MULTIVARIATE CONDITIONAL QUANTILE DEPENDENCE BETWEEN ENERGY PRICES AND CLEAN ENERGY STOCK RETURNS

Andrea Ugolini[a] e Juan C. Reboredo[b]

a. Departament of Quantitative Analysis, Universidade do Estado do Rio de Janeiro, Brazil
b. Department of Economics, Universidade de Santiago de Compostela, Spain.

Resumo

Avaliamos o impacto dos movimentos quantílicos dos preços da energia nos quantis de retornos dos preços das ações de energia limpa usando uma configuração de dependência de Vine-cópula multivariada. Para o período de 2009 a 2016, nossas evidências mostram que, por um lado, os preços do petróleo e da eletricidade contribuíram principalmente para a dinâmica dos retornos de estoque de energia limpa nos EUA e na UE, respectivamente. Por outro, os preços do carvão desempenharam um papel menor na elaboração de retornos dos preços das ações de energia limpa. Além disso, encontramos evidências de um impacto simétrico no preço da energia, de modo que os movimentos extremos de preços de energia para cima ou para baixo tiveram um impacto semelhante nos retornos de estoque de energia limpa. Esta evidência tem potenciais implicações para a tomada de decisão de gerenciamento de risco por investidores de energia e para a tomada de decisão de formulação de políticas em relação ao suporte para implantação de energia limpa.

Palavras-chave: Preços de energia, Retornos dos preços das ações de energia limpa, Cópulas

Abstract

We assessed the impact of quantile energy price movements on the quantiles of clean energy stock price returns using a multivariate vine-copula dependence setup. For the period 2009- 2016, our evidence shows that oil and electricity prices were major contributors to the dynamics of clean energy stock returns in the USA and the EU, respectively, whereas coal prices played a minor role in shaping clean energy stock price returns. Furthermore, we found evidence of a symmetric energy price impact, so extreme upward or downward energy price movements had a similar impact on clean energy stock returns. This evidence has potential implications for risk management decision making by energy investors and for policy maker decision making regarding support for clean energy deployment.

Keywords: Energy prices, clean energy stock price returns, copulas

Introduction

The United Nations Climate Change Conference, held in Paris in 2015, drew attention to the importance of pouring money into the clean energy sector to foster its development and meet the challenges posed by climate change. Private investment in renewable energies has recently been gaining ground, although maintaining these investments over time crucially depends on the profitability and financial risks associated with renewable energy companies.

The dynamics of energy prices is one of the main energy-related risk factors affecting the financial performance of clean energy investment projects, rendering the substitution of exhaustible for sustainable energy resources more or less viable on economic grounds (see, e.g., Kumar et al., 2012; Reboredo, 2015). Therefore, identifying how different energy prices impact on the value of renewable energy companies is of particular interest to investors wishing to assess the sensitivity of their renewable energy investments to energy prices, in particular, when energy prices are especially low or high. Policy makers, in the interest of optimally managing public investment efforts, are also interested in how fluctuations in energy prices shape renewable energy stock prices, as market forces driving energy prices may provide investors with market-based incentives to invest in green energies.

Previous empirical studies have scrutinized the link between clean energy stock prices and oil prices. Henriques and Sadorsky (2008) and Managi and Okimoto (2013) reported evidence of causality from crude oil prices to renewable energy stocks listed on US stock exchanges. Reboredo et al. (2017) studied co-movement and causality between oil prices and renewable energy stock prices at different time scales, finding that dependence strengthened towards the long run, and that causality was non-linear and mainly ran from energy indices to oil prices at different time horizons. Kumar et al. (2012) found that while oil prices, interest rates and technology stock price fluctuations impacted clean energy stock prices, carbon allowance prices had no significant impact. Broadstock et al. (2012) reported that oil price dynamics impacted on energy stocks in China and that the correlation increased significantly after the onset of the recent global financial crisis.

Another strand of the literature has studied the transmission of volatility between oil prices and renewable energy stock prices. Sadorsky (2012a), finding evidence of volatility spillovers from oil prices to renewable energy stock prices, suggested that oil is a useful hedge for clean energy stocks. Wen et al. (2014) also studied the volatility spillovers for Chinese renewable energy stock prices, finding that renewable energy and fossil fuel stocks exhibited significant mean and volatility spillovers, with renewable energy stocks carrying more risk than fossil fuel stocks. Sadorsky (2012b) found that oil prices increased the beta of renewable energy companies. More recently, Reboredo (2015) reported that oil price dynamics play a prominent role in shaping downside and upside risk in renewable energy companies.

Objective

Our study contributes to the extant empirical literature by considering the impact of prices for different kinds of energy — oil, gas, electricity and coal — on new energy stock prices in a multivariate setup, in which we measured dependence between different energy prices and renewable stock prices, taking into account direct and indirect price transmission channels. More specifically, we characterized the multivariate dependence structure between oil, gas, electricity and coal prices and clean energy stock prices using vine copula models (Joe, 1996), which characterize high-dimensional joint distributions using a hierarchical structure comprised of a set of bivariate copulas that capture dependence between two variables. This empirical approach offers modelling flexibility, as the marginal models and multivariate dependence structures are modelled independently. In particular, the conditional quantile dependence between renewable energy price fluctuations on energy prices — and vice versa — could be assessed, taking into account both direct and indirect channels of influence. This conditional dependence information could also be used to compute the contribution of each energy price change to clean energy stock price movements.

Material and Method

Let o_t, g_t, c_t and e_t be the (log) change in oil, gas, electricity and coal prices, respectively, and let r_t be the (log) change in the renewable energy stock price. The impact of a fluctuating energy price (for oil, say) of a size given by its β-quantile on the α-quantile of the clean energy stock price return distribution, given the prices for other energy prices, can be measured as:

$$P(r_t \leq q_{\alpha,\beta,t}^{r_t|o_t} \mid o_t \leq q_{\beta,t}^{o_t}, g_t, c_t, e_t) = \alpha , \qquad (1)$$

where $q_{\alpha,\beta,t}^{r_t|o_t}$ is the conditional α-quantile of renewable energy returns at time t and where $q_{\beta,t}^{o_t}$ is the unconditional β-quantile of oil prices, which can be obtained from the inverse of their distribution functions F as:

$$q^{r_t|o_t}_{\alpha,\beta,t} = F^{-1}_{r_t|o_t \le q^{o_t}_{\beta,t},\, g_t, c_t, e_t}(\alpha)\,, \tag{2}$$

$$q^{o_t}_{\beta,t} = F^{-1}_{o_t}(\beta)\,. \tag{3}$$

We can thus measure the impact of oil price fluctuations of different sizes on renewable energy stock prices under different market circumstances, as given by the stock price quantiles. We can also assess the contribution of oil price movements to renewable energy prices at the α-quantile by considering the difference between its conditional and unconditional values:

$$\gamma_{o_t} = q^{r_t|o_t}_{\alpha,\beta,t} - q^{r_t}_{\alpha,t}\,, \tag{4}$$

where $q^{r_t}_{\alpha,t} = F^{-1}_{r_t}(\alpha)$ is the unconditional α-quantile of the return distribution. Note that, when $\gamma_{o_t} = 0$, oil price changes have a negligible impact on stock returns, and when $\gamma_{o_t} < 0\,(> 0)$, oil price movements move stock returns in the same (opposite) direction.

Similarly, we can consider the quantile impact arising from other energy price changes, namely, g_t, c_t and e_t, and compute γ_{g_t}, γ_{c_t} and γ_{e_t}, respectively. As the values of values of γ could have different signs, we can normalize the contribution of energy price changes to stock returns as:

$$\hat{\gamma}_{o_t} = \frac{|\gamma_{o_t}|}{|\gamma_{o_t}| + |\gamma_{g_t}| + |\gamma_{c_t}| + |\gamma_{e_t}|}\,. \tag{5}$$

Note that now, by construction, the values of γ s lie between 0 and 1.

We can also summarize the contribution of energy price movements to renewable energy prices over the time period $t = 1, \ldots, N$ as:

$$\bar{\gamma}_{o_t} = \frac{1}{N}\sum_{t=1}^{N} \hat{\gamma}_{o_t}\,. \tag{6}$$

According to Eqs. (2)-(4), the computation of the contribution of energy prices to renewable energy stock returns requires knowledge of the conditional and unconditional distributions of renewable stock prices and energy prices. Their multivariate distribution can be obtained from a multivariate copula function, given that the Sklar's (1959) theorem states that:

$$F\left(r_t, o_t, g_t, c_t, e_t\right) = C\left(F_r(r_t), F_o(o_t), F_g(g_t), F_c(c_t), F_e(e_t)\right), \tag{7}$$

where $C(\cdot)$ is a copula function and where $F_i\left(x_i\right)$ are the marginal unconditional distribution functions of the variable x_i, for $i = r_t, o_t, g_t, c_t, e_t$. If F_i and C are differentiable, then the joint density function f can be decomposed as the product of the marginal densities $f_i(x_i)$ and the multivariate copula density $c(\cdot)$ as:

$$f\left(r_t, o_t, g_t, c_t, e_t\right) = f_r(r_t) f_o(o_t) f_g(g_t) f_c(c_t) f_e(e_t)\ c\left(F_r(r_t), F_o(o_t), F_g(g_t), F_c(c_t), F_e(e_t)\right), \tag{8}$$

where the density copula captures dependence between each x_i. Different copula specifications account for different symmetric and asymmetric dependence structures.

Eq. (1) can now be expressed in terms of the copula function as:

$$C_{r_t, o_t | g_t, c_t, e_t}\left(F_{r_t | g_t, c_t, e_t}\left(q^{r_t|o_t}_{\alpha,\beta,t}\right), F_{o_{2t} | g_t, c_t, e_t}\left(q^{o_t}_{\beta,t}\right)\right) = \alpha\beta\,, \tag{9}$$

where $C_{r_t, o_t | g_t, c_t, e_t}(.)$, that is, the conditional bizvariate copula between oil and renewable energy returns, can be obtained by partially deriving the copula function in Eq. (7). Next, given the values for α and β, and given that $F_{o_{2t} | g_t, c_t, e_t}\left(q^{o_t}_{\beta,t}\right) = \beta$, we can solve from the copula specification in Eq. (9) to obtain $F_{r_t | g_t, c_t, e_t}\left(q^{r_t|o_t}_{\alpha,\beta,t}\right)$. We obtain $q^{r_t|o_t}_{\alpha,\beta,t}$ by inverting the conditional distribution function of r_t, which can be obtained from the conditional copula. The same procedure was applied to the other energy prices in order to obtain their conditional quantiles.

We characterized multivariate dependence using a vine copula, which factorizes multivariate copula density in terms of a successive mixing of 5(5-1)/2 bivariate linking copulas with a hierarchical structure (see Joe, 1997; Bedford and Cooke, 2001, 2002; Kurowicka and Cooke, 2006; Aas et al., 2009). Specifically, we considered the C-vine, D-vine and R-vine copulas. The five-dimensional C-vine is given by:

$$\begin{aligned} f\left(x_1, x_2, x_3, x_4, x_5\right) = \prod_{k=1}^{5} f_k\left(x_k\right) \prod_{h=2}^{5} c_{1,h}\left(F_1\left(x_1\right), F_h\left(x_h\right)\right) \\ \prod_{j=2}^{5-1} \prod_{i=1}^{5-j} c_{j,j+i|1,K,j-1}\left(F\left(x_j \mid x_1, K, x_{j-1}\right), F\left(x_{j+i} \mid x_1, K, x_{j-1}\right)\right) \end{aligned}, \tag{10}$$

where $c_{j,j+i|1,K,j-1}$ is the conditional copula and where the conditional distribution function of the x_i variable, given the variable x_j, is given by (Joe, 1997):

$$F_{i|j}(x_i \mid x_j) = \frac{\partial C_{ij}\left(F_i(x_i), F_j(x_j)\right)}{\partial F_j(x_j)}. \tag{11}$$

For the C-vine copula, we have a star-shaped hierarchical tree structure, where in the first tree — indicated by the second term in Eq. (10) — one variable plays a pivotal role. The tree is expanded in such a way that the nodes of each tree are configured by the edges of the previous tree. Dependence in successive trees is measured with respect to the pivotal variables using the conditional bivariate copulas as indicated in the third term in Eq. (10). The pivotal variable is identified as the variable that maximizes the sum of pairwise dependencies as measured by Kendall's tau.

The five-dimensional density function of the D-vine model is given by:

$$\begin{aligned} f\left(x_1,x_2,x_3,x_4,x_5\right) &= \prod_{k=1}^{5} f_k\left(x_k\right)\prod_{h=1}^{5-1} c_{h,h+1}\left(F_h\left(x_h\right),F_{h+1}\left(x_{h+1}\right)\right) \\ &\prod_{j=2}^{5-1}\prod_{i=1}^{5-j} c_{i,i+j|i+1,K,i+j-1}\left(F\left(x_i \mid x_{i+1},K,x_{i+j-1}\right),F\left(x_{i+j} \mid x_{i+1},K,x_{i+j-1}\right)\right) \end{aligned} .(12)$$

In the D-vine copula, variables are treated equally and conditional dependence is determined by the variable ordering of the first tree, which is determined so as to capture as much dependence as possible (see Nikoloulopoulos et al., 2012).

Finally, the five-dimensional density function of the R-vine model is given by:

$$\begin{aligned} f\left(x_1,x_2,x_3,x_4,x_5\right) &= \prod_{k=1}^{5} f_k\left(x_k\right) \\ &\prod_{i=1}^{5-1}\prod_{e\in E_i} c_{j(e),k(e)|D(e)}\left(F\left(x_{j(e)} \mid x_{D(e)}\right),F\left(x_{k(e)} \mid x_{D(e)}\right)\right) \end{aligned}, \tag{13}$$

where E_i denotes the nodes and where $x_{D(e)}$ is the subvector of x, indicated by the indices contained in the conditional set $D(e)$. We chose the appropriate R-vine structure using the maximum spanning tree that solved the following optimization problem for each tree:

$$\max \sum_{\text{edges } e=\{i,j\} \text{ in spanning tree}} \left|\hat{\tau}_{ij}\right|, \tag{14}$$

where $\hat{\tau}_{ij}$ denotes the pairwise empirical Kendall's tau and a spanning tree is a tree on all nodes. Marginal models in Eq. (9) are given by an average ARMA (p,q) with TGARCH components.

Results and Discussion

We used daily data for energy prices for the EU and the USA (expressed in EUR and USD, respectively) for the period 2 January 2009-1 September 2016. The data were sourced from Bloomberg as follows: (a) for crude oil, the Brent and WTI benchmark prices for the EU and the USA, respectively; (b) for gas, the UK natural gas futures for the EU and natural gas futures (NYMEX) for the USA; (c) for coal, the ARA (Argus/McCloskey) for Europe and the Nymex Clearport Central Appalachian Coal Futures for the USA; and (d) for electricity, the Phelix index for the EU and the NYMEX PJM Electricity futures for the USA. Finally, for renewable energy prices, we used the European Renewable Energy Index (ERIX) for the EU and the ECO Clean Energy Index (ECO) for the USA. Figure 1 depict the temporal dynamics of energy and renewable energy prices in the EU and the USA, respectively. Both figures show that renewable energy prices co-moved with energy prices, although the size and timing of co-movement differed according to market and energy price and over time. Likewise, the size and dynamics of price volatility also differed across countries.

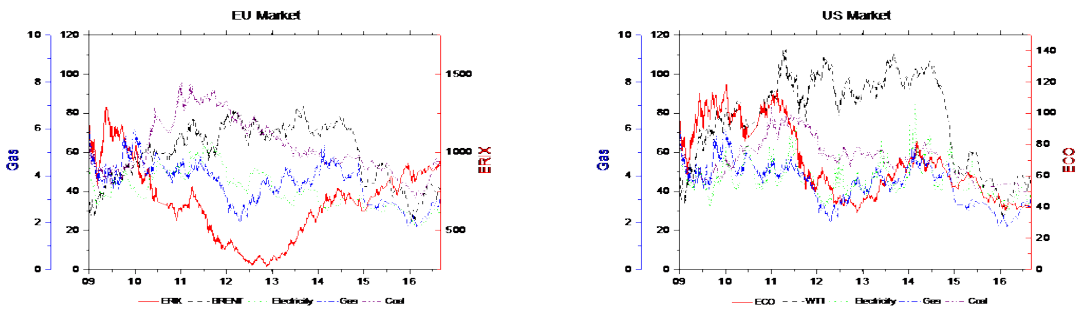

Figure 1 – Energy and renewable energy prices in the EU and USA.

Source: Reboredo and Ugolini, 2018

Figures 2 and 3 depict the estimated multivariate dependence structures for the EU and the USA, respectively. In both cases, the best fit was offered by the C-vine copula structure. Electricity prices played a pivotal role in the EU, whereas oil prices were central in the USA. Our estimates also show that the Student-t copula was the best fitting bivariate copula in most cases, indicating that symmetric dependence characterized multivariate dependence between energy price movements and clean energy stock returns.

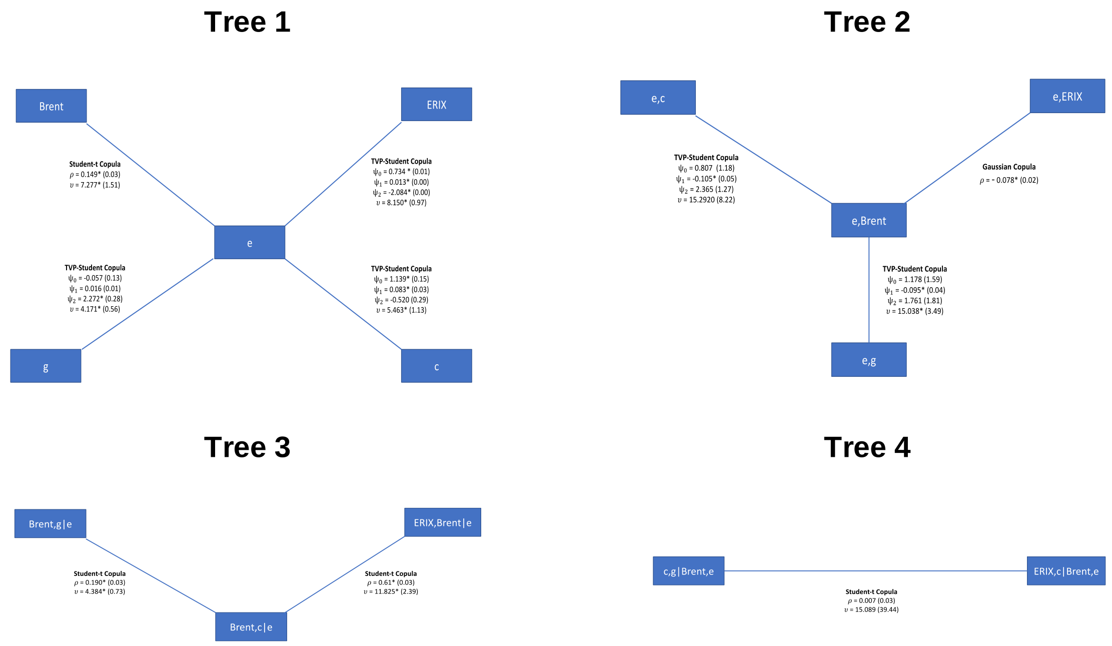

Figure 2 – Vine-copula structure for the EU.

Source: Reboredo and Ugolini, 2018

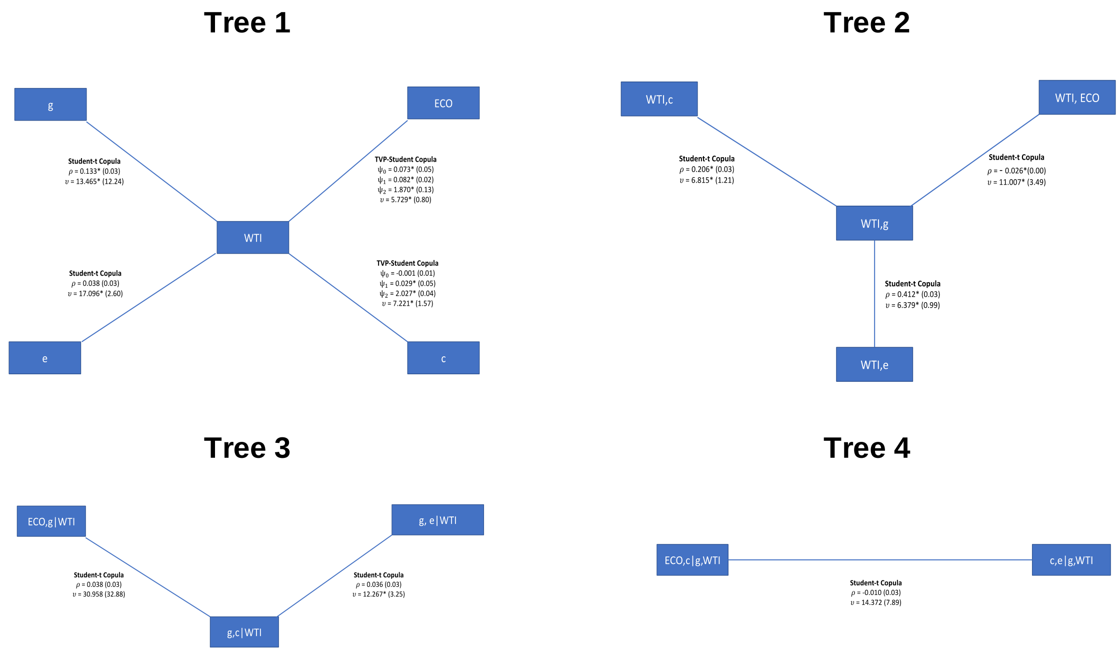

Figure 3 – Vine-copula structure for the USA.

Source: Reboredo and Ugolini, 2018

From the C-vine hierarchical structure, the best pair-copula fit and marginal estimates, we computed the conditional and unconditional quantiles in Eqs. (2)-(3) for oil, gas, electricity and coal price fluctuations and then, using Eqs. (4)-(6), we measured the contribution of the

β-quantile of those energy price fluctuations to clean energy stock prices. We considered different values for the β-quantile: (a) extreme downward and upward energy price changes, since these are crucial for investors in terms of downside and upside risk management of renewable energy investments, so $\beta = 0.05$ and $\beta = 0.95$ (note that for $\beta = 0.95$ we have, e.g., for oil, that $P(o_t \geq q_{\beta,t}^{o_t}) = 0.05$, so $q_{\beta,t}^{o_t} = 1 - F_{o_t}^{-1}(0.05)$); and (b) moderate downward and upward energy price movements, so $\beta = 0.25$ and $\beta = 0.75$. We also measured the impact of the β-quantile energy price changes on the α-quantile of clean energy price changes by considering that $\alpha = \beta$, thereby considering the impact of extreme (or moderate) energy price movements on extreme (or moderate) values of clean energy stock returns.

Tables 1 and 2 report results of the effect of energy price fluctuations of different sizes on the corresponding clean energy stock return quantile as per Eq. (4). The empirical evidence for the EU (Table 1) indicates that, at different quantiles of energy price changes, electricity prices are the main driver of changes in the ERIX index and that oil and gas prices play a less prominent role than coal prices in affecting clean energy stock returns. Furthermore, we observed that extreme or moderate downward movements in electricity, gas and coal prices had a negative impact on clean energy stock returns, whereas the opposite occurred for extreme or moderate upward movements in energy prices; this evidence is consistent with the positive dependence of electricity, gas and coal returns on ERIX reported in Figure 2. However, for oil we observed a positive impact of extreme downward movements on clean energy stock returns and a negative impact for upward price movements that is consistent with the conditional negative dependence between ERIX and Brent indicated in tree 2 in Figure 2. Strikingly, the estimated impact of energy price fluctuations gradually moderated and converged to zero as the size of the energy price change approached its median value. Our evidence also points to the fact that the impact of extreme upward or downward energy price movements on clean energy stock returns is symmetric for all energy prices; this evidence is consistent with the symmetric dependence given by the Student-t copula.

Quantile		Electricity	Brent	Coal	Gas
0.05	Mean	-0.018	0.002	-0.007	-0.004
	Std. Dev.	0.005	0.006	0.009	0.009
	Max	-0.011	0.020	0.003	0.006
	Min	-0.060	-0.097	-0.118	-0.107
0.25	Mean	-0.005	0.001	-0.002	-0.001
	Std. Dev.	0.002	0.003	0.003	0.004
	Max	-0.002	0.017	0.006	0.009
	Min	-0.019	-0.046	-0.052	-0.044
0.75	Mean	0.005	-0.001	0.002	0.001
	Std. Dev.	0.001	0.003	0.003	0.004
	Max	0.018	0.042	0.048	0.041
	Min	0.002	-0.017	-0.006	-0.008
0.95	Mean	0.016	-0.002	0.006	0.003
	Std. Dev.	0.004	0.006	0.008	0.008
	Max	0.054	0.088	0.107	0.097
	Min	0.009	-0.019	-0.003	-0.006

Table 1 – Summary statistics for difference between conditional and unconditional clean energy quantiles for the UE.

Source and Note: The table reports summary statistics for differences between conditional and unconditional ERIX quantile returns as per Eq. (4). Reported are the means, standard deviations (Std. Dev.), maximum (Max) and minimum (Min) values over the sample period. Reboredo and Ugolini 2018

Quantile		Electricity	Brent	Coal	Gas
0.05	Mean	0.003	-0.037	0.003	0.003
	Std. Dev.	0.020	0.014	0.018	0.019
	Max	0.151	-0.022	0.153	0.146
	Min	-0.212	-0.147	-0.165	-0.225
0.25	Mean	0.000	-0.013	0.000	0.001
	Std. Dev.	0.014	0.005	0.014	0.014
	Max	0.121	-0.008	0.122	0.120
	Min	-0.107	-0.050	-0.105	-0.099
0.75	Mean	-0.001	0.009	-0.001	-0.002
	Std. Dev.	0.012	0.004	0.012	0.012
	Max	0.076	0.038	0.075	0.070
	Min	-0.125	0.005	-0.127	-0.124
0.95	Mean	-0.003	0.026	-0.003	-0.003
	Std. Dev.	0.014	0.010	0.013	0.014
	Max	0.146	0.103	0.113	0.154
	Min	-0.120	0.015	-0.121	-0.115

Table 2 – Summary statistics for difference between conditional and unconditional clean energy quantiles for the USA.

Source and Note: The table reports summary statistics for differences between conditional and unconditional ECO quantile returns as per Eq. (4). Reported are the means, standard deviations (Std. Dev.), maximum (Max) and minimum (Min) values over the sample period. Reboredo and Ugolini, 2018.

As for the USA, the empirical evidence (Table 2) indicates that oil prices account for the greatest impact of energy prices on the ECO index, whereas electricity and coal prices play a secondary role. Likewise, we observed that extreme or moderate downward movements in oil had a negative impact on clean energy stock returns, whereas the opposite occurred for extreme or moderate upward movements in the other energy prices. This response in clean energy stock returns is consistent, first, with the evidence regarding the positive dependence between oil and clean energy stock returns reported in Figure 3, and, second, with the low and negative dependence (see Figure 3) between the other energy prices and the ECO index. Conversely, we estimated a positive impact of extreme upward movements in oil prices and a negative impact of the remaining energy prices on clean energy stock returns. As happened with the ERIX index, we observed that the impact of energy prices gradually diminished as the energy price change approached its median value. We also found symmetry, as the impact of extreme upward or downward energy price movements were similar in size, a result that is consistent with the symmetric dependence given by the Student-t copula.

Tables 3 and 4 report empirical evidence for the normalized contribution of energy price fluctuations to stock returns as per Eq. (5). Empirical estimates for the EU indicate that extreme upward or downward changes in electricity prices accounted for about 60% of extreme ERIX fluctuations caused by extreme energy price fluctuations. Remarkably, the contribution of electricity price changes to fluctuations in clean energy returns moderated as electricity price movements approached the median value, reflecting a U-shaped curve across quantiles. Coal prices accounted for 18% of extreme ERIX fluctuations, whereas Brent and gas prices explained about 12% and 11%, respectively. Moreover, the contribution of Brent and gas price changes to fluctuations in clean energy returns strengthened as the price movement moved towards the median value, so the contribution of these energy prices to fluctuations in clean energy prices reflected an inverted U-shaped curve across quantiles. The contribution of coal prices remained almost constant across quantiles. We observed that the contribution of all the energy prices to extreme ERIX fluctuations was symmetric.

Quantile		Electricity	Brent	Coal	Gas
0.05	Mean	0.59	0.12	0.18	0.11
	Std. Dev.	(0.14)	(0.06)	(0.11)	(0.09)
0.25	Mean	0.48	0.20	0.17)	0.15
	Std. Dev.	(0.13)	(0.10)	(0.11)	(0.09)
0.75	Mean	0.47	0.22	0.16	0.15
	Std. Dev.	(0.12)	(0.11)	(0.11)	(0.09)
0.95	Mean	0.58	0.13	0.18	0.11
	Std. Dev.	(0.13)	(0.06)	(0.11)	(0.09)

Table 9 – Contribution of energy prices to changes in ERIX.

Source and Note: The table reports summary statistics for differences between conditional and unconditional ERIX returns. Reported are the means and standard deviations (Std. Dev.) over the sample period. Reboredo and Ugolini, 2018.

Quantile		Electricity	WTI	Coal	Gas
0.05	Mean	0.14	0.58	0.13	0.14
	Std. Dev.	(0.06)	(0.17)	(0.06)	(0.06)
0.25	Mean	0.19	0.44	0.19	0.18
	Sd. Dev.	(0.07)	(0.21)	(0.08)	(0.08)
0.75	Mean	0.20	0.41	0.20	0.20
	Std. Dev.	(0.07)	(0.21)	(0.08)	(0.08)
0.95	Mean	0.15	0.56	0.14	0.15
	Std. Dev.	(0.06)	(0.17)	(0.06)	(0.06)

Table 10 – Contribution of energy prices to changes in ERIX.

Source and Note: The table reports summary statistics for differences between conditional and unconditional ECO returns. Reported are the means and standard deviations (Std. Dev.) over the sample period. Reboredo and Ugolini, 2018.

Assessments of the contribution of energy price fluctuations to the ECO index in the USA (Table 4) reveal that oil prices accounted for most of the upward or downward movements in the ECO index caused by extreme movements in energy prices and also show that this contribution was symmetric. Likewise, the contribution of oil price changes to fluctuations in ECO returns moderated as oil price changes moved towards the median value, displaying thus a U-shaped form across quantiles. Moreover, we found that the contribution of gas and electricity prices was similar in size (about 14%) and symmetric, whereas the contribution of coal prices was slightly less but also symmetric. We also corroborated that the contribution of those energy price fluctuations increased as their size approached median values, again showing an inverted U-shape across quantiles. Finally, we observed that the contribution of all energy prices to extreme fluctuations in the ECO index was symmetric.

Overall, our evidence indicates that electricity and oil prices are the main contributors to fluctuations in clean energy returns in the EU and USA, respectively, mainly when those prices experience extreme movements. However, when fluctuation in electricity and oil prices are moderate, they lose their prominence and the fluctuations of other energy price acquire greater importance.

Our evidence for the EU and USA indicates that green investors should pay attention to electricity and oil price fluctuations, respectively, as they are the main contributors to downside and upside risk associated with clean energy investments. Given that these investments are acquiring importance in individual and institutional investor portfolios, specific energy price risk factors should be taken into account when making risk management decisions. Likewise, our evidence for oil, gas and coal prices in the UE and for gas, coal and electricity prices in the USA indicate that those energy prices make a limited contribution to extreme risk, even though their contribution, and thus their relevance as risk generators, increases as their price fluctuations approaches the centre of the distribution.

Furthermore, our evidence of positive dependence between clean energy stock returns and most of the energy prices studied indicate that energy markets offer limited hedging opportunities for investors in clean energies. Our empirical evidence on symmetric tail dependence and symmetric energy price contribution to extreme clean energy stock price fluctuations would suggest similar risk management strategies in short and long positions in clean energy stocks and has implications for the pricing of renewable assets in terms of energy price movements. Thus, clean energy investors in the USA and in the EU should receive a greater risk premium for supporting an oil price and electricity price risk, respectively. Tail dependence also has important implication for clean energy safety-first investors (that is, investors who minimize the probability of a loss that may drive them out of business; see Susmel, 2001). They should, thus, pay specific attention to oil price swings when investing in the USA and electricity price swings when investing in the EU.

Our evidence shows that energy prices — mainly electricity prices in the EU and oil prices in the USA — play an active role in shaping the profitability of clean energy investments. Hence, the market forces pushing electricity prices in the EU or oil prices in the USA up (or down) provide market-based incentives to invest in the green economy. Specifically, when those energy prices are high, investment in clean energy gains attractiveness as the profitability of renewable energy projects increases. In these circumstances, since the market provides adequate incentives to the deployment of clean energy investments, policy makers can relax public expenditure on clean energy projects. Contrarily, when energy prices are low, the value of clean energy companies decreases, which means that the energy market is unable to provide adequate incentives to develop clean energies. In this case, policy makers need to redouble efforts to support the deployment of clean energies. Policies should therefore be implemented asymmetrically, that is, supporting the profitability of clean energy companies when energy prices are low and relaxing this support when energy prices are high. Our analysis should also enable governments to identify the type and size of energy price risk to which it should pay greater attention.

Conclusão

Deployment of renewable energies as a way to fight climate change has spurred the interest of private investors in clean energies as a new alternative investment opportunity. Since energy prices are an important factor in determining the profitability of clean energy companies, investors need to assess the energy price risk so as to accurately gauge the risk of investing in environmentally friendly companies. Likewise, policymakers need to identify how energy prices shape clean energy stock prices in order to make policies more effective, that is, by combining their efforts with market incentives to encourage investors to pour money into clean energies.

We characterized multivariate dependence between oil, gas, electricity and coal prices and new energy stocks and measured the quantile impact of energy price fluctuations on the quantiles of clean energy stock returns. For the period January 2009-September 2016, our evidence for the EU and for the USA indicates that the multivariate dependence structure was given by a C-vine hierarchical structure and also that electricity and oil prices played a central role in determining conditional dependence in the EU and the USA, respectively. The analysis of quantile impacts revealed that movements in energy prices played an important role in renewable energy price dynamics, especially when energy prices experienced large downward or upward fluctuations. Furthermore, electricity prices in the EU and oil prices in the USA were the main contributors to fluctuations in new energy stock prices. Our empirical results also revealed that extreme upward or downward energy price movements had a similar impact on stock prices, and that, in general, the contribution of energy price changes to fluctuations in clean energy prices moderated as the size of the energy price change approaches the median value, displaying thus, a U-shaped curve across quantiles.

Our evidence has implications for both investors and policy makers. Thus, investors should pay particular attention to extreme energy price fluctuations — especially electricity prices in the EU and oil prices in the USA — as they generate downside or upside risks. As for policy makers, in implementing their policies, they need to be aware that downward energy price movements discourage incentives to investments in renewables, whereas upward energy price movements could boost renewable investment without specific support from energy policies.

Referências

AAS, K. et al. Pair-copula constructions of multiple dependence. **Insurance: Mathematics and economics**, Elsevier, v. 44, n. 2, p. 182–198, 2009.

BEDFORD, T.; COOKE, R. M. Probability density decomposition for conditionally dependent random variables modeled by vines. **Annals of Mathematics and Artificial intelligence**, Springer, v. 32, n. 1-4, p. 245–268, 2001.

BEDFORD, T.; COOKE, R. M. Vines: A new graphical model for dependent random variables. **Annals of Statistics**, JSTOR, p. 1031–1068, 2002.

BROADSTOCK, D. C.; CAO, H.; ZHANG, D. Oil shocks and their impact on energy related stocks in china. **Energy Economics**, Elsevier, v. 34, n. 6, p. 1888–1895, 2012

HENRIQUES, I.; SADORSKY, P. Oil prices and the stock prices of alternative energy companies. **Energy Economics**, Elsevier, v. 30, n. 3, p. 998–1010, 2008

JOE, H. Families of m-variate distributions with given margins and m (m-1)/2 bivariate dependence parameters. **Lecture Notes-Monograph Series**, JSTOR, p. 120–141, 1996

JOE, H. **Multivariate models and multivariate dependence concepts**. [S.l.]: CRC Press, 1997

KUMAR, S.; MANAGI, S.; MATSUDA, A. Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. **Energy Economics**, Elsevier, v. 34, n. 1, p. 215–226, 2012

KUROWICKA, D.; COOKE, R. M. **Uncertainty analysis with high dimensional dependence modelling**. [S.l.]: John Wiley & Sons, 2006

MANAGI, S.; OKIMOTO, T. Does the price of oil interact with clean energy prices in the stock market? **Japan and the World Economy**, Elsevier, v. 27, p. 1–9, 2013

NIKOLOULOPOULOS, A. K.; JOE, H.; LI, H. Vine copulas with asymmetric tail dependence and applications to financial return data. **Computational Statistics & Data Analysis**, Elsevier, v. 56, n. 11, p. 3659–3673, 2012

REBOREDO, J. C. Is there dependence and systemic risk between oil and renewable energy stock prices? **Energy Economics**, Elsevier, v. 48, p. 32–45, 2015

REBOREDO, J. C.; RIVERA-CASTRO, M. A.; UGOLINI, A. Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. **Energy Economics**, Elsevier, v. 61, p. 241–252, 2017

SADORSKY, P. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. **Energy Economics**, Elsevier, v. 34, n. 1, p. 248–255, 2012

SADORSKY, P. Modeling renewable energy company risk. **Energy Policy**, Elsevier, v. 40, p. 39–48, 2012

SKLAR, M. Fonctions de repartition an dimensions et leurs marges. **Publ. Inst. Statist. Univ. Paris**, v. 8, p. 229–231, 1959

SUSMEL, R. Extreme observations and diversification in latin american emerging equity markets. **Journal of International Money and Finance**, Elsevier, v. 20, n. 7, p. 971–986, 2001

WEN, X. et al. How do the stock prices of new energy and fossil fuel companies correlate? evidence from china. **Energy Economics,** Elsevier, v. 41, p. 63–75, 2014

Anexo

Referências Pacote utilizado:

Eike Christian Brechmann, Ulf Schepsmeier. Modeling Dependence with C- and D-Vine Copulas: The R Package CDVine. **Journal of Statistical Software**, 52(3), 1-27, 2013. URL: http://www.jstatsoft.org/v52/i03/.

Ulf Schepsmeier, Jakob Stoeber, Eike Christian Brechmann, Benedikt Graeler, Thomas Nagler and Tobias Erhardt. VineCopula: Statistical Inference of Vine Copulas. R package version 2.1.4. 2018. URL: https://CRAN.R-project.org/package=VineCopula

Ugolini A.. R Code CoVaR with Copula. 2016. URL: https://github.com/andrugo/RCoVaRCopula

Script:

```
rm(list=ls(all=TRUE))


setwd("/Users/andreaugolini/Desktop/Work/Energy Network USA-EU")


#####################################################

#### 1 - Emparelhamento das datas sobre os dados ####

#####################################################


# Cargar estas funciones


source("R/Functions/dataset-20091007.R")      ## General datasets managing

source("R/Functions/text-functions-20090305.R")                 ## General txt managing

source("R/Functions/BLManage-Functions-dev.R")           ## Specific Bloomberg datasets
management


file.data <- "Data/Database_US.csv"  # Nombre do File .CSV

dir.out   <- "Data/Single"


#### Split data

data <- .BL.split.data(file = file.data, dir.out = dir.out,
```

```
                    format = "%d/%m/%y", check.closedDays = TRUE)



file.data <- "Data/Database_EU.csv"  # Nombre do File .CSV
dir.out   <- "Data/Single_EU"

#### Split data
data <- .BL.split.data(file = file.data, dir.out = dir.out,
                    format = "%d/%m/%y", check.closedDays = TRUE)

source("R/Functions/YFManage-Functions-dev.R")    ## Specific datasets management

file.out <- "Data/Data-US-Merged.txt"  # Nombre del file de output
date.range <- c(20090101, 20160908) # escoje la fecha de inicio y de fin de la muestra

info <- c(
  "WTI_US","Data/Single/CL1-Comdty-data.txt",1,
  "Elec_US","Data/Single/CYMEPJN3-Index-data.txt",1,
  "Gas_US","Data/Single/NRGSNG3-Index-data.txt",1,
  "Coal_US","Data/Single/NRGSQZ3-Index-data.txt",1,
  "Ren_Index_US","Data/Single/ECO-Index-data.txt",1,
  "Brent_EU","Data/Single_EU/CO1-Comdty-data.txt",1,
  "Elec_EU","Data/Single_EU/GT1-Comdty-data.txt",1,
  "Gas_EU","Data/Single_EU/QR1-Comdty-data.txt",1,
  "Coal_EU","Data/Single_EU/NN1-Comdty-data.txt",1,
  "Ren_Index_EU","Data/Single_EU/ERIX-Index-data.txt",1)
info <- matrix(data = info, ncol = 3, byrow = TRUE)
```

```
colnames(info) <- c("ticker", "file", "append")


#### Build indicators
.merge.all(fileInfo = info, date.range = date.range, file.out = file.out)


##########################
### Data & Statistics  ###
##########################
setwd("/Users/andreaugolini/Desktop/Work/Energy Network USA-EU")


rm(list=ls(all=TRUE))


source("R/Functions/ManageData_function.R")
source("R/Functions/stat.descriptive_function.R")


data<-read.table("Data/Data-US-Merged.txt",  header=T,  na.strings="NA",stringsAsFactors  =
FALSE)
colnames(data)<-gsub('.close','',colnames(data))


yieldsData<-.rent(data,data$date)
rent=as.matrix(yieldsData$r)


Matcorr=cor(yieldsData$r[,-1])


## Statistics
Statarent=.stat.descriptive.all(data=yieldsData$r)
```

```
## Print Results in Excel

write.csv(data, "Results/Price.csv")
write.csv(rent, "Results/rent.csv")
write.csv(Statarent, "Results/stata.csv")
write.csv(Matcorr, "Results/Matcorr.csv")

###################
### Vine Copula ###
###################

rm(list=ls(all=TRUE))

Umatrix<-read.table("Data/U_data.txt", header=T, na.strings="NA",stringsAsFactors = FALSE)
UmatrixUS <- Umatrix[c(1,2,3,4,5)]
UmatrixEU <- Umatrix[c(6,7,8,9,10)]

Umatrix <- UmatrixUS
name=colnames(Umatrix)

###########################
## Select Structure Vine ##
###########################

library(CDVine)
library(VineCopula)
```

```
######################
## R-Vine structure ##
######################

Rvine=RVineStructureSelect(Umatrix, familyset=c(1:10),type=0,rotation=F)
RVM=RVineMatrix(Rvine$Matrix,Rvine$family,Rvine$par,Rvine$par2)

RAIC=RVineAIC(Umatrix,RVM)
RBIC=RVineBIC(Umatrix,RVM)
RAIC
RBIC
ll <- RVineLogLik(Umatrix, RVM, separate = FALSE)
ll$loglik

RVM$names<-colnames(Umatrix)
P=RVineTreePlot(data=NULL,RVM,tree="ALL",type=1,edge.labels=c("family","theotau"),P=NULL,method = "mle",legend = TRUE)

######################
## C-Vine structure ##
######################
#selection Best Canonical Vine Copula
Cvine=RVineStructureSelect(Umatrix,familyset=c(1:10) ,type=1,rotations = F)

Matrix=Cvine$Matrix
```

```
fam=Cvine$family

par=Cvine$par

par2=Cvine$par2

CVM=RVineMatrix(Matrix,fam,par,par2)


C_AIC=RVineAIC(Umatrix,CVM)

C_AIC

C_BIC=RVineBIC(Umatrix,CVM)

C_BIC

ll <- RVineLogLik(Umatrix, CVM, separate = FALSE)

ll$loglik


Tau=RVinePar2Tau(CVM)

CVM$names<-colnames(Umatrix)


P=RVineTreePlot(data=NULL,CVM,type=1,tree="ALL",edge.labels=c("family","par"),legend=
T,interactive = T)


######################

## D-Vine structure ##

######################


#selection Best Canonical Vine Copula

Dvine=CDVineCopSelect(Umatrix, familyset=c(1:7,9,13:14), type=2,selectioncrit="AIC")


sel<-data.frame(Dvine)

family=sel[,1]
```

```
par=sel[,2]

par2=sel[,3]


D_AIC=CDVineAIC(Umatrix,family,par,par2,type=2)

D_AIC

D_BIC=CDVineBIC(Umatrix,family,par,par2,type=2)

D_BIC

logLik1 = CDVineLogLik(Umatrix,family,par,par2,type=2)

sum(logLik1$ll)

logLik1$loglik


#Plot trees of a Canonical Vine Copula

CDVineTreePlot(Umatrix,family,par,par2,type=2,edge.labels=c("family","emptau"))
```