Engle and Colacito (2006) among others (Franses and Hafner, 2003; Cappiello et al., 2006; Billio et al., 2006; Aielli, 2007; and Pesaran and Pesaran, 2007) examined alternative models in regard with correlation and variances. Below paragraphs present some modifications of Engle's model.

Aielli (2007) modified Engle's model and proposed a corrected dynamic conditional correlation (cDCC) model. Results indicated that DCC and cDCC models are similar, despite that the cDCC model has a wider applications' range. This new approach led Engle et al. (2011) and Engle and Kelly (2012) to employ relevant applications. Lin et al. (2009) used the DCC model to test the variance, covariance and correlation between the Chinese and the international financial markets. Authors divided in two their sample, to group A which consists of firms offered to Chinese investors and group B which includes firms offered to foreign investors. Findings support that stocks in group A are not correlated with international financial markets while stocks of group B have a low correlation with west countries' financial markets and slightly higher with the Asian financial markets. Jondeau and Rockinger (2009) continued the multivariate GARCH model proposed by Engle and Ng (1993) regarding announcements impact on volatility. Their findings indicate that

portfolios may be hedged effectively against the local volatility when they include foreign stocks after good news, but a bad hedge when bad news are announced. Corsetti et al. (2005) found evidence that financial contagion in other markets does not exist for the sample. Chong and Miffre (2005) concluded that the conditional correlations among commodity futures and global equity returns dropped during crisis. Kuper and Lestano (2008) confirmed time-varying negative correlations in pre-crisis and post-crisis periods and they found extreme negative correlations at the height of crises. Kenourgios et al. (2011) found an asymmetric increase in dependence among stock markets during five crises and that the multivariate regime-switching copula model captured a higher level of dependence than the AG-DCC approach. Samitas and Tsakalos (2013) examined the Greek contagion phenomenon during the Eurozone debt crisis and concluded that financial contagion exists.

In regard with the copulas, Sklar (1959) presented his theorem for continuous conditional distributions. Researchers' interest has increased in the last decade, during which several authors have employed copulas (Frees and Valdez, 1998; Cherubini et al., 2004; Oaks, 1994; Genest et al., 1995; Shih and Louis, 1995; Joe and Xu, 1996; Patton, 2006, 2009; Chen and Fan, 2005a, 2006a, 2006b; Heinen and Valdesogo, 2008, Syriopoulos and Roumpis, 2010; Meucci, 2010; Hafner and Manner, 2012).

Chen et al. (2004) use integral transforms and kernel estimation to test the dependence between financial time series. Patton (2009) uses the concept of the conditional copula to model the time-varying correlation of exchange rates. Li and Kazemi (2007) reject the presence of asymmetry in the conditional correlation between daily hedge fund returns and other investment instruments.

More recently, some other researchers applied copula models to capture the dependence between financial markets. Bhatti and Nguyen (2012) studied the tail dependence between the Australian and other international financial markets, using the conditional extreme value theory and the time-varying copula. Results show that the combination of both found to be useful in determining the tail dependence. Wagener et al. (2012) examined the asymptotic properties of quantile processes under random censoring and they concluded that there is weak convergence of the quantile process is only linear in the investigated region. Nguyen and Bhatti (2012) examined the dependence among oil and emerging financial markets using data from Vietnam and China and applying copula methods. Results provide evidence that there is left tail

dependence between oil price and Vietnam financial market, but no significant dependence compared with the Chinese financial market. Bucher et al. (2012) proposed a new method to test the hypothesis that a bivariate copula is an Archimedean copula and this test is consistent against this hypothesis.

Regarding energy sector, Westner and Madlener (2012) applied real options to analyze investors' decision problem about a non reversible energy investment. Results confirmed energy characteristics have a significant impact on real options value as well as the best time of investment. Wen et al. (2012) examined contagion effect between energy and stock markets during financial crisis and they found evidence of contagion, increased tail dependence; and symmetry characterize all the paired markets, albeit contagion effect was found to be much weaker for China than the US. Reboredo (2011) investigated the correlation oil products' prices employing copulas with different conditional correlation structures. Findings confirmed that symmetric correlations between the oil products' prices exist both in bullish and bearish markets. Also, oil market acts as a huge pool and doesn't differ geographically. Remillard (2012) extended the multivariate model frame of copulas which was initially proposed by Chen and Fan (2006). Authors estimate series independently and use copulas to measure US and Canadian exchange rates' dependence as well as oil future contracts. Wu et al. (2012) support that US dollar devaluation led to oil price increase and that oil prices' and exchange rate's returns are leptokurtic and asymmetric. Authors suggest a dynamic GARCH copula model to test the dependence between us dollar and oil price indices. Lu et al. (2011) combine GARCH copulas to create a conditional joint distribution to estimate the risk value of a portfolio which includes oil and natural gas future contracts. Results confirmed that the most accurate method to estimate their dependence is the Student's t copula. Nguyen and Bhatti (2012) adopted parametric and non parametric copulas to analyze the Chinese and Vietnamese oil prices. Authors concluded that there is a high correlation between the Vietnamese market and oil prices, while the Chinese had the opposite results. Gronwald et al. (2011) used several copula models to test the correlation between the EU gas emissions future options' and other energy future products' returns. Researchers used Gaussian and Student's t copula and confirmed the positive relation between these products which is getting higher during turbulent economic periods.

Despite that literature review recommends various copula models, in our study we did use the Normal, Clayton and the Symmetrized Joe-Clayton copulas.

Copulas were selected after making a goodness-of-fit test. Results propose the previously mentioned copulas which – in most of the cases – fit better in our sample. Also, elliptical copulas (normal copula) give us flexibility to measure efficiently the correlation per pair, while the Archimedean one (Clayton copula) allows us to quantify the dependence to the down tail correlation.

2. Data and methodology

2.1. Data. The sample employed consists of eight international financial indices and two widely accepted world energy indices. The financial indices are the following: MSCI World Index, S&P 500 Index (USA), FTSE-100 (UK), Nikkei 225 (Japan), Hang Seng (Hong Kong), Shanghai Composite (China), Dax (Germany) and Dow Jones (USA). On the other hand the energy indices are the: MSCI World Energy Index and S&P 500 Energy Sector Index. Authors selected previous indices to cover a wide range of financial markets, focusing not only on the common “west economies”, but also on regions where there is intense activity of the energy sector. Thus, apart from the two global indices of Morgan Stanley and Standard & Poor’s, authors use another index based in U.S.A., two European indices – but economies with different currency – and two financial markets based in Far East. The data are obtained from Bloomberg. The sample contains daily observations beginning on January 2,

2005 and ending on April 14, 2011. The examination period is divided into 2 periods: a) the pre-crisis period (Jan 2, 2005 until Dec 31, 2007), b) the Subprime Crisis period (Jan 2, 2008 until April 14, 2011). The period under investigation includes a mature economic environment (pre-crisis period) and a turbulent financial field.

The MSCI World Energy Index captures the large and mid cap segments across 23 developed country markets (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK and the USA). On the other hand, the S&P 500 Energy Index comprises those companies included in the S&P 500 that are classified as members of the Global Industry Classification Standard (GICS) energy sector and is a common benchmark index employed by researchers. Both indices include firms being listed and operating in different regions. This characteristic enables us to use them as global energy benchmarks and compare their performance with different markets, either in America, Europe or Asia.

The following table (Table 1) presents research sample’s descriptive statistics (log returns). The median is higher than the mean in most of the cases, while all indices are positive. All indices appear to have kurtosis higher than three.

Table 1. Descriptive statistics

	DAX 30	Dow Jones	Hang Seng	MSCI Energy	MSCI World	Nikkei 225	S&P 500	S&P Energy	FTSE-100	Shanghai Comp
Maximum	0,1080	0,1051	0,1341	0,1359	0,0910	0,1323	0,1096	0,1696	0,0938	0,0903
Minimum	-0,0743	-0,082	-0,1358	-0,1367	-0,0733	-0,1211	-0,0947	-0,1688	-0,0927	-0,0926
Median	0,0008	0,0004	0,0004	0,0012	0,0007	0,0000	0,0005	0,0007	0,0000	0,000
Mean	0,0003	0,0001	0,0003	0,0003	0,0001	-0,0001	0,0001	0,0004	0,0002	0,2085
St. deviation	0,0142	0,0129	0,0175	0,0176	0,0119	0,0165	0,0141	0,0202	0,0132	0,0165
Kurtosis	11,8686	13,9348	12,2757	13,001	12,4216	12,7622	13,7395	14,086	11,8465	6,9303
Skewness	0,1603	0,0171	0,0816	-0,5543	-0,4285	-0,5934	-0,2592	-0,3882	-0,1154	-0,3183
Observations	1640	1640	1640	1640	1640	1640	1640	1640	1640	1640

2.2. Methodology. The following subsections present the methodologies used to examine if the contagion phenomenon exists. The A-DCC model together with the copula functions are employed to quantify the dependence among the above mentioned markets. The literature provided us with these models to investigate the contagion phenomenon since they lead to safe conclusions. There are several studies which employed these models to measure the dependence between different indices or commodities. Results are remarkable and, according to the theoretical background, clarify the positive or negative relation among them.

2.2.1. Asymmetric dynamic conditional correlation (A-DCC). As we mentioned in previous sections, Engle (2000) first proposed the multivariate Garch

DCC model. The DCC model is based on the constant conditional correlation (CCC) model which was proposed by Bollerslev (1990) and is given by the following relation:

$$H_t = D_t R D_t, \text{ where } D_t = \text{diag} \left\{ \sqrt{h_{i,t}} \right\},$$

where R is the correlation matrix containing the conditional correlations.

The expressions for h are similar to those of the univariate GARCH models, but we can include other predetermined variables as well. Engle (2000) proposed an estimator called the dynamic conditional correlation model, or DCC. The DCC model differs only in allowing R to vary over time. Therefore, the form of Engle’s DCC is as follows:

$$H_t = D_t R_t D_t,$$

$$\text{where } R_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1}$$

$$\text{and } Q_t = [1 - \alpha(1) - \beta(1)]\Gamma + \alpha(L)\eta_{t-1}\eta'_{t-1} + \beta(L)Q_{t-1}.$$

As discussed in Engle (2000), the R parameterizations have the same requirements as those of H , with the exception that the conditional variances must be at unity.

However, this model's handicap was the lack to calculate the asymmetries in conditional variances, covariances and correlations until Cappiello et al. (2006) proposed a modification of this model, which addresses asymmetries in conditional variances, covariances and correlations of two assets. The Asymmetric DCC Model form is as follows:

$$Q_t = (1 - \alpha - b)\bar{Q} - q\bar{N} + az_{t-1}z'_{t-1} + bQ_{t-1} + gn_{t-1}n'_{t-1},$$

where a and b are scalar parameters, g is the asymmetry term, \bar{Q} is the unconditional covariance of the standardized residuals, \bar{N} is the covariance matrix of z_t and n_t is a function indicator that takes the value 1 if the residuals are negative and 0, otherwise.

This model is used by several authors (Jithendranathan, 2005; Gupta and Donleavy, 2009) and led literature to new ways of quantifying the dependence and the contagion phenomenon since it is used to investigate time-varying conditional correlations between financial indices.

2.2.2. *Copula functions.* Copulas introduced before decades and their proponent, Sklar (1959), helped us to understand their versatility to various subjects lately. The need to quantify the relation between two different assets required useful tools which

$$C_N(u, v; \rho) = \Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v)),$$

$$C_N(u, v; \rho) = \frac{1}{\sqrt{1 - \rho^2}} \exp \left\{ \frac{\Phi^{-1}(u)^2 + \Phi^{-1}(v)^2 - 2\rho\Phi^{-1}(u)\Phi^{-1}(v)}{2(1 - \rho^2)} + \frac{\Phi^{-1}(u)^2\Phi^{-1}(v)^2}{2} \right\}, \rho.$$

The Clayton copula Kimeldorf and Sampson copula in Joe (1997)] form is presented below:

$$C_C(u, v; \theta) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta},$$

$$C_C(u, v; \rho) = (1 + \theta)(uv)^{-\theta-1}(u^{-\theta} + v^{-\theta} - 1)^{-2\frac{1}{\theta}}, \theta \in [-1, +\infty] \setminus \{0\}.$$

The Symmetrized Joe-Clayton copula is defined below:

$$C_{SJC}(u, v | \tau^U, \tau^L) = 0.5[C_{SJC}(u, v | \tau^U, \tau^L) + C_{SJC}(1-u, 1-v | \tau^U, \tau^L)] + u + v - 1.$$

would not only lead us to “logical” results, but to help us investigate different time series which might not have direct impact to each other. Normal, Clayton and Symmetrized Joe-Clayton copulas – presented below – are used to reach the above mentioned goal:

Copula functions were introduced by Abe Sklar in 1959. These functions are restrictions to $[0, 1]^2$ of bivariate distribution functions whose margins are uniform in $[0, 1]$. In short, Sklar showed that if H is a bivariate distribution function with margins $F(x)$ and $G(y)$, then there exists a copula C such that:

$$H(x, y) = C(F(x), G(y)).$$

More specifically, Sklar's theorem for continuous conditional distributions is the following (Patton, 2009 & Patton, 2012):

Let F be the conditional distribution of $X|Z$, G be the conditional distribution of $Y|Z$, and H be the joint conditional distribution of $(X, Y)|Z$. Assume that F and G are continuous in x and y , and let z be the support of Z . Therefore, there exists a unique conditional copula C such that:

$$H(x, y|z) = C(F(x|z), G(y|z)|z), \forall (x, y) \in \bar{R} \times \bar{R} \text{ and each } z \in z:$$

In this research, we employ a Normal copula, a Clayton copula and a Symmetrized Joe-Clayton copula to obtain the information needed to produce a conclusion. The literature has proposed several copula functions to be used in a range of cases, but the most common are the ones used in this study. The role of copula functions in this study is to reconfirm the A-DCC model's results and measure market dependence with specific parameters.

The Normal copula has the following form:

where τ^U , τ^L , govern the upper and the lower tails of the distribution, respectively.

The main advantage of copula functions is that they allow us to distinguish between the dependence and the marginal distribution and to model them separately. Copulas are simple and help researchers to define nonparametric measures of dependence for pairs of random variables.

3. Empirical results

3.1. Asymmetric dynamic conditional correlation results. Table 2 presents the A-DCC model results obtained by using all sectors, where the g -term is always positive which is a clear evidence that there are asymmetry movements. Moreover, terms a and b found to be also positive, despite their summation is lower than the unique ($a + b < 1$) which supports the existence of dynamic correlations. Generally, the

financial contagion phenomenon exists, as it was initially expected. Even though the contagion phenomenon is clear, energy market is fundamental sector and a key factor which keeps energy shares' financial value at high levels. Results provide evidence regarding the correlation increase during the financial crisis period. During the pre-crisis period the a and b terms fluctuate at lower levels compared to the crisis period in most of the cases. Therefore, high financial markets' volatility affected the energy sector as well. In addition, energy sector is a dynamic sector which promises high profits to investors and attracts investment funds.

Moreover, we employ copula functions to reassess the dependence level and the aforementioned results. Normal, Clayton and Symmetrized Joe-Clayton functions provide additional insights into the debt crisis and its consequences for other markets.

Table 2. Empirical results: asymmetric DCC

Index	Pre-crisis period			crisis period		
	a_i	b_i	g_i	a_i	b_i	g_i
S&P 500 Energy	0.0514*	0.0861*	0.9059*	0.0472*	0.0441*	0.9384*
MSCI World Energy	0.0412*	0.0772*	0.9143	0.0391*	0.0566*	0.8949
S&P 500	0.0398*	0.1023*	0.8924*	0.0307*	0.0494*	0.9384*
MSCI World	0.0651*	0.0941	0.8971*	0.0714	0.0732*	0.9094*
Dow Jones	0.0952*	0.1130*	0.8831*	0.0799*	0.0451*	0.9437*
Nikkei 225	0.0237	0.1619*	0.8121*	0.0208*	0.0838*	0.9052*
FTSE 100	0.0973*	0.0975*	0.8935	0.0926*	0.1129	0.8768*
Hang Sheng	0.0198*	0.0842*	0.9103*	0.0034*	0.0673*	0.9269*
Shanghai Composite	0.0155	0.0911	0.8922	0.0072	0.0726	0.9182
DAX	0.0727*	0.0963*	0.8961*	0.0877*	0.1130*	0.8389*

Note: * 5% significant level.

Figures presented in Appendix show the dynamic correlations between financial and energy markets. Despite confirmed results the contagion phenomenon figures portray better the dependence relation. Volatility is getting higher during the crash period.

Figure 1 (see Appendix) presents the correlation between the MSCI World Energy index and the selected financial indices during the normal period where we observe the low correlation level with the far east markets (about 0.2) despite the occasional high levels, although correlation with China index is around 0.4. On the other hand, the correlation with the general Morgan Stanley index – the MSCI World index – fluctuates around 0.7.

Figure 2 (see Appendix) shows clearly the Lehman Brothers' collapse and the higher correlation between the indices in examination. Correlation levels are still lower than 0.5 with some exceptions due to energy market singularity.

In Figure 3, the MSCI World Energy index has a higher dependence relation with the west countries'

indices which fluctuates between the range of 0.4 to 0.7 on average. We should also mention that energy sector booms in west economies in comparison with the rest of the world. In Figure 4, we observe a higher correlation between the Morgan Stanley energy index and the Dow Jones, FTSE-100, DAX και S&P 500 indices during the crisis period and, especially, after the Lehman Brothers issue and the panic that conducted to the financial markets.

Figures 5 to 8 present the correlation between the S&P 500 Energy index with the relevant financial market indices. Thus, Figure 5 points out the correlation between the S&P 500 Energy and the Asian markets – Nikkei 225, Shanghai Composite and Hang Seng – as well as the S&P 500 index. Results are similar with Figure 1. The correlation with the first three indices ranges from 0.1 to 0.4. On the other hand, the dependence with the Standard & Poor's index is higher and varies between 0.6 and 0.8. This is an evidence which correlation climbs together with the volatility.

Figure 6 portrays the relevant relation during the crash period. Correlation climbed to levels around 0.8 for the Standard & Poor's indices and at a much lower level between the S&P 500 Energy and the far east indices while Chinese index seems to be diversified due to economies' financial strength.

Figure 7 and Figure 8 state the correlation between the S&P 500 Energy and the west countries' indices (Dow Jones, FTSE-100, DAX and MSCI World) during the pre-crisis and the crisis period. Despite we should expect that we shouldn't have any big differences, the Standard & Poor's energy index is high correlated with the American and the Morgan Stanley index. In this case, the correlation ranges between 0.5-0.7, while the relevant correlation with the European indices varies between 0.2-0.5.

In respect with the financial crisis period, correlation levels increase in all cases. Correlation between the energy index and the European ones fluctuates around 0.55 and gets higher (0.7) after the third quarter of 2008. At the same time, the volatility increases, too. Similar are the findings for the Dow Jones and the MSCI World indices since correlation ranges between 0.6-0.8 till the third quarter of 2008 and rises to the level of 0.8 the period after that.

Figures 1-8 as well as Table 2 prove the asymmetry since factor g is always positive. Moreover, there are dynamic correlations and the contagion phenomenon exists, as expected. However, energy sector is a fundamental sector for countries' economies and despite it follows financial markets' volatility, attracts huge investment funds. The main reason is energy products' importance for the global economy.

3.2. Copula functions' results. Copula functions (Normal, Clayton and Symmetrized Joe-Clayton) employed to re-test financial and energy indices correlation. There are many different methodologies which help researchers to test the correlation between some financial indices, products, stocks etc. Previous sections referred to the A-DCC model and the empirical findings were very close to the expected ones. Despite we could stand on these findings and support our policy implications, we employed copulas to confirm previous results.

Table 3 (see Appendix) presents the empirical findings of the copula functions we adopted, Normal, Clayton and the Symmetrized Joe-Clayton (SJC) copulas. In Table 3, the dependence level rises during the volatile period. Most of the figures presented arise from one period to the following. During the pre-crisis period, the calculated numbers show an existing low correlation, albeit in many cases this is logical. On the other hand, when crisis

period begins, this correlation is getting higher implying the interdependence among the financial indices of our sample. Energy indices, as well as far east indices (Hang Seng, Shanghai Composite and Nikkei) have lower dependence compared with the rest financial markets and the two widely accepted indices built from Morgan Stanley and Standard & Poors' (MSCI World και S&P 500).

More specifically, the MSCI World Energy compared with the German index, the DAX 30, has a clear impact after the financial crash not only with the normal and the Clayton copula functions, but also with the SJC copula. Thus, the dependence level climbs from 0.4504 and 0.6122 to 0.6952 and 1.5037, respectively, while the SJC copula also rises from 0.1571/0.000 to 0.4398/0.0000. Similar are the findings compared with the Dow Jones index, where all three methods indicate a significant rise from 0.5116 (Normal copula), 0.7569 (Clayton copula) and 0.3293/0.0010 (SJC) to the level of 0.7608, 2.0496 and 0.4739/0.0078, respectively.

Regarding the Hang Seng index, results are the same, despite the impact is much lower than before either with the Normal (from 0.1846 to 0.3509), the Clayton (from 0.2645 to 0.5159) and the SJC (from 0.1101/0.0000 to 0.3499/0.0017) copula. As we pronounced the Japanese index, the Nikkei 225, has the same impact level with the Hang Seng index since the pre-crisis levels (0.1416, 0.1981 and 0.2814/0.0011) increased during the crash period (0.2004, 0.2796 and 0.4597/0.0590). Similar are the results for the Chinese Index, the Shanghai Composite, from 0.1577 to 0.2407 (Normal copula), from 0.2001 to 0.4872 (Clayton copula) and from 0.1510/0.0000 to 0.2943/0.0000 (SJC copula). The British index – FTSE 100 – confirms the enlarged dependence levels and the financial crisis impact is portrayed both with the Normal copula (from 0.5545 to 0.7067), the Clayton copula (from 0.8562 to 1.6215) and the SJC copula (0.1432/0.0000 to 0.3100/0.0000).

In respect to the "global" indices of Morgan Stanley (MSCI World) and Standard & Poor's (S&P 500), results follow a positive relation and correlation increases. Thus, compared to the MSCI World index, research findings indicate that the Normal copula mounts from 0.5800 to the level of 0.7877, the Clayton copula from the level of 0.9192 to 2.2968 and the SJC copula from 0.2795/0.000 to 0.4288/0.0022. Along with the previous indices, the two energy indices are highly correlated. Basing on the Normal copula, results state that there is a significant dependence from 0.9289 to 0.9422, while the Clayton copula climbs to 5.3912 from the level of 4.1608 during the pre-crisis period and SJC copula rises to 0.4467/0.0014 from the level of 0.2293/0.0000.

With respect to the S&P 500 Energy, results are similar to all the benchmark indices. The German index, DAX 30, has a significant correlation lift with the S&P 500 Energy with the Normal copula (0.3069 to 0.5754), the Clayton copula (0.3690 to 1.1060) and the SJC copula (0.1122/0.0000 to 0.3904/0.0001). The other European index (FTSE-100) takes the values of 0.3835, 0.4936 and 0.1904/0.0001 during the pre-crisis period and the values 0.5576, 1.0596 and 0.4965/0.0146 during the crash period.

Regarding the American index, there is a substantial rise from the levels of 0.5461, 0.8628 and 0.2105/0.0000 to the levels of 0.8115 (Normal copula), 2.5030 (Clayton copula) and 0.4211/0.0015 (SJC copula), respectively. On the other hand, the asian indices – Hang Seng, Shanghai Composite and Nikkei 225 – have a lower impact on their correlation with the Standard & Poor's energy index. Hang Seng fluctuated from 0.1306, 0.1767 and 0.1761/0.0001 to the levels of 0.2787 (Normal copula), 0.3814 (Clayton copula) and 0.3128/0.0001 (SJC copula) during the volatile period. The second asian index – Nikkei 225 – found to be correlated at the levels of 0.0951 (Normal copula), 0.1447 (Clayton copula) and 0.1202/0.0000 (SJC copula) during the first sub period which strengthens during the crash period (0.1294, 0.1931 and 0.3702/0.0016, respectively). Same for the Shanghai Composite, from 0.1103 to 0.1923 (Normal copula), from 0.01548 to 0.2225 (Clayton copula) and from 0.1324/0.0000 to 0.4599/0.0015 (SJC copula).

Finally, the Standard & Poor's energy index is highly correlated with the S&P 500 since the normal copula increases (0.6192 to 0.8390), the other two confirm the results (1.0647 to 2.8526, Clayton and 0.1895/0.0000 to 0.4591/0.0049). In same order, the correlation with the MSCI World index climbs (0.5944, 0.9628 and 0.1783/0.0000, the normal period and 0.8092, 2.4270 and 0.4789/0.0031, the crash period basis the Normal, Clayton and SJC copula, respectively).

We do observe that all three copula methods lead us to the same empirical results with the A-DCC model. The increased correlation is clear and supports the contagion phenomenon and the increased volatility. In all cases, Figures tend to increase during the crash period. Even though increased correlation was diagrammatically portrayed in previous section, copula methods nominate the validity of the financial contagion. However, the main empirical finding and contribution to the current literature is that energy sector reacts similarly with the financial markets of our sample. This parallel fluctuation, together with

industry's global nature, strengthens our position regarding the contagion phenomenon.

Despite the ongoing volatile economic sentiment, many authors point out the significance that energy has in the current economic environment. We all see a continuous change in energy map where major transactions between countries and companies are more often than previous decades. After forty years, USA – a huge oil consumer – exported oil and has several export plans after the recent developments in shale gas production. However, when the fluctuation of the financial markets is spiky, investors need to have a clear evidence in regards with the reaction that energy sector would have after a financial shock. Therefore, our study confirms the level of dependence among some of the biggest financial markets and energy industry. Study, also, provides evidence about the financial contagion which is a lead for market makers and interested parties. Energy is a very sensitive sector and several different factors may influence its market value. Energy firms operate in a global environment and its prosperity is in positive relation with major global financial markets.

Conclusion

This research adopted the copula methods and the A-DCC model to quantify the correlation between the two energy indices and the financial market indices. Findings support the contagion phenomenon and the asymmetry movements' existence. Neither the copula function nor the A-DCC model results oppose each other and the results are interesting not only for the energy sector but also for the global economy since the Subprime crisis together with the Eurozone debt crisis affected the correlation between the above mentioned markets. Dependence lifts during the volatile period and results provide evidence for the contagion phenomenon.

Despite the positive long-run expectations for the energy market, energy sector attracts investors since energy market is a safe investment and gives financiers the option to diversify their portfolios and secure their investments. Portfolio allocation is very important due to the turbulent economic environment the last five years. Therefore, investors examine potential niche energy markets as well as well established energy firms to minimize their risk and increase their profits.

In respect to the energy market, it is noteworthy that energy market is a useful political weapon or shield against any kind of political dispute (Baran, 2007). Since energy was governments' monopoly, until the deregulation now, energy market was one of the major fields of politics. It's worth to mention that one of the main reasons that lead countries to lengthy

battles is energy. Iraq, Libya, Iran, Russia, Nigeria, Israel, USA are among the countries which got involved to various conflicts in regards with the oil and natural gas exploration. Thus, energy is one of the most important subjects which affect geopolitical strategies and political stability worldwide.

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Appendix

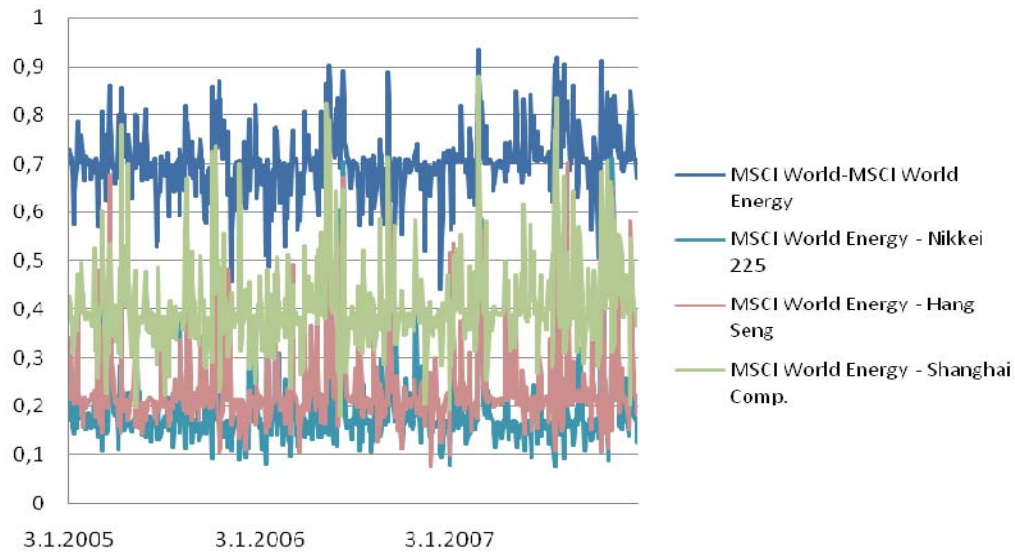


Fig. 1. Pre-crisis correlation: MSCI World Energy Vs MSCI World, Nikkei 225, Shanghai Composite & Hang Seng

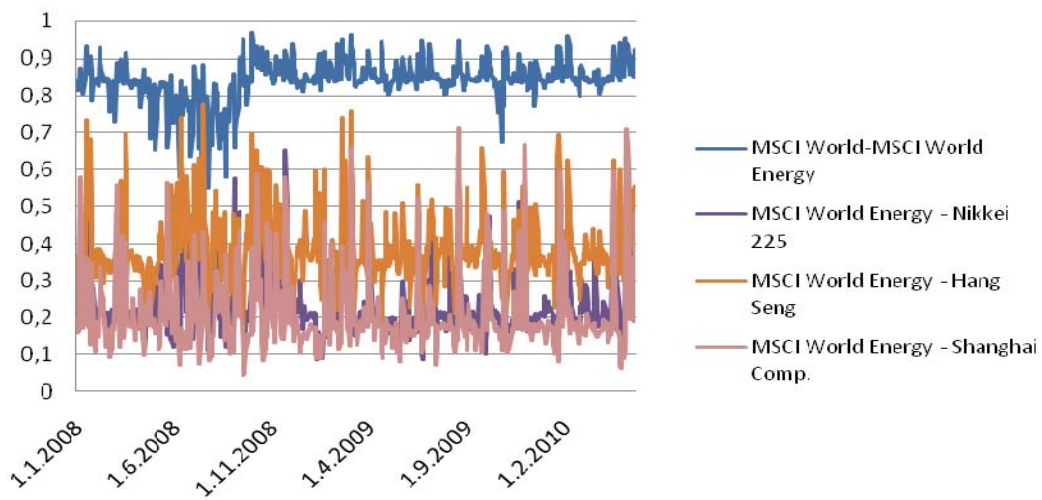


Fig. 2. Crisis correlation: MSCI World Energy Vs MSCI World, Nikkei 225, Shanghai Composite & Hang Seng

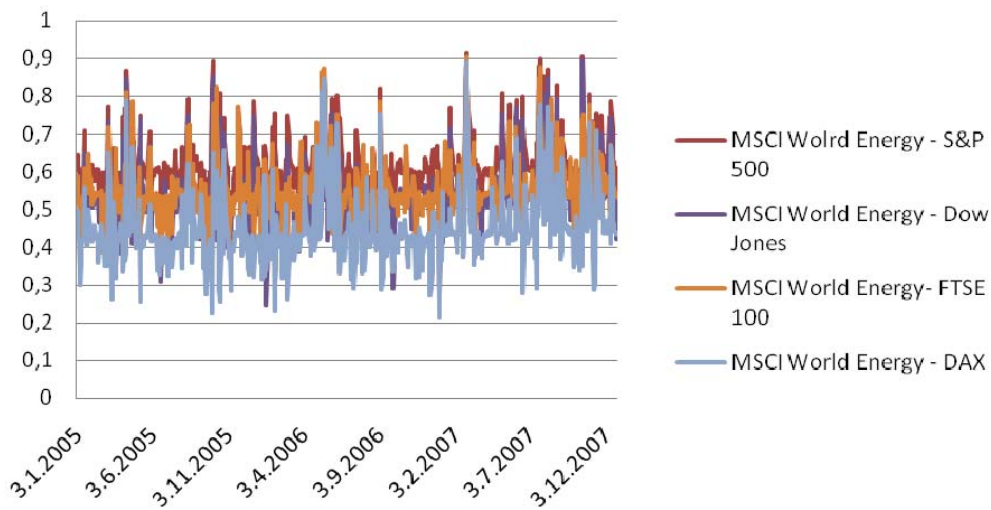


Fig. 3. Pre-crisis correlation: MSCI World Energy Vs S&P 500, Dow Jones, FTSE-100 & DAX

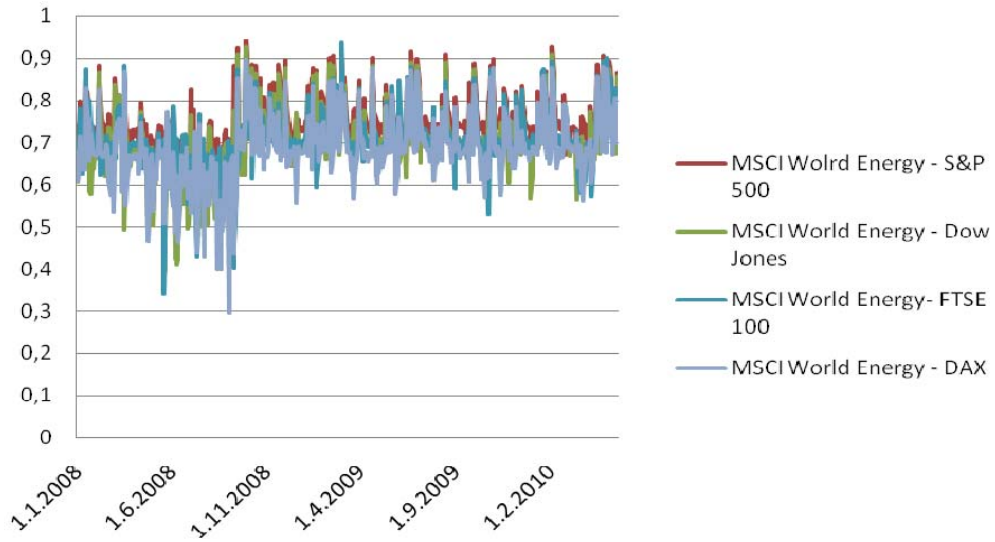


Fig. 4. Crisis correlation: MSCI World Energy Vs S&P 500, Dow Jones, FTSE-100 & DAX

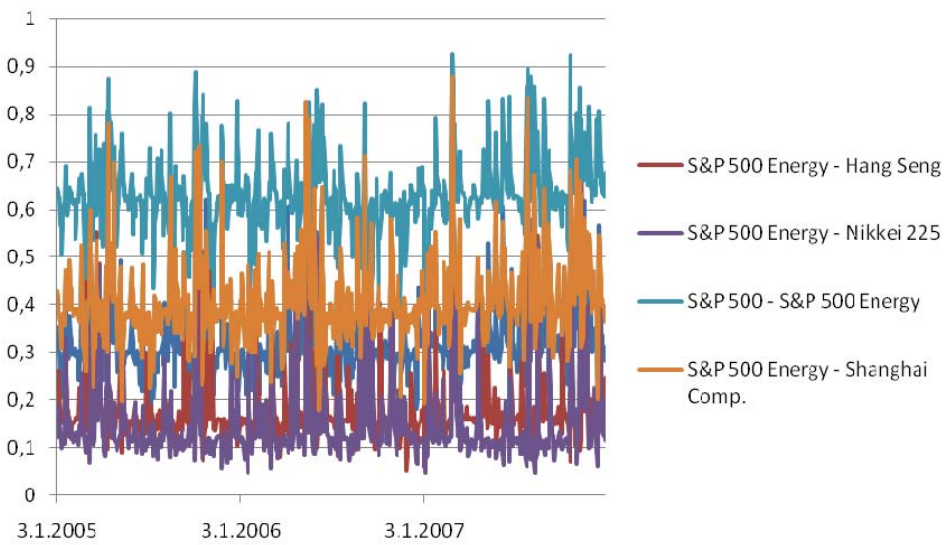


Fig. 5. Pre-crisis correlation: S&P 500 Energy Vs S&P 500, Nikkei 225, Shanghai Composite & Hang Seng

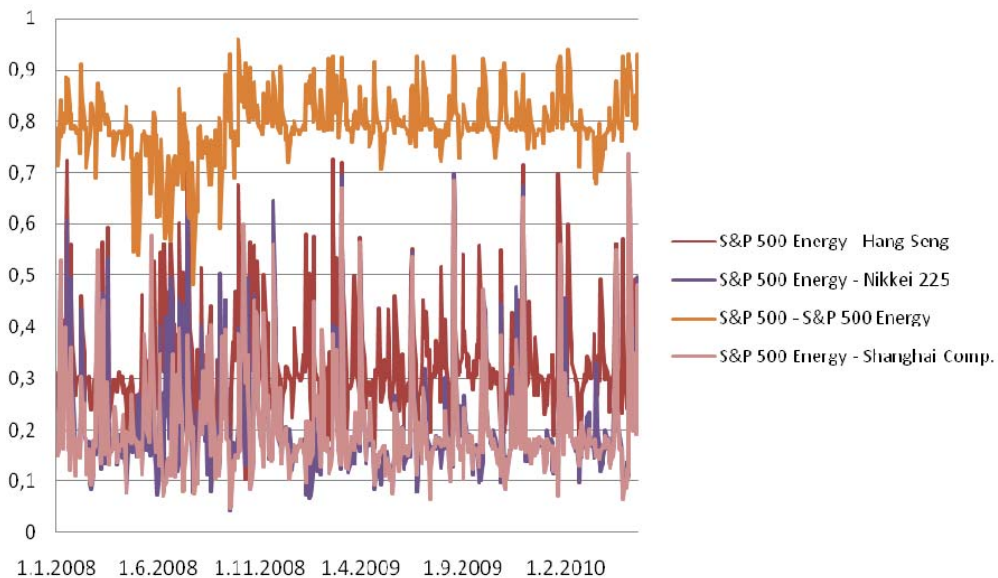


Fig. 6. Crisis correlation: S&P 500 Energy Vs S&P 500, Nikkei 225, Shanghai Composite & Hang Seng

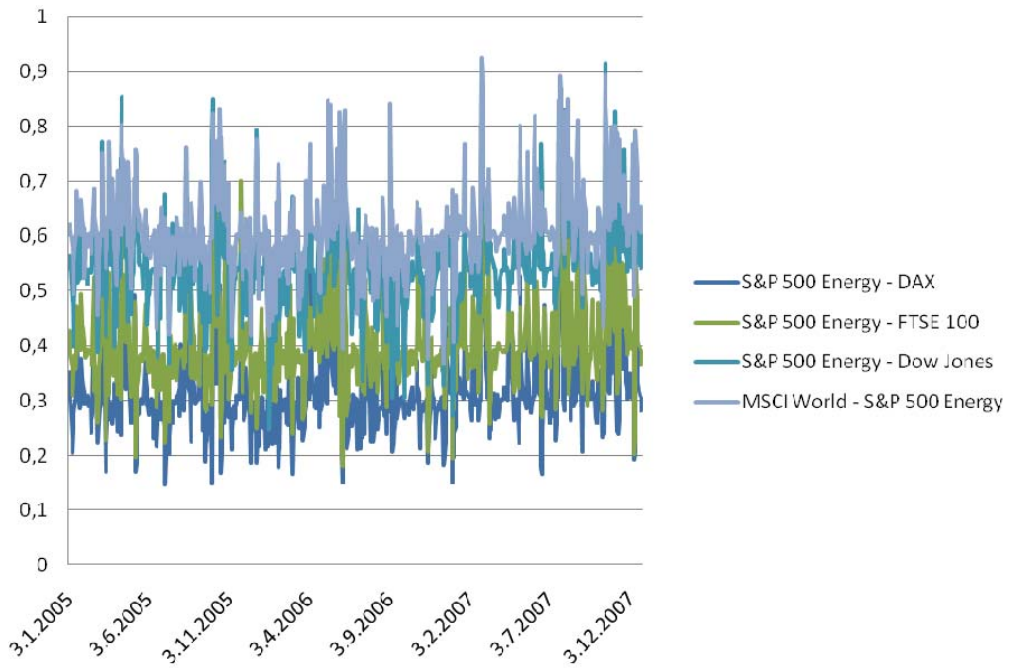


Fig. 7. Pre-crisis correlation: S&P 500 Energy Vs Dow Jones, FTSE-100, MSCI World & DAX

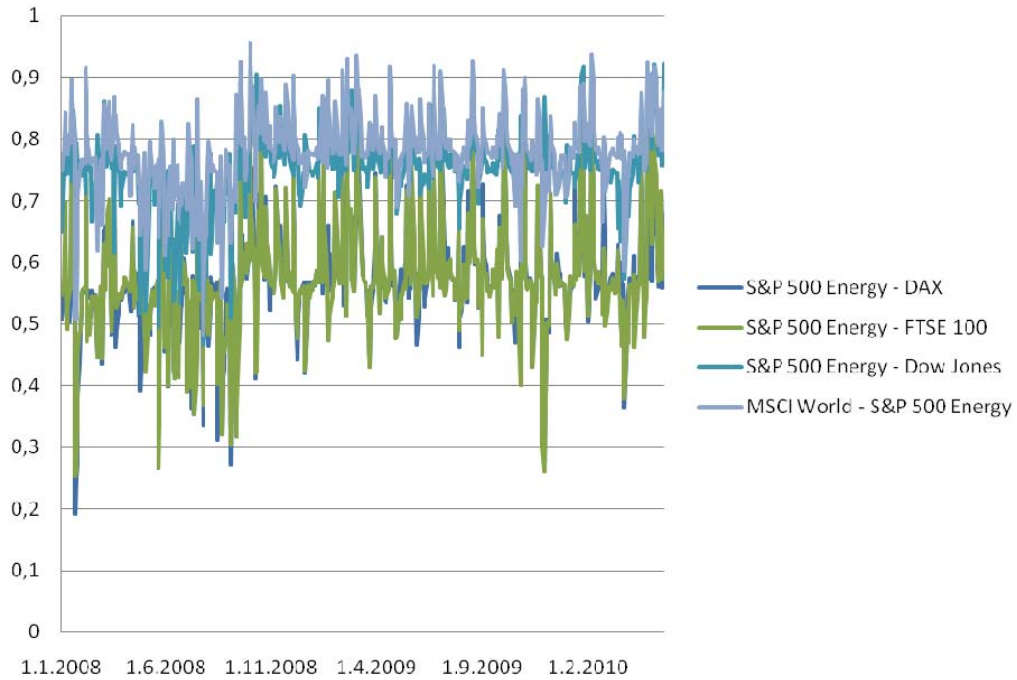


Fig. 8. Crisis correlation: S&P 500 Energy Vs Dow Jones, FTSE-100, MSCI World & DAX

Table 3. Empirical results: copula functions

MSCI World Energy										
Copula	Period	DAX 30	Dow Jones	Hang Seng	FTSE-100	Nikkei	S&P 500	Shanghai Composite	MSCI World	S&P Energy
Normal	Pre-crisis	0.4504	0.5116	0.1846	0.5545	0.1416	0.58	0.1577	0.699	0.9289
	Crisis	0.6952	0.7608	0.3509	0.7067	0.2004	0.7877	0.2407	0.8797	0.9422
Clayton	Pre-crisis	0.6122	0.7569	0.2645	0.8562	0.1981	0.9192	0.2001	1.3111	4.1608
	Crisis	1.5937	2.0496	0.5159	1.6215	0.2796	2.2968	0.4872	3.5407	5.3912
S. Joe-Clayton (Upper/lower tail)	Pre-crisis	0.1571/0.000	0.3293/0.0010	0.1101/0.0000	0.2814/0.0011	0.1432/0.0000	0.2795/0.0000	0.1510/0.0000	0.2293/0.0000	0.2801/0.0047
	Crisis	0.4398/0.000	0.4739/0.0078	0.3499/0.0017	0.4597/0.0590	0.3100/0.0000	0.4288/0.0022	0.2943/0.0000	0.4467/0.0014	0.4896/0.0154
S&P Energy										
Copula	Period	DAX 30	Dow Jones	Hang Seng	FTSE-100	Nikkei	S&P 500	Shanghai Composite	MSCI World	MSCI World Energy
Normal	Pre-crisis	0.3069	0.5461	0.1306	0.3835	0.0951	0.6192	0.1103	0.5944	0.9289
	Crisis	0.5754	0.8115	0.2787	0.5576	0.1294	0.839	0.1923	0.8092	0.9422
Clayton	Pre-crisis	0.369	0.8628	0.1767	0.4936	0.1447	1.0647	0.1548	0.9628	4.1608
	Crisis	1.106	2.503	0.3814	1.0596	0.1931	2.8526	0.2225	2.427	5.3912
Symm. Joe-Clayton (Upper/lower tail)	Pre-crisis	0.1122/0.000	0.2105/0.0000	0.1761/0.0001	0.1904/0.0001	0.1202/0.0000	0.1895/0.0000	0.1324/0.0000	0.1783/0.0000	0.1914/0.0024
	Crisis	0.3904/0.0001	0.4211/0.0015	0.3128/0.0001	0.4965/0.0146	0.3702/0.0016	0.4591/0.0049	0.4599/0.0015	0.4789/0.0031	0.5187/0.0201