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About the relationship between renewable energy and oil markets

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LO Gaye Del[1].

Abstract

This paper examines the link between oil and renewable energy markets. To this end, on the one hand, we identify high and low volatility states of oil markets, using the regime-switching EGARCH (1,1) model, and analyze its effects on the renewable energy market. On the other hand, we develop a methodology to identify positive and negative oil shocks and investigate their implications for renewable energy markets. We show that: (1) state shifts are clearly present in the oil and renewable energy data; (2) the volatility links between oil and renewable energy markets are regime-dependent. When the oil market is in a high-volatility regime, it exacerbates the volatility of renewable energy markets, but in a low-volatility regime, it has no effect or a stabilizing effect on the volatility of renewable energy market; (3) the results also reveal that the renewable energy market reacts positively to extreme upward movements of oil prices and negatively to extreme downward movements. These

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results have several implications in terms of policies, portfolio optimization and risk management.

JEL classification: Q42, E44, C58.

Keywords: renewable energy; oil price; EGARCH(1,1); markov-switching; VaR.

1 Introduction

The relationship between the oil and renewable energy markets is a crucial issue involving several actors with sometimes differing objectives. For governments, the goal is firstly to limit fossil-fuel dependence and improve energy security. However, they are also motivated by environmental protection concerns, the threats posed by climate change and, in particular, by the need to successfully implement the 2015 Paris Agreement[2]. Consequently, mobilizing investment and financing in low-carbon energy technologies, and especially in renewable electricity, is now central to implementing the Paris Agreement OCDE [2016]. This would be mainly achieved through institutional and individual investors, so it is crucial for them to have a sound understanding of the interactions between these markets, to enable them to optimize their capital allocations. For investors, renewable energy provides an opportunity to diversify their energy portfolios. In fact, in the light of fossil fuel scarcity and environmental awareness, green energy-related assets have attracted considerable attention and offer the market investment alternatives Gormus and Sarkar [2014]. Therefore, in terms of technology and maturity, investors are more interested in solar and wind energy.

The trend for global renewable energy investments has been upward, led mainly by solar and wind power. For example, between 2007 and 2008, solar energy increased by 57% and wind energy rose by 22.4% (see Figure 1). A similar situation was observed between 2010 and 2011 but with lower growth rates (49.5% for solar and 17.1% for wind). This performance was mainly attained in China, the Asia-Oceania regions and Europe. In 2015, developing countries represented the majority ($156 billion) of the investment commitment to renewables, led by China ($102.9 billion), India ($10.2 billion) and Brazil ($7.1 billion). Developed markets invested $130 billion in 2015, led by Europe ($48.8 billion), the United States ($44.1 billion) and Japan ($36.2 billion) [3]. However, the 18% decrease in investment in 2016 compared

[2]concluded by the 21st Conference of the Parties (COP21) of the United Nations Framework Convention on Climate Change (UNFCCC).

[3]World Economic Forum, 2016. http://www3.weforum.org/docs/WEF_Renewable_Infrastructure_Investment_Handbook.pdf

to 2015 was partly due to the Chinese economic downturn and to the drop in prices of solar panels and other equipment.

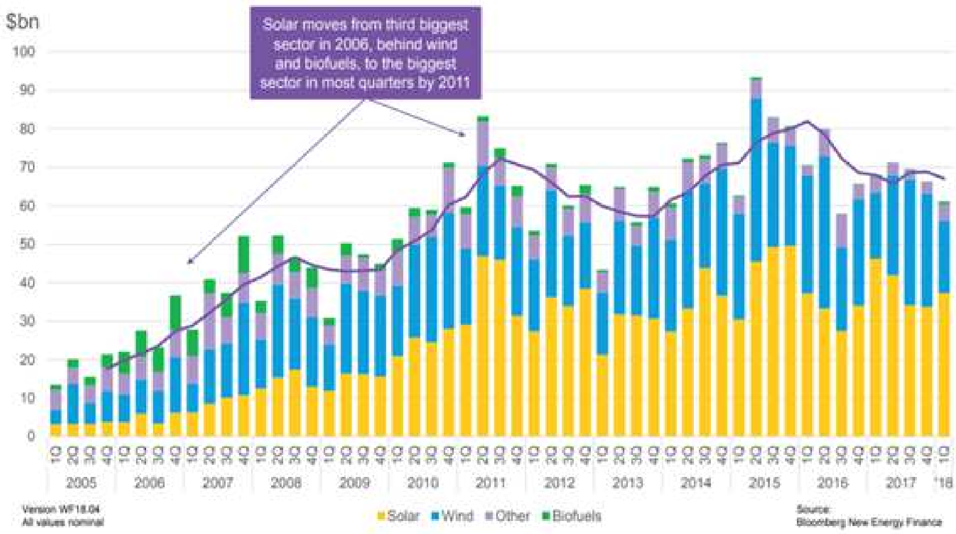


Figure 1: Global New Investment in Clean Energy by Sector

Source: Bloomberg New Energy Finance

Renewable energy and oil price stocks share differences and similarities, in terms of investment opportunities. In this way, renewable energy investments must be sustainable in order to improve their competitiveness against non- renewable energies. As the costs of producing renewable energy come down while the costs of producing fossil fuels rise, a substitution effect will occur between fossil fuel sources and renewable energy sources Sadorsky [2012b]. The links between the oil and renewable energy markets have attracted a great deal of attention from researchers, investors and public decision-makers. However, very little is known about the relationships between clean energy stock prices and various other important macroeconomic variables Sadorsky [2012a], and these links have not been clearly established in the literature. In fact, Henriques and Sadorsky [2008], Inchauspe et al. [2015] find a weak dependence between oil prices and renewable energy returns while Reboredo [2015], Reboredo et al. [2017], Bondia et al. [2016], Kumar et al. [2012], Sadorsky [2012a], Managi and Okimoto [2013], found a significant relationship. The connection between oil and renewable energy markets seems to be more occasional than permanent, and it is stronger during periods of uncertainty.

The main purpose of this paper is to assess the extent and evolution of the links between oil and renewable energy markets. In other words, in the first part, we identify high and low oil volatility periods and investigate their effects on renewable energy markets. In the second part, we develop a strategy based on VaR violation, in order to identify positive and negative oil shocks and investigate their implications for renewable energy markets. Our strategy allows us to evaluate whether the transmission of oil price shocks is immediate or if it occurs a few days before or after an oil market shock. These aspects could be addressed by the following questions: how do renewable energy markets react to low and high oil price volatility? Do the dates of high oil price volatility periods coincide with the dates of high renewable energy price volatility periods? How do renewable energy markets respond to extreme upward or downward movements in oil prices? Does the renewable energy market respond immediately? In other words, does the renewable energy market anticipate oil price shocks? How quickly do oil price shocks dissipate?

We consider that there is an extreme movement (up or down) if the VaR (positive or negative) is exceeded. This paper is related to the study by Reboredo [2015] who investigates the systemic risk of oil prices on renewable energy stock prices. However, (1) to the best of our knowledge, we introduce Regime-Switching EGARCH Models into this context for the first time, in order to enable the oil price volatility process to shift between high and low volatility states and analyze their impacts on the renewable energy market. (2) Then, we focus on the impact of extreme oil price movements on renewable energy returns, using dummy variables to capture extreme upward or downward movements based on VaR violation. (3) Our methodology has the advantage of dating the day of transmission extremely accurately, while also enabling an assessment of whether oil price shocks are anticipated or are persistent. To the best of our knowledge, our paper is the first empirical study to document these issues. (4) Our study distinguishes and compares the effects of upward and downward movements of oil prices on renewable energy markets.

Our empirical results show a positive link between oil and renewable energy prices. In fact, the oil market is characterized by low and high volatility regimes. When the oil market is in a low volatility regime, it has no effect on the SOLAR and SPGCE index but tends to stabilize the volatility of TECH market. The results of the WIND and ERIX index are different from those of other energy sectors. These markets do not react immediately to oil price shocks, compared with other markets (SOLAR, SPGCE, TECH). When the oil market is in a high volatility regime, the WIND market reacts a few days later, which may coincide with the transition from a high oil market volatility regime to a low volatility regime. However, these results do not indicate whether the volatility is due to oil prices rising or falling. We therefore identified upward and downward movements of oil prices, based on VaR violation. The results obtained show that an extreme upward movement in oil prices only has a significant positive impact on SOLAR and SPGCE returns. The WIND, ERIX and TECH indexes do not react to extreme upward movements of oil prices. However, downward movements of oil prices are highly negatively correlated to renewable energy indexes. It is important to underline that the reaction of the renewable energy market, following an oil market shock, seems to be immediate, excepting the WIND index which reacts one day later. The TECH index anticipates oil prices shocks one to two days before, while these shocks are not anticipated by the other indexes (SOLAR, WIND, ERIX, SPGCE). Shock persistence varies among renewable markets. For TECH, SPGCE and ERIX, the effect of the shock disappears quickly. However, for SOLAR, shocks are more likely to persist for two to three days, and at least five days for WIND. The remainder of this paper is organized in the following manner. We present a review of the literature in Section 2 and describe the methodological approach in Section 3. Section 4 describes the data and Section 5 presents the empirical results. We present our concluding remarks and implications in Section 6.

2 Literature review

Promoting the Green economy is partly dependent on renewable energy deployment and therefore on the performance and economic viability of companies operating in this sector. Consequently, the identifying factors, which determine the performance of these companies, have attracted the attention of many researchers. In this context, oil prices are considered as one of the main factors that could impact the returns of renewable energy companies. This is the idea behind many studies in the literature Reboredo [2015],Reboredo et al. [2017]. Other authors include other potential determinants, such as the technology market (Henriques and Sadorsky [2008], Sadorsky [2012a], Inchauspe et al. [2015]), or the carbon market Kumar et al. [2012]. However, the relationship between renewable energy market and technology market seems to have more consensus in the literature than the relationship between renewable energy and oil markets. Indeed, the stock prices of technology and alternative energy companies are highly and positively correlated (Henriques and Sadorsky [2008]; Sadorsky [2012a]; Bondia et al. [2016]; Inchauspe et al. [2015]; Kumar et al. [2012]). Investors consider renewable energy and technology stocks to be similar asset classes.

Regarding the relationship between oil and renewable energy prices, there is no consensus in the literature.Henriques and Sadorsky [2008], Sadorsky [2012a], Inchauspe et al. [2015] found a weak correlation while Kumar et al. [2012], Managi and Okimoto [2013], Reboredo [2015] conclude that there is a significant positive relationship.

Henriques and Sadorsky [2008], analyzes the relationship between oil prices, alternative energy stock prices, technology stock prices, and interest rates. Using vector autoregressive (VAR) methodology, they show that renewable energy markets react weakly to shocks resulting from the oil market. Sadorsky [2012a], extends this analysis by taking into account the volatility spillover and shows that the dynamic conditional correlations between clean energy stock and technology stock prices are higher than those of clean energy stock and oil prices. Kumar et al. [2012] integrates the carbon market into this analysis and shows a positive relationship between oil and clean energy companies' stock prices. However, carbon prices do not explain the stock price movements of clean energy companies. Also, the results of this study support the idea that investors do not see any difference between the assets of clean energy companies and high tech companies. Taking structural changes into account, Managi and Okimoto [2013] analyzes the relationships between oil prices, clean energy stock prices, and technology stock prices. Using the Markov-switching vector autoregressive (MSVAR), he shows that the oil market was characterized by permanent structural changes between the end of 2007 and the middle of 2008, a period in which oil prices rose sharply. The results obtained show a positive and significant impact after the structural change. Focusing on the Chinese market, Wen et al. [2014], aims to capture the spillover effects that occur in stock returns and volatilities of new energy and fossil fuel companies. The results of this study show that good news on the new energy stock market causes a drop in fossil fuel returns on the following day, whereas good news about fossil fuel stock returns leads to a rise in new energy returns on the subsequent trading day. However, negative news about new energy (fossil fuel) stock returns causes larger changes in fossil fuel (new energy) stock returns.

Reboredo [2015], studies systemic risk and dependence between oil and renewable energy markets using copulas and the conditional value-at-risk, for the period from 30 December 2005 to 12 December 2013. Indeed, he initially uses different specifications of time-varying copula to analyze the dependence structure between oil and renewable energy index returns. He then uses CoVaR to capture risk spillovers from oil prices to renewable energy prices. The results show a positive correlation between oil and renewable energy stock returns and conclude in favor of oil and renewable energy market integration, given the evidence of symmetrical tail dependence. The contribution of oil price dynamics to the downside and upside risk of renewable energy companies is around 30%. Reboredo et al. [2017] extends this analysis, using wavelets and linear and non-linear Granger causality tests to investigate the dependence and direction of causality between oil and renewable energy stock returns at different time scales. The results for the January 2006 to March 2015 period reveal a weak association between oil and renewable energy prices in the short term. In the long term, the dynamics of this interaction gradually increased, with observed differences between the global and sectoral index and between different periods. The causality analysis concludes in favor of non-linear causality at both low and high frequencies. However, they observed a unidirectional and bidirectional linear causality according to the time scale. Inchauspe et al. [2015] is interested in this debate and proposes a state-space multi-factor asset-pricing model to capture the influence of oil prices, technology stocks and the MSCI World stock market index on renewable energy stocks. The results indicate that oil prices are weakly correlated with renewable energy prices and that this relationship has been reinforced in recent years. On the other hand, renewable energy returns are highly correlated with the MSCI World Index and technology stock returns. Ferrer et al. [2018] has recently shown that crude oil prices and financial markets have become highly efficient and that shocks are transmitted very quickly from one market to another. This connectivity is strengthened during periods of financial turmoil. Their results also show that crude oil has a minor impact on the performance of renewable energy stocks. Other authors have also been interested in this relationship Lundgren et al. [2018], Ahmad [2017], Zhang and Du [2017], Sun et al. [2019], Dutta et al. [2018].

Our study is related to this literature and introduces Regime-Switching EGARCH models to enable the oil price volatility process to shift between high and low volatility states. The distinction between calm periods and periods of turbulence seems to be important because it allows us to assess how renewable energy markets react under different regimes (low or high volatility). In this paper, we also use a strategy based on VaR violation to capture extreme movements in oil prices and compare the effects of upward and downward movements of oil prices on renewable energy markets.

3 Methodology

3.1 Model specification

This section aims to present an intuitive method for identifying extreme upward and downward movements in oil prices and analyzing the effects of oil prices on renewable energy stock prices. It is based on the oil market Value-at-risk (VaR) calculation. The VaR technique can be applied to such risky assets in order to quantify losses in each asset or commodity. It measures the maximum loss in value of a risky portfolio that would be expected to occur due to changes in market prices over a period, for a given confidence interval. Several variants of VaR approaches exist in the literature. However, in this study, the Gaussian method is employed. The efficiency of the VaR estimates depends on the accurate approximation of the return series distribution. The Gaussian method, for instance, assumes that $L(l) \sim$ N($\mu L(l)$, $\sigma^2 L(l)$), where $L(l)$ is the loss function over a time period l and $\mu L(l)$, $\sigma^2 L(l)$ denote respectively the mean and the variance for this loss distribution. The VaR for a confidence level α can be given then by:

$$P(L(l) \geq VaR_{l\alpha}) \leq 1-\alpha \tag{1}$$

Consider a series of observed losses on the oil market $L_t(l^{oil})$ with $t = 1, \ldots, n$ and $Var_{\alpha l^{Oil}}$ being the maximum loss of oil stock prices that would be expected over a period l, for a given confidence level α. Defining the event $l_t^{oil} > VaR_{\alpha l^{oil}}$ as the violation, which means that a situation in which the observed loss at the date t exceeds the anticipated VaR, we denote a dummy variable D_t such that:

$$\begin{cases} D_t &= 1 \ if \ l_t^{oil} > VaR_{\alpha l^{oil}} \\ D_t &= 0 \ otherwise \end{cases}$$

In other words, this variable is 1 if there is an extreme movement in the oil market and 0 otherwise. We can thus define D_t^+, D_t^- as dummy variables respectively capturing extreme upward and extreme downward movements. We use an ARMA-GARCH specification to study the reaction of the renewable energy market following extreme upward and downward movements in oil prices. The general form of the GARCH (p,q) model Bollerslev [1986] is given by:

$$r_t = \mu + \epsilon_t \tag{2}$$

$\epsilon_t \sim$ N(0, σ_t^2) and

$$\sigma_t^2 = w + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{3}$$

Where r_t is the returns at time t, μ is the mean value of the returns, ϵ_t is the error term at time t, q is the order of ARCH process, p is the order of the GARCH process, σ_t^2 is the conditional variance at time t, and w is the unconditional variance. Hence, the volatility response to market movements is measured by α_i, whereas the persistence of shocks on conditional variance is given by β_j. Unlike the GARCH model, the EGARCH model Nelson [1991] allows positive (upside) shocks and negative (downside) shocks to have different effects on volatility.

In the EGARCH (p,q) model, the conditional variance is given by:

$$ln\sigma_t^2 = w + \delta_i(|z_{t-1}| - E[|z_{t-1}|]) + \alpha_i\epsilon_{t-1}^2 + \beta_i ln\sigma_{t-1}^2 \tag{4}$$

z_{t-i} is white noise and w, δ, α, β are the parameters. The parameter δ captures the asymmetry effect. Taking into account the dummy variable D_t in the mean equation according to ARMA(m,n)-EGARCH(1,1), we can model:

$$r_t^{RE} = \phi_0 + \sum_{i=1}^{m} \phi_i r_{t-i} + \epsilon_t + \sum_{j=1}^{n} \theta_j \epsilon_{t-j} + \sum_{j=-5}^{5} c_k D_t^+(k) \tag{5}$$

$$r_t^{RE} = \phi_0 + \sum_{i=1}^{m} \phi_i r_{t-i} + \epsilon_t + \sum_{j=1}^{n} \theta_j \epsilon_{t-j} + \sum_{j=-5}^{5} c_k D_t^-(k) \tag{6}$$

$$ln\sigma_t^2 = w + \delta_i(|z_{t-1}| - E[|z_{t-1}|]) + \alpha_i\epsilon_{t-1}^2 + \beta_i ln\sigma_{t-1}^2 \tag{7}$$

Where r_t^{RE} is the continuously compounded daily returns of the renewable energy stock, ${}_t^+(k)$ ($D_t^-(k)$) is a dummy variable which is 1 when the day t occurs within day k relative to the extreme movement date, the day before or after the extreme movement date, and 0 otherwise, with k $\in$ {*-5, -4, -3, -2, -1, 0, +1, +2, +3, +4, +5*}. For example, $k = -1$ means one day before the extreme movement date, $k = +1$ means one day after the extreme movement date and $k = 0$ means the extreme movement date, and so on. The sequence of events around the extreme movement date is explained by the following diagram:

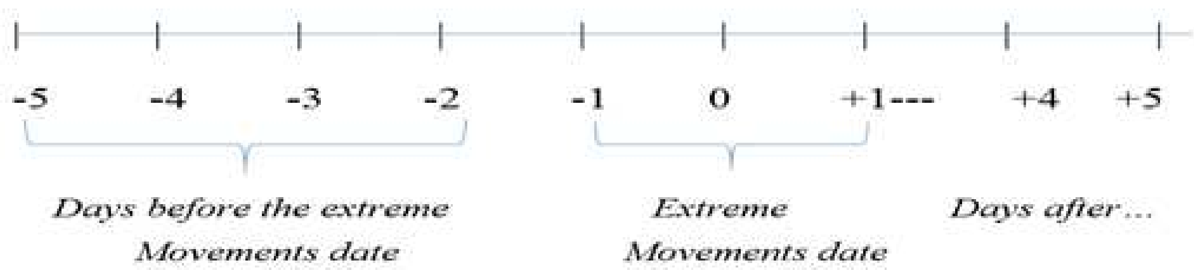


Figure 2: Sequence of events of extreme movements

3.2 Implications

The renewable energy market's response to oil market shocks depends on the degree of integration of these markets. We can draw several implications from the above-mentioned model:

i- Since the renewable energy market adjusts according to oil price fluctuations, the coefficients associated with extreme price-movement periods (coefficients for k = *0*) must be non-zero: *Market integration hypothesis.*

ii- The effect of oil price fluctuations varies according to whether oil prices rise or fall. The coefficients for k = *0* must be positive in the case of extreme upward movements in oil prices, and negative in the case of extreme downward movements in oil prices: *Positive dependence hypothesis*

iii- During days before an extreme movement period, the effect of oil prices on renewable energy markets might be null or non-null: the coefficients for k = *- 5 to -1* might be significant or non-significant according to the degree of integration of renewable energy and oil markets: If the coefficients for k = *- 5 to -1* are significant, it means that the renewable energy market anticipates oil market shocks: *Anticipation effect.*

iv- If the renewable energy market is slow to react to oil market shocks, the coefficient associated with extreme movement periods (*coefficient for* k = *0*) will be zero, with the market reaction occurring after the periods of extreme movement (*coefficient for* k = *2, 3,...*).

v- If the renewable energy market responds to oil market shocks at k and the associated coefficients for *k+1, k+2,...* are significant: *Persistence effect.*

4 Data

In this paper, we examine global and sectoral renewable energy data. We use Brent oil prices as a proxy for the oil market. Daily data are used, ranging from 02/01/2006 to 30/11/2016. The global renewable energy indexes used for this study are the S&P Global Clean Energy Index (SPGCE) and the European Renewable Energy Index (ERIX), which cover the major companies operating in the renewable energy field worldwide. The ERIX index is composed of the ten largest companies in the renewable energy fields, including the wind, solar, biomass and water sectors. For SPGCE, it includes 30 companies from around the world. To capture the specificities of individual renewable energy sectors, we use three sectoral indexes: the NYSE Bloomberg Global Solar Energy Index (SOLAR), the NYSE Bloomberg Global Wind Energy Index (WIND) and the NYSE Bloomberg Global Energy Smart Technologies Index (TECH). The SOLAR index includes companies operating in the solar energy value chain, including the manufacture of photovoltaic or solar thermal components and equipment, and the financing, development and operation of solar projects. The WIND index includes companies specializing in wind energy, including in the manufacture of generating equipment and the financing, development, and operation of wind projects. Finally, the TECH index includes companies operating in the advanced transportation, digital energy, energy efficiency, and energy storage sectors. All the renewable energy data originated from Bloomberg, and oil price data were obtained from the US Energy Information Agency (EIA) database.

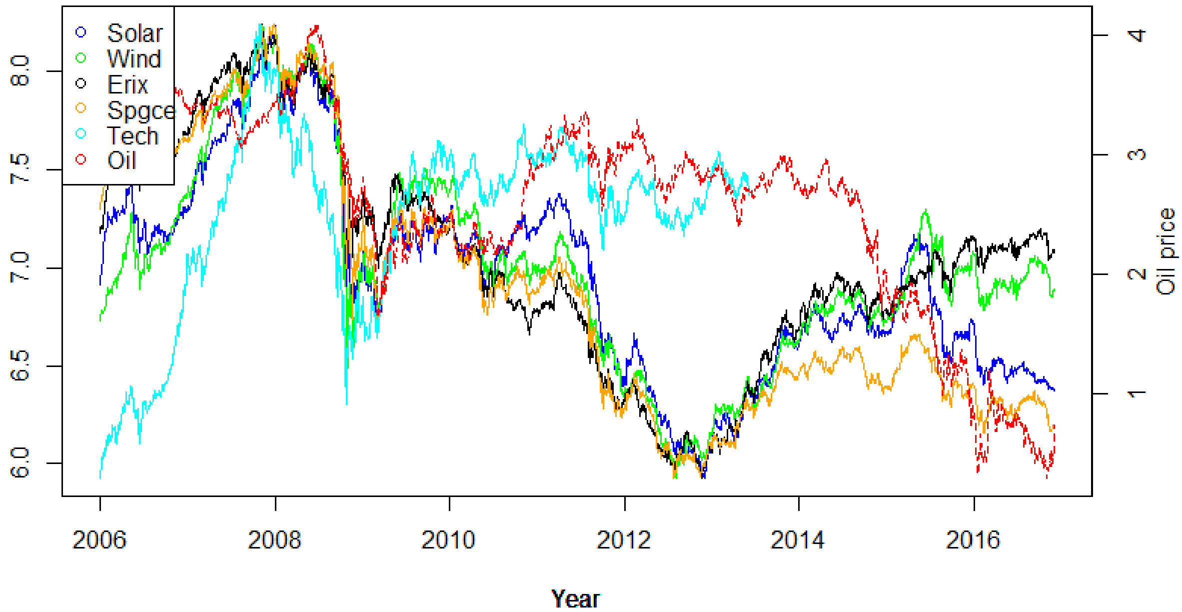


Figure 3: log(price) dynamics for Brent oil and renewable energy indexes.

In order to analyze the effects of oil prices on renewable energy prices, the returns of series r_t are calculated according to continuously compounded rates of return as follows: $r_t = log(\frac{P_t}{P_{t-1}})$, where P_t and P_{t-1} are prices of the current and previous period, respectively.

The dynamics of renewable energies and oil prices (Figure 3) show that they are highly volatile. The renewable energy market is characterized by a downward trend from 2008 to 2013 and an upward trend from 2013.

Table 1 shows the descriptive statistical results. The high values of the kurtosis statistic suggest that the distribution of returns have fat tails. All renewable energy returns are skewed to the left and to the right for oil prices. In addition, the Jarque-Bera Statistic rejects the normality hypothesis for all series and the Ljung-Box statistic indicates strong evidence of autocorrelation in squared returns. The value of standard deviations confirms the presence of volatility in these markets, but it is more pronounced in the oil market. The autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) statistic indicates the presence of ARCH effects in all series.

Our descriptive analysis detects the presence of ARCH effect in all return series. Therefore, the volatility of renewable energy and crude oil markets can be appropriately estimated using the GARCH family models.

Table 1: Descriptive statistics

	Excess returns					
	Solar	Wind	ERIX	TECH	SPGCE	Oil
Mean	0.00019	0.00004	−0.00003	0.00048	−0.00039	−0.00094
Median	0.00017	0.00056	0.00053	0.00056	−0.00039	0.00000
Minimum	−0.12630	−0.13950	−0.14990	−0.11480	−0.14970	−0.20560
Maximum	0.51900	0.12190	0.14590	0.11750	0.18090	0.25180
Sd	0.02063	0.01551	0.02032	0.01809	0.02025	0.03965
Skewness	−0.51450	−0.81540	−0.44360	−0.0966	−0.48470	0.02821
kurtosis	6.929	17.900	6.610	5.108	11.510	4.051
JB 10^2	58.26*	141.50*	52.81*	158.30*	21.18*	19.50*
$LB^2(20)10^2$	43.91*	39.61*	41.16*	57.36*	14.56*	12.50*
ARCH-LM	743.6*	795.8*	763.9*	963.9*	340.8*	402.3*

JB is the the Jarque-Bera test statistic. LB^2 is the Ljung–Box statistic for the squared returns serial correlation. ARCH-LM is Engle's LM test for heteroskedasticity. (*) indicates rejection of the null hypothesis at the 1% level.

5 Empirical results

This section aims to present the empirical results of renewable energy market volatility (5.1) and analyze their reaction to oil market shocks (5.2). Indeed, in the first step, we use a GARCH model to measure renewable energy market volatility (5.1.1). We then introduce Regime-Switching GARCH Models to enable the volatility process to shift between regimes (5.1.2). This approach will be used to identify high and low volatility periods in the oil market and analyze their effects on the renewable energy market (5.2.1). In section (5.2.2), the methodology developed in section (3) is used to identify positive and negative shocks and investigate their implications for the renewable energy market.

5.1 Renewable energy market volatility modeling

5.1.1 GARCH modeling

We estimated GARCH and EGARCH models and we selected the best model according to the Akaike information criterion (AIC) and the log-likelihood statistics. The no-correlation hypothesis was verified by the Ljung-Box test. For all indexes, except for TECH, the GARCH specification seems to be the best. The results obtained for the GARCH model are shown in Table 2. The coefficients are highly significant for all renewable energy markets. In addition, β is close to 1 for all markets, suggesting high persistence of shocks. The ARCH effect as measured by α is significant for all markets apart from the SOLAR market. The asymmetric coefficient δ is positive and statistically significant for the TECH index.

Table 2: Estimation of GARCH(1,1)

	Renewable energy returns				
Coeffi	SOLAR	WIND	ERIX	SPCGE	TECH
ω	0.00001**	0.00001***	0.00001***	0.00001**	−0.10044***
	(0.00000)	(0.00000)	(0.00000)	(0.16516)	(0.00753)
α	0.07224***	0.11490***	0.09713***	0.09783***	−0.03870***
	(0.00886)	(0.00795)	(0.00606)	(0.01031)	(0.01357)
β	0.91523***	0.84401***	0.87038***	0.88413***	0.98697***
	(0.01128)	(0.00981)	(0.00835)	(0.01169)	(0.00093)
δ					0.13848***
					(0.02081)
Loglikelihood	7483.57	8300.25	7474.14	7799.54	5312.96
AIC	−5.2606	−5.8349	−5.2540	−5.4828	−5.4760
$LB^2(15)$	5.284	20.74	9.21	9.72	19.86
ARCH test	5.113	19.42	9.41	9.61	20.4

Standard deviations are in parentheses.*** Significant at 1%, ** Significant at 5%, * Significant at 10%. For the wind index, the EGARCH(1,1) model presents traces of heroscedasticity, which is why we used a GARCH model that took better account of the non-constancy of variance. For ERIX index, the EGARCH model seems to be the best, but the asymmetry coefficient is not significant so the GARCH specification is used.

It appears from this analysis that renewable energy markets are highly volatile and the GARCH (1,1) model seems better for describing the characteristics of series[4]. The Ljung-Box statistic rejects the autocorrelation hypothesis of squared returns. The ARCH-LM test indicates the non-rejection of the null hypothesis. The TECH index is characterized by a positive asymmetry, suggesting that it is more responsive to positive innovations of returns than negative innovations with the same magnitude.

In addition, Figure 4 shows that renewable energy returns are characterized by high and low volatility periods. Consequently, the Markov switching model seems appropriate for taking account of the variability of market conditions.

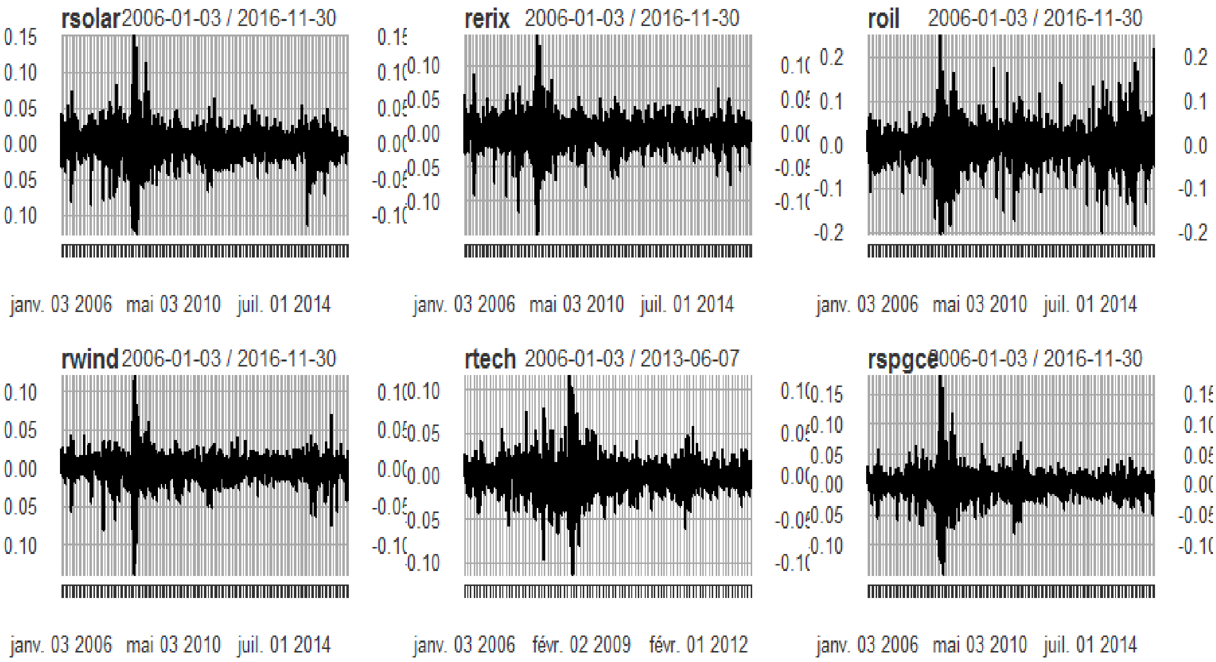


Figure 4: Dynamics of renewable energy and oil price returns

5.1.2 Evidence from the Markov Switching GARCH

Financial series are characterized by quiet and turbulent periods, often with volatility clusters. The GARCH models presented in section (5.1), (despite their ability to describe the characteristics of financial series) have certain weaknesses related to the presence of structural changes in the volatility of returns (Diebold [1986], Lamoureux and Lastrapes [1990]). Indeed, Diebold [1986] and Lamoureux and Las-

[4]Except for the TECH index, in which we use the EGARCH model

trapes [1990] attribute the high persistence of shocks to conditional variance due to structural change. The Markov switching model proposed by Hamilton [1988] is therefore an alternative for considering the effects of structural change in financial and economic time series. However, this model may not capture all characteristics of variance Cai [1994]. This weakness of the Markov switching model is taken into account by Cai [1994], which combines the Markov switching model of Hamilton [1988] with the ARCH model of Engle [1982]. Gray [1996] and Dueker [1997] extend this approach to GARCH model. As in Henry [2009], we examine an EGARCH and GARCH specification in which we allow the parameters of the model to switch between different regimes in order to describe the behaviors of renewable energy and oil markets.

As in Catania et al. [2018], we assume that r_t has a zero mean. The conditional variance of r_t follows a GARCH model (equation 8) for SOLAR, WIND, ERIX, SPGCE and an exponential GARCH model for TECH (equation 9):

$$h_{kt} = \alpha_{0,k} + \alpha_{1,k}\epsilon_{t-1}^2 + \beta_k h_{k,t-1} \tag{8}$$

$\alpha_{0,k} > 0$, $\alpha_{1,k} > 0$ and $\beta_k \geq 0$ to ensure positivity. The covariance–stationarity in each regime is obtained by requiring that $\alpha_{1,k} + \beta_k < 1$.

$$ln(h_{kt}) = \alpha_{0,k} + \alpha_{1,k}(|z_{k,t-1}| - E[|z_{k,t-1}|]) + \alpha_{2,k}\epsilon_{t-1}^2 + \beta_k ln(h_{k,t-1}) \tag{9}$$

$\epsilon_{it} \mid \Omega_{t-1} \longrightarrow N(0, h_{it})$ where $s_t \in \{1, 2\}$.

This specification takes into account the leverage effect, where past negative observations have a larger influence on the conditional volatility than past positive observations of the same magnitude. There is no parameter positivity constraint and the model allows for two unconditional variances: high unconditional variance and low unconditional variance.

The regime-switching is assumed to follow a first-order Markov process with transition probability: $P(s_t = j|s_{t-1} = i) = P_{ij}$, defined as the probability that the regime switches from state i at t-1 into state j at t. We can thus write:

$P(s_t = 1|s_{t-1} = 1) = P_{11}$

$P(s_t = 2|s_{t-1} = 1) = P_{21}$

$P(s_t = 2|s_{t-1} = 2) = P_{22}$

$P(s_t = 1|s_{t-1} = 2) = P_{12}$

Where P_{11} is the transition probability for state $s_t = 1$ conditional on state 1 and P_{22} the transition probability for state $s_t = 2$ conditional on state 2. P_{21} (P_{12}) is the transition probability for state $s_t = 2$ (1) conditional on state 1 (2). The basic principle of this model is to enable the model parameters to switch between different regimes or states. The regime is highly persistent if P_{ii} is close to 1.

The MS-GARCH (1,1) estimates are given in Table 4. A comparison of the performances of the MS-GARCH (1,1) and GARCH (1,1) models concludes in favor of the former. Indeed, Table 3 shows that the loglikelihood value of the MS-GARCH (1,1) model is greater than that of the GARCH (1,1) model for all series. For SOLAR, the loglikelihood value is 7483.57 for the GARCH (1,1) model and 7549.97 for the MS-GARCH (1,1) model. The same observation can be made for all series. In addition, the likelihood ratio (LR) statistic obtained by: $LRstat = 2 * (logL(\hat{\theta}) - logL(\bar{\theta}))$ is highly significant for all series, where $L(\hat{\theta})$ is the likelihood of the unconstrained model and $logL(\bar{\theta})$ is the likelihood of the constrained model. The null hypothesis (that the GARCH (1,1) model is the correct model) is rejected for all markets and according to AIC statistics, the MS-GARCH (1,1) model is the best. Therefore, the MS-GARCH (1,1) model describes the data more accurately than the GARCH(1,1) model.

As presented at the beginning of this section, it is assumed that the Markov switching model allows the switching of the conditional variance between two regimes.

Table 3: Summary statistics for EGARCH and MS-GARCH models

	Clean energy returns				
Coefficients	SOLAR	WIND	ERIX	SPCGE	TECH
Log-likelihood					
GARCH(1,1)	7483.57	8300.25	7474.14	7799.54	5312.96
MS-GARCH(1,1)	7549.97	8351.6516	7503.99	7841.26	5340.75
LR Statistics					
LR stat	132.8^{***}	102.80^{***}	59.7^{***}	83.4^{***}	55.58^{***}
AIC					
EGARCH(1,1)	-5.26064	-5.8349	-5.2540	-5.4828	-5.4760
MS-EGARCH(1,1)	-15083.94	-16687.30	-15666.52	-14991.98	-10661.51
Number of paramet.					
EGARCH(1,1)	3	3	3	3	4
MS-EGARCH(1,1)	8	8	8	8	10

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. For the TECH index, we compare the EGARCH (1,1) with MS-EGARCH(1,1) model.

For all of the considered series, the observed heterogeneity in the estimated coefficients, as well as the unconditional volatility dynamic, suggest the existence of a low-volatility state (regime 1) and a high-volatility state (regime 2). In fact, the unconditional volatility for regime 1 is 0.150, 0.066, 0.192, 0.140 for SOLAR, WIND, SPGCE and ERIX respectively, and for regime 2, it is evaluated at 0.775, 0.718, 0.855, 1.108 for the same index. Regime 1 can be interpreted as the normal state and regime 2 as a period of uncertainty.

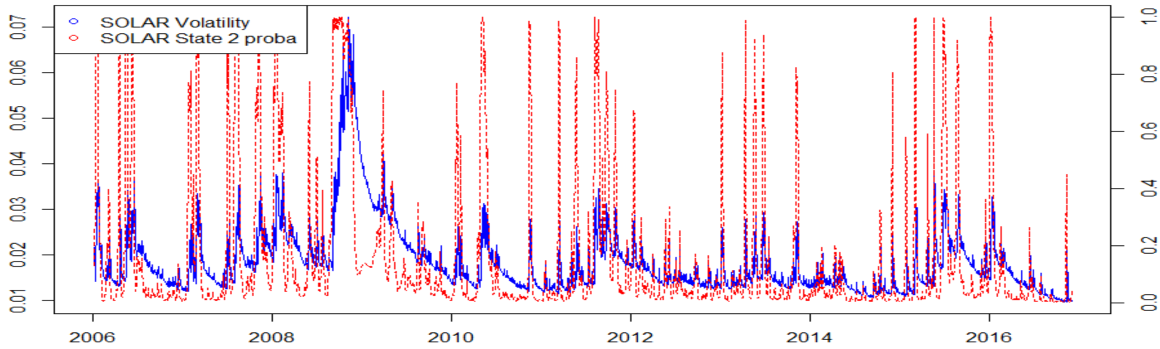
The analysis per sector shows that for SOLAR, the GARCH term estimated at $\hat{\beta}$ is significantly high in both regimes, which means that volatility stocks are highly persistent in regimes 1 & 2. The $\hat{\alpha_{11}}$ is positive and statistically significant and $\hat{\alpha_{12}}$ is also positive but not significant. This suggests that incoming news is more likely to amplify volatility in regime 1 than in regime 2. The analysis of the estimated coefficients for other sectors (ERIX, WIND, SPGCE) shows that the low volatility state is more sensitive to incoming news than the high volatility state, but this effect is more accentuated for the WIND index. The GARCH coefficient $\hat{\beta}$ is significantly high for all series and for both regimes, excepting the TECH index for regime 1, where the estimated coefficient is 0.4419***: these markets are characterized by an extremely high degree of volatility persistence and shocks are more likely to persist in regime 1 than regime 2, except for the TECH index. The asymmetry coefficients are negative and statistically significant for TECH in both regimes. d_1 and d_2 measure the regime duration. Regime 1 lasts for an average of 28 days while regime 2 lasts from 2 to 47 days with an average of about 16 days. Regime 1 is more persistent for all series except for the TECH index.

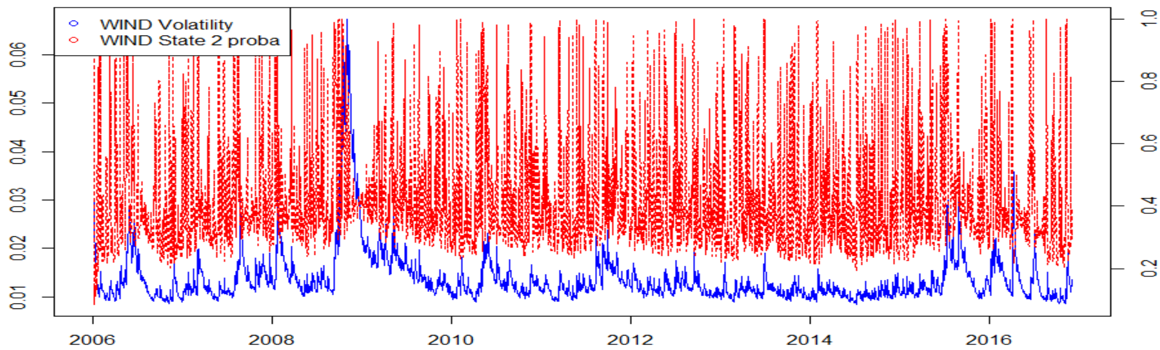
Table 4: Estimates of the Markov-switching GARCH model

	Clean energy returns				
Coeffi	SOLAR	WIND	ERIX	SPCGE	TECH
α_{01}	0.0000***	0.0000***	0.0000***	0.0000***	−5.0750***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_{02}	0.0001**	0.0000	0.0000**	0.0000**	−0.3204***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_{11}	0.0156**	0.0283***	0.0241*	0.0063**	−0.1309***
	(0.0114)	(0.0203)	(0.0254)	(0.0031)	(0.0000)
α_{12}	0.0707	0.1981*	0.0992	0.0781	0.0787***
	(0.0587)	(0.1494)	(0.0797)	(0.1343)	(0.0000)
α_{21}					−0.1445***
					(0.0000)
α_{22}					−0.1066***
					(0.0000)
β_1	0.9716***	0.9388***	0.9403***	0.9838***	0.4419***
	(0.0031)	(0.0118)	(0.0103)	(0.0020)	(0.0000)
β_2	0.9068***	0.7897***	0.8881***	0.9185***	0.9564***
	(0.0151)	(0.0106)	(0.0104)	(0.0062)	(0.0000)
P_{11}	0.9746***	0.6628***	0.9633***	0.9760***	0.9712***
P_{22}	0.8515***	0.5355***	0.8729***	0.8850***	0.9788***
d_1	35	3	27	40	35
d_2	7	2	8	14	47
Loglikelihood	7549.97	8351.65	7503.99	7841.26	5340.75
AIC	−15083.94	−16687.30	−15027.05	−15666.52	−10661.51
$LB^2(15)$	3.541	21.75	15.51	8.993	10.93
ARCH test	3.481	21.16	15.75	8.967	10.86

The standard deviations are in parentheses. *** Significant at 1%, ** Significant at 5%, * Significant at 10%. The MS-EGARCH (1,1) is estimated for the TECH index.

Figure 5 describes the association between high and low probability regimes and the conditional volatility of the renewable energy markets. These markets are relatively dominated by low volatility periods. Indeed, during the studied periods, the transition probability of remaining in regime 2 is several times closer to zero than one. The TECH and SPGCE indexes are more volatile compared to other indexes. However, the WIND index switches very frequently between high volatility and low volatility states. The 2006-2010 period was marked by increased volatility and the switching between high and low volatility was more frequent during this period. This phenomenon was more pronounced during the recent global financial market crisis, when renewable energy investments dropped significantly due to uncertainties in the financial markets.





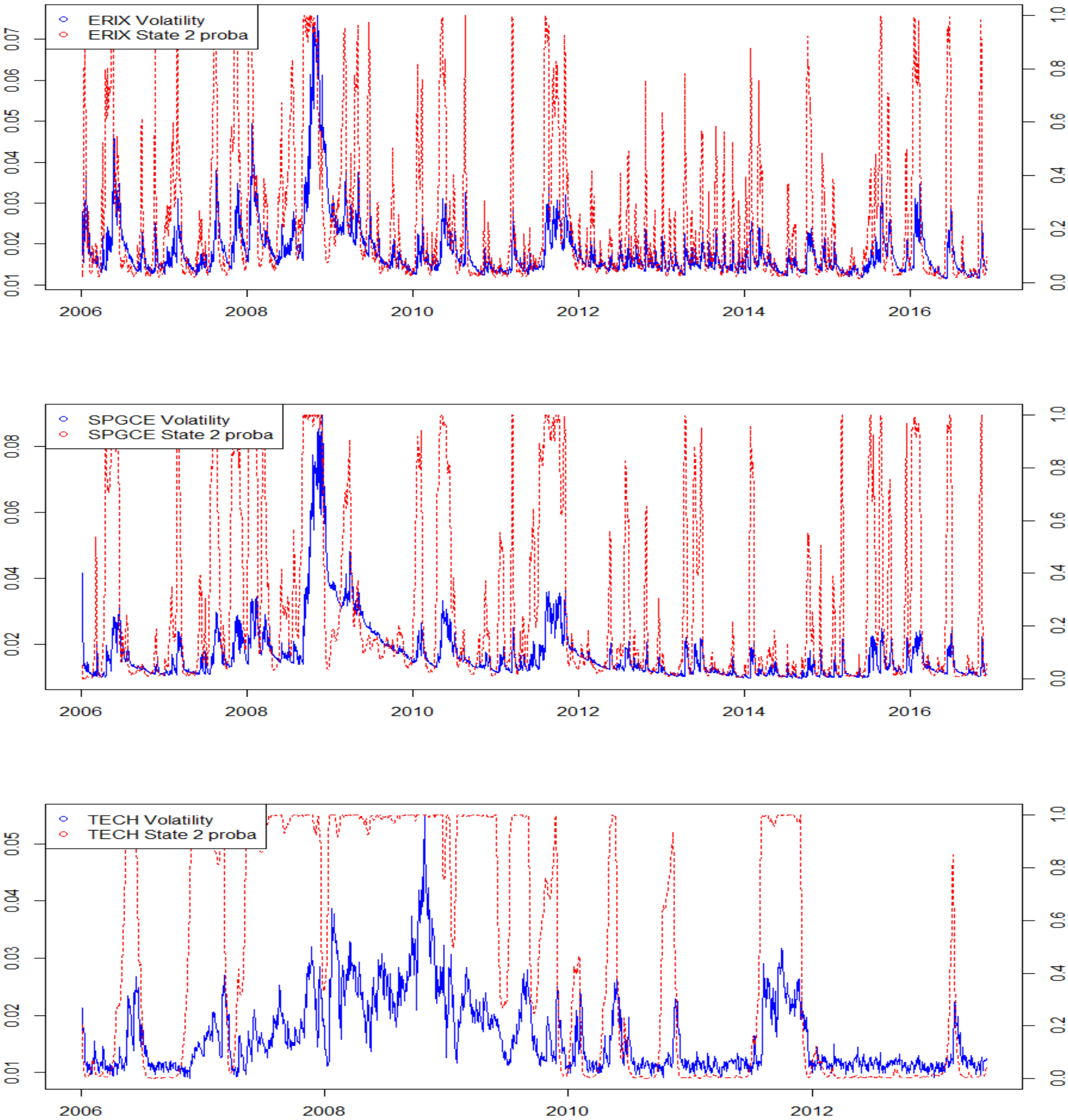


Figure 5: MS-GARCH (1, 1) estimation for Renewable energies series

5.2 The relationship between renewable energy stocks and oil prices

5.2.1 Asymmetric volatility spillovers between oil and renewable energy markets

Section (5.1.2) shows that the renewable energy market is characterized by quiet periods marked by low volatility, but also by periods of turbulence. The same characteristics are observed in the oil market. The following question then arises: how do high and low volatility states in the oil market affect the renewable energy market? To answer this question, we will adopt the same approach as Chiang et al. [2011]. More precisely, we incorporate the conditional variance obtained by MS-EGARCH(1,1) model estimates for oil into the conditional variance equation for the renewable energy index, such that:

$$r_t^{RE} = \phi_0 + \sum_{i=1}^{m} \phi_i r_{t-i} + \epsilon_t + \sum_{j=1}^{n} \theta_j \epsilon_{t-j} \tag{10}$$

$$\epsilon_{it} \mid \Omega_{t-1} \longrightarrow N(0, h_{it})$$

$$ln\sigma_t^2 = w + \delta_i(|z_{t-1}| - E[|z_{t-1}|]) + \alpha_i \epsilon_{t-1}^2 + \beta_i ln\sigma_{t-1}^2 + \lambda_i.h_{r,t}.I_d \tag{11}$$

Where r_t^{RE} is the continuously compounded daily returns of the renewable energy stock, $h_{r,t}$ is the conditional variance, obtained by the MS-EGARCH(1,1) model estimates for oil, and σ_t^2 is the conditional variance of the renewable energy market. I_d is a dummy variable, such that:

$$I_d = 1 \;\; if \;\; prob\,(s_t = 1|\Omega_{t-1}) \; > 0.5 \tag{12}$$

$$I_d = 0 \;\; if \;\; prob(s_t = 1|\Omega_{t-1}) \; \leq 0.5 \tag{13}$$

And:

$$I_d = 1 \;\; if \;\; prob\,(s_t = 2|\Omega_{t-1}) \; > 0.5 \tag{14}$$

$$I_d = 0 \;\; if \;\; prob(s_t = 2|\Omega_{t-1}) \; \leq 0.5 \tag{15}$$

Equations (12) and (13) describe a low-volatility regime for the oil market while equations (14) and (15) describe a high volatility regime for the same market.

$$ln\sigma_t^2 = w + \delta_i(|z_{t-1}| - E[|z_{t-1}|]) + \alpha_i \epsilon_{t-1}^2 + \beta_i ln\sigma_{t-1}^2 + \lambda_{low}.h_{r,t}.I_d \tag{16}$$

$$ln\sigma_t^2 = w + \delta_i(|z_{t-1}| - E[|z_{t-1}|]) + \alpha_i\epsilon_{t-1}^2 + \beta_i ln\sigma_{t-1}^2 + \lambda_{high}.h_{r,t}.I_d \qquad (17)$$

λ_{low} describes how oil market volatility affects the renewable energy market when it is in a state of low volatility. λ_{high} describes the oil market's impact on the volatility of renewable energy markets when it is in a state of high volatility.

Figure 6 shows the time-varying probability of the oil market remaining in regime 2 and we observe that the probability is sometimes close to one, and sometimes close to zero. If the probability is smaller than 0.5, the volatility remains low, and if the probability is larger than 0.5, the volatility remains high.

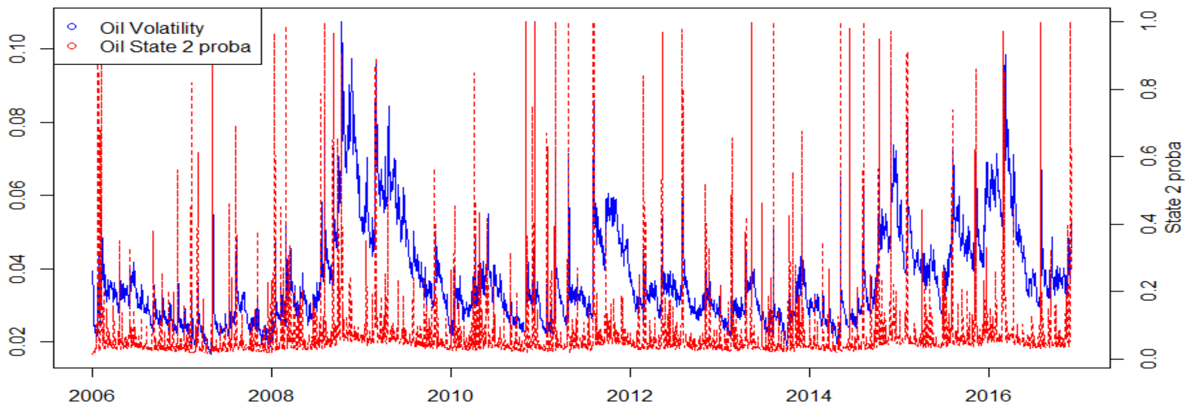


Figure 6: MS-EGARCH (1, 1) estimation for oil

Table 5 gives the results of volatility spillover between the oil and renewable energy markets. The ARCH effect coefficient α is significant for all series except for SOLAR. The β parameter is close to 1, suggesting the persistence of shocks. The asymmetry coefficient is positive and significant for all series. The results obtained also reveal that λ_{high} is positive and statistically significant for all indexes, except for the ERIX and WIND indexes. This result suggests a transmission of volatility from the oil market to the renewable energy market. When the oil market is in the high volatility regime, it exacerbates the volatility of the renewable energy market (SOLAR, SPGCE, TECH). However, this effect is greater for the TECH and SPGCE indexes.

The λ_{low} coefficient is not significant for the SOLAR, SPGCE and ERIX index.

When the oil market is in a normal state, it does not impact the renewable energy market, but when there is new information (good or bad news) leading to significant oil price fluctuations, the renewable energy market will not be unaffected. A surge in oil prices seems to have short-term consequences on the renewable energy market Managi and Okimoto [2013]. λ_{low} is negative and significant for the TECH index. In a low volatility regime, the oil market tends to stabilize or triggers a drop in TECH index volatility. The results for the WIND and ERIX indexes are different from other energy sectors. Indeed, the λ_{high} coefficient is not significant, and the λ_{low} coefficient is significant at 5% for WIND and 10% for the ERIX index. This result could be explained by the fact that these markets do not react immediately like other markets. In others words, when the oil market is in a high volatility regime, the WIND market responds a few days later, which may coincide with the oil market's transition from a high volatility regime to a low volatility regime.

Table 5: Volatility links between oil and renewable energy markets

	Clean energy returns				
Coeffi	SOLAR	WIND	ERIX	SPCGE	TECH
μ	0.00014	0.00082***	0.00032	−0.00001	0.00058**
	(0.00016)	(0.00027)	(0.00027)	(0.00041)	(0.00028)
ϕ_1	0.16988***	0.41612**	0.36074***	0.17014***	
	(0.01934)	(0.17607)	(0.04673)	(0.02262)	
θ_1		−0.31154*	−0.28983***		0.01612
			(0.04744)		(0.02310)
θ_2					0.01262
					(0.02282)
θ_3					0.06468***
					(0.02459)
ω	−0.15246***	0.00000	−0.34376***	−0.15504***	−0.06116***
	(0.01066)	(0.00000)	(0.04300)	(0.01818)	(0.02072)
α	−0.01173	0.11984***	−0.07679***	−0.04175***	−0.02841***
	(0.00822)	(0.02465)	(0.01185)	(0.00984)	(0.00926)
β	0.98134***	0.81736***	0.95918***	0.98152***	0.99127***
	(0.00104)	(0.04334)	(0.00451)	(0.00177)	(0.00196)
γ	0.14884***		0.17069***	0.16586***	0.12332***
	(0.01388)		(0.01670)	(0.01712)	(0.03536)
λ_{high}	2.67005**	0.00000	1.77404	4.13862***	4.46104***
	(1.30295)	(0.00029)	(1.55096)	(1.30427)	(1.37369)
λ_{low}	0.14497	0.00035***	0.47063*	0.06373	−0.27078**
	(0.17844)	(0.00010)	(0.27660)	(0.20295)	(0.13264)
Loglikelihood	7524.31	8332.3	7492.98	7839.54	5322.93
AIC	−5.2857	−5.8539	−5.2630	−5.5074	−5.4801
LB(15)	17.04	10.29	11.67	5.904	17.9
$LB^2(15)$	7.328	23.61	12.67	12.61	18.98
ARCH test	6.836	22.69	13.17	12.35	19.38

Standard deviations are in parentheses. *** Significant at 1%, ** Significant at 5%, * Significant at 10%. Comparing the GARCH and EGARCH models shows that the EGARCH model is better for all series other than the WIND index. The EGARCH (1,1) model presents traces of heroscedasticity, which is why we use a GARCH(1,1) model as this takes better account of the non-constancy of variance.

5.2.2 Measuring connectedness from the perspective of extreme movements

The dynamics of oil price returns confirm the unstable nature of the oil market, which could impact renewable energy prices. Therefore, upward and downward movements in oil prices are identified using the periods in which the VaR is violated, as shown in Figure 7. It should be recalled that the VaR limit is "violated" if a loss on a given day exceeds the $VaR_{99\%}$.

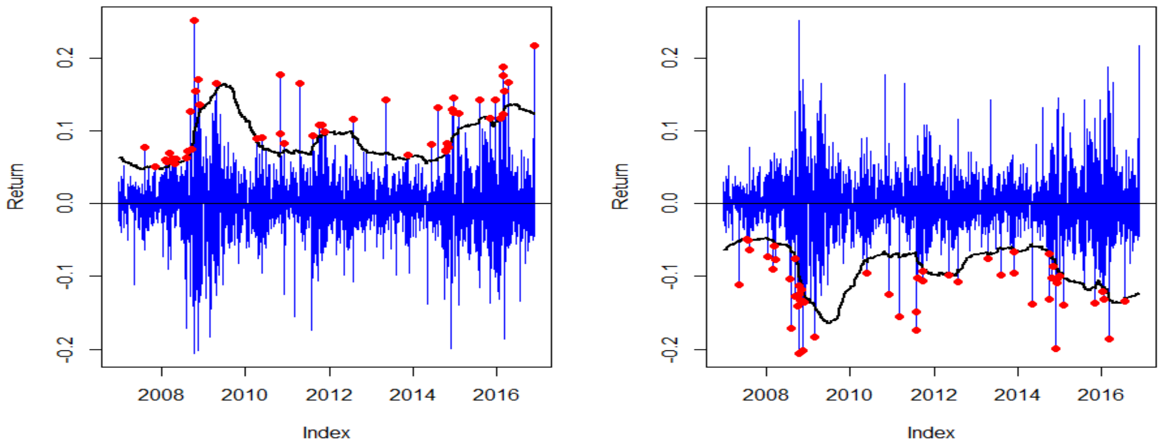


Figure 7: Extreme oil movements

Simple and partial correlograms reveal the presence of auto-correlation in all series (the Ljung Box test confirms this result). We therefore used the Box Jenking methodology to determine the appropriate ARMA (p,q) specifications for each series. The models were chosen using the AIC and loglikelihood criteria.

The results obtained are shown in Tables 6 to 10. The first part of the tables shows the estimated coefficients of the mean equation (ARMA model), followed by the dummy variables used to capture the days before (c_{-1}, c_{-2}, c_{-3}, c_{-4}, c_{-5}) and the days after (c_1, c_2, c_3, c_4, c_5) the extreme movement date (c_0). The coefficients c_{-1}, c_{-2}, etc. precisely describe one day, two days, etc. before the extreme movement date, and c_1, c_2, etc. describe one day, two days, etc. after the extreme movement date. Finally, we present the coefficients related to the variance equation. The Ljung Box autocorrelations test of the returns or squared returns for the first twenty lags does not invalidate the null hypothesis and the ARCH test does not invalidate the homoscedasticity hypothesis.

Table 6: Estimation results for the Solar Energy Index

		Effects of extreme oil movements			
	Coef.	Upward		Downward	
ARMA coefficients	μ	0.00005	(0.00050)	0.00049	0.000374
	ϕ_1	0.16866***	(0.01865)	0.16815***	(0.01824)
Days before the extreme movement date	c_{-5}	−0.00019	(0.00232)	0.00287	(0.00227)
	c_{-4}	−0.00156	(0.00235)	0.00125	(0.00235)
	c_{-3}	−0.00385	(0.00238)	−0.00382	(0.00233)
	c_{-2}	−0.00168	(0.00232)	0.00176	(0.00236)
	c_{-1}	−0.00136	(0.00227)	−0.00105	(0.00235)
Extreme movement date	c_0	0.00674***	(0.00237)	−0.01456***	(0.00246)
Days after the extreme movement date	c_1	0.00336*	(0.00182)	−0.00701***	(0.00234)
	c_2	0.00283***	(0.00076)	−0.00452*	(0.00232)
	c_3	0.00142***	(0.00051)	0.00336	(0.00234)
	c_4	−0.00160	(0.00239)	−0.00056	(0.00235)
	c_5	0.00037	(0.00231)	−0.00251	(0.00233)
Variance equation	w	−0.12882***	(0.00815)	−0.12000***	(0.01470)
	α	−0.01214	(0.00819)	−0.01078***	(0.00816)
	β	0.98331***	(0.00099)	0.98447***	(0.00171)
	γ	0.15320***	(0.01378)	0.15006	(0.01811)
Log-likelihood		7529.22		7549.12	
AIC		-5.2829		-5.2968	
$LB(15)$		17.52		15.96	
$LB^2(15)$		7.24		6.004	
ARCH test		6.757		5.677	

Standard deviations are in parentheses. *** Significant at 1%, ** Significant at 5%, * Significant at 10%.

The results obtained for the SOLAR index show that extreme upward (Upward column) and extreme downward (Downward column) movements in oil prices would positively impact the SOLAR market. The c_{-k}, k=1 to 5 coefficients are not significant whatever the nature of oil price movements. The associated extreme upward movement coefficient for oil prices c_0 is positive and statistically significant. This coefficient is negative and statistically significant in the case of downward oil price movements. For coefficients related to days after the extreme movement date, $\hat{c_1}$, $\hat{c_2}$, $\hat{c_3}$ are only positive and statistically significant in the case of extreme upward movements. For extreme downward movements in oil prices, only $\hat{c_1}$ and $\hat{c_2}$ are significant and negative. It can be noted from these results that an extreme upward movement in oil prices has a positive impact on SOLAR index returns, while a decrease negatively impacts it. However, a drop in oil prices has a greater impact on the SOLAR market than a downward movement in oil prices. These results also suggest that the SOLAR market does not anticipate the shocks induced by the oil market and these shocks are more likely to persist in the case of upward movements (three days) than downward movements (two days).

Unlike the SOLAR index, the ERIX and TECH indexes (see Table 10 in the appendix) do not react to extreme upward movements in oil prices. However, they respond negatively to extreme downward movements in oil prices. The $\hat{c_0}$ is estimated at -0.01221^{***} for ERIX, -0.00717^{**} for TECH and -0.01456^{***} for the SOLAR; therefore, the effects of extreme downward movements in oil prices are more pronounced for the ERIX index than for the SOLAR and TECH indexes. The results also reveal that the ERIX index does not anticipate shocks and that they are not persistent, whereas for the TECH index, shocks are anticipated one to two days before they occur, but they do not persist.

Table 7: Estimation results for the ERIX Energy Index

	Coef.	Oil extreme movement effects: Upward		Downward	
ARMA coefficients	μ	0.00034	(0.00035)	0.00054	(0.00030)
	ϕ_1	0.35845***	(0.06292)	0.30893	(0.12254)
	θ_1	−0.28877***	(0.06444)	−0.23364	(0.12262)
Days before the extreme movement date	c_{-5}	−0.00257	(0.00207)	0.00043	(0.00240)
	c_{-4}	−0.00144	(0.00256)	−0.00089	(0.00246)
	c_{-3}	−0.00025	(0.00250)	−0.00234	(0.00247)
	c_{-2}	−0.00036	(0.00248)	−0.00317	(0.00245)
	c_{-1}	−0.00133	(0.00243)	0.00343	(0.00243)
Extreme movement date	c_0	0.00363	(0.00255)	−0.01221***	(0.00250)
Days after the extreme movement date	c_1	0.00466*	(0.00254)	0.00049	(0.00246)
	c_2	−0.00326	(0.00325)	−0.00011	(0.00256)
	c_3	0.00043	(0.00248)	0.00412*	(0.00241)
	c_4	0.00058	(0.00247)	−0.00256	(0.00247)
	c_5	−0.00215	(0.00246)	−0.00410	(0.00257)
Variance equation	w	−0.26959***	(0.02592)	−0.26748***	(0.02642)
	α	−0.07663***	(0.01157)	−0.07161***	(0.01147)
	β	0.96609***	(0.00316)	0.96632***	(0.00321)
	γ	0.17031***	(0.01650)	0.17129***	(0.01644)
Log-likelihood		7496		7507.4	
AIC		-5.2588		-5.2668	
$LB(15)$		11.2		12.55	
$LB^2(15)$		13.4		12.97	
ARCH test		13.78		13.33	

Standard deviations are in parentheses. *** Significant at 1%, ** Significant at 5%, * Significant at 10%.

As for the SOLAR index, the results obtained for the SPCGE index point towards a broad transmission of oil market shocks to this index. The response of the SPGCE index varies according to the nature of the shock: it reacts positively (0.00696***) to extreme oil price rises and negatively (−0.01289***) to extreme downward movements. A drop in oil prices has more impact and its effects are slow to disappear, lasting from two to four days. Like the SOLAR and ERIX indexes, these results also suggest that shocks induced by the oil market are not anticipated by the

SPGCE index.

The results for the WIND index (see appendix) confirm those obtained with the GARCH model. The WIND index does not react to extreme rises or falls in oil prices. Its response comes one day later and tends to persist for at least five more days. This result suggests that the integration of other markets is more complete than that of the wind market.

Table 8: Results obtained for the SPCGE Energy Index

		Effects of extreme oil price movements			
	Coef.	Upward		Downward	
ARMA coefficients	μ	-0.00010	(0.00014)	0.00034	(0.00027)
	ϕ_1	0.16422^{***}	(0.01709)	0.16685^{***}	(0.01906)
Days before the oil price movement date	c_{-5}	-0.00023	(0.00213)	0.00057	(0.00194)
	c_{-4}	-0.00158	(0.00217)	0.00189	(0.00202)
	c_{-3}	-0.00339^{*}	(0.00189)	-0.00042	(0.00126)
	c_{-2}	0.00083	(0.00051)	0.00062	(0.00060)
	c_{-1}	-0.00300	(0.00203)	0.00122	(0.00202)
Oil extreme movement date	c_0	0.00696^{***}	(0.00214)	-0.01289^{***}	(0.00208)
Days after the extreme oil price movement date	c_1	0.00252	(0.00210)	-0.00433^{**}	(0.00203)
	c_2	0.00226	(0.00209)	-0.00410^{**}	(0.00204)
	c_3	0.00050	(0.00216)	0.00237	(0.00175)
	c_4	0.00018	(0.00207)	-0.00285^{***}	(0.00100)
	c_5	-0.00002	(0.00207)	-0.00308	(0.00204)
Variance equation	w	-0.13747^{***}	(0.01803)	-0.13051^{***}	(0.01621)
	α	-0.04306^{***}	(0.00992)	-0.04324^{***}	(0.00959)
	β	0.98292^{***}	(0.00209)	0.98384^{***}	(0.00188)
	γ	0.17147^{***}	(0.01998)	0.16333^{***}	(0.01901)
Log-likelihood		7843.05		7860.07	
AIC		-5.5036		-5.5155	
$LB(15)$		5.605		6.075	
$LB^2(15)$		13.72		13.49	
ARCH test		13.33		12.980	

Standard deviations are in parentheses. *** Significant at 1%, ** Significant at 5%, * Significant at 10%.

Overall, the results show a positive relationship between oil and renewable energy prices and vary according to the renewable energy sector and the direction of the extreme oil price movement: upward or downward. This result could be explained by a substitution effect. As technical improvements occur, alternative energy becomes relatively inexpensive, and because oil becomes relatively expensive, this leads to substitution in certain areas Managi and Okimoto [2013].

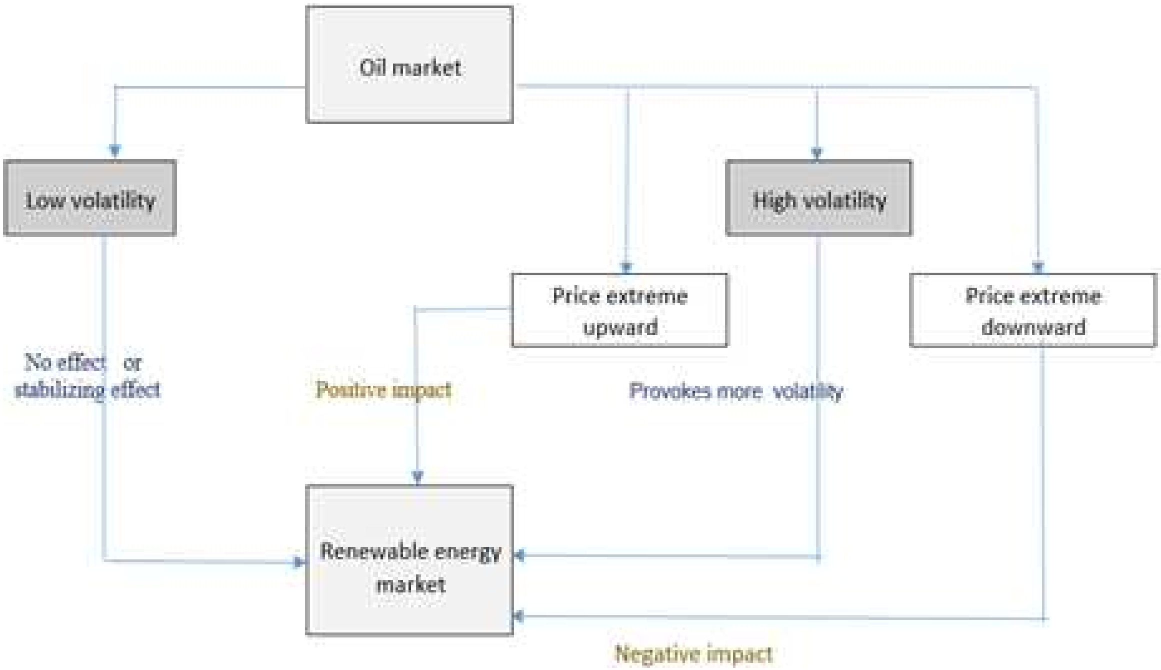


Figure 8: Oil and renewable energy market analysis

After showing that when the oil market is in a low volatility regime, it has no impact or a stabilizing effect on renewable energy volatility, but the oil market causes more instability in renewable energy markets when it is in a high volatility regime (Figure 8), we can summarize the findings of the connectivity analysis as follows: (1) renewable energy indexes are more responsive to extreme downward movements in oil prices than to extreme upward movements. In fact, among the considered indexes, only the SOLAR and SPGCE indexes are sensitive to extreme upward and downward movements in oil prices. The other indexes (ERIX, TECH, WIND) are only sensitive to extreme downward movements in oil prices. This effect is probably due to the fact that the SOLAR energy index has a longer development record than other new-energy sectors and that solar energy assets are widely accepted in fossil fuel-based energy portfolio investments Reboredo [2015]. (2) renewable energy seems to respond immediately to oil price shocks; the renewable energy and oil sectors experience the same booms and crashes together Reboredo [2015], which suggests that the oil and renewable energy markets seem to be integrated. (3) the results also reveal that renewable energy markets do not anticipate oil market shocks (except for the TECH index which anticipates oil price shocks one to two days before they occur). The persistence of shocks from upward or downward movements in oil prices varies from market to market. Oil price shocks are not persistent for TECH, SPGCE and ERIX: their effects disappear quickly, but they are more likely to persist for the SOLAR index (three days for upward movements and two days for downward movements) and the WIND index (tending to persist at least five days later).

6 Conclusion

The relationship between the oil and renewable energy markets is subject to much discussion in the literature, but a consensus on this issue has not yet been reached. This paper aims to provide additional information using a Markov-switching GARCH model and an intuitive methodology based on VaR violation. The results show a positive link between oil prices and renewable energy indexes. The estimates of the Markov-switching EGARCH model, show that the oil market is characterized by low and high volatility regimes. Therefore, its effects on the renewable energy market will depend on the state of the market: in a low volatility regime, the oil market has no impact on the SOLAR and SPGCE indexes, but it tends to stabilize the TECH market. For the WIND and ERIX indexes, the λ_{high} coefficient is not significant, and the λ_{low} coefficeint is positive and significant at 5% for WIND and 10% for the ERIX index. This result could be explained by the fact that these markets do not react immediately like the other markets. When the oil market is in a high volatility regime, the WIND market reacts a few days later, which may coincide with the oil market's transition from a high volatility regime to a low volatility regime. If the oil market is in a highly volatile state, its effects on renewable energy markets are significant. In fact, for all of the considered markets (excepting the WIND and ERIX markets), we find that volatility spillover only occurs if the oil market is in a high volatility regime. This effect is greater for TECH and SPGCE. However, these results do not indicate whether the volatility is due to a rise or fall in oil prices. This information seems to be relevant, because the reaction of renewable energy markets differs according to the nature of extreme movements in oil prices. Therefore, we identified upward and downward oil price movements, and the results show that the impact of extreme upward movements in oil prices is only positive and significant for the SOLAR and SPGCE returns indexes. The WIND, ERIX and TECH indexes do not react to extreme upward movements in oil prices. However, downward oil price movements are highly negatively correlated to the renewable energy index. It is important to underline that the renewable energy market seems to react to oil market shocks immediately, except for the WIND index, which reacts one day after their occurrence. The TECH index anticipates oil price shocks one to two days before they occur, while these shocks are not anticipated by the other indexes (SOLAR, WIND, ERIX, SPGCE). The persistence of shocks varies between the renewable energy markets: for TECH, SPGCE, and ERIX, the effects of the shocks disappear quickly. However, for the SOLAR market, oil price shocks are more likely to persist for two to three days and at least five days for WIND.

The results of this study have several implications in terms of policy and risk management. Fossil fuels and renewable energy are substitutable, and are therefore in competition in certain areas. However, it should be noted that when the oil market is in a low volatility regime, its impact on the renewable energy market is not significant or tends to have a stabilizing effect. However, in a high volatility regime, it increases the renewable energy market's instability. Consequently, a subsidy policy can be envisaged when the oil market is experiencing a period of turbulence, in order to boost the profitability of renewable energy companies. More precisely, an upward movement in oil prices would encourage renewable energy investment projects, while a drop in oil prices would have a negative effect on renewable energy returns. A subsidy policy would thus control and focus on lower oil prices because a rise in oil prices would stimulate investment in renewable energy. In terms of hedging strategies, as demonstrated by Sadorsky [2012a], oil futures can be used to hedge investments in clean energy stock prices.

Appendix

Table 9: Estimation results for Wind Energy Index

	Coef.	Effects of extreme oil movements: Upward		Downward	
ARMA coefficients	μ	0.00082^{***}	(0.00028)	0.00103^{***}	(0.00028)
	ϕ_1	0.44046^{**}	(0.19650)	0.39928^{**}	(0.17730)
	θ_1	-0.34202^{*}	(0.20633)	-0.29942	(0.18494)
Days before the extreme movement date	c_{-5}	0.00027	(0.00180)	-0.00245	(0.00180)
	c_{-4}	-0.00363^{*}	(0.00186)	-0.00267	(0.00177)
	c_{-3}	-0.00025	(0.00182)	0.00265	(0.00179)
	c_{-2}	-0.00295	(0.00180)	-0.00051	(0.00181)
	c_{-1}	-0.00200	(0.00185)	-0.00190	(0.00183)
Extreme movement date	c_0	-0.001409	(0.00188)	-0.00095	(0.00185)
Days after the extreme movement date	c_1	-0.00068	(0.00185)	0.00267	(0.00180)
	c_2	0.00263	(0.00180)	-0.00815^{***}	(0.00184)
	c_3	0.00247	(0.00188)	-0.00334^{*}	(0.00184)
	c_4	0.00155	(0.00182)	-0.00430^{**}	(0.00188)
	c_5	-0.00141	(0.00187)	0.00379^{**}	(0.00185)
Variance equation	w	0.00001^{***}	(0.00000)	0.00001^{***}	(0.00000)
	α	0.12094^{***}	(0.00829)	0.12425^{***}	(0.00834)
	β	0.83619^{***}	(0.01017)	0.83217^{***}	(0.01061)
	γ				
Log-likelihood		8327.44		8343.1	
AIC		-5.8442		-5.8552	
$LB(15)$		10.17		9.5020	
$LB^2(15)$		21.09		0.125	
ARCH test		19.93		19.68	

Standard deviations are in parentheses. *** Significant at 1%, ** Significant at 5%, * Significant at 10%. For the wind index, the EGARCH (1,1) model presents traces of heroscedasticity; therefore, we used a GARCH(1,1) model which took better account the non-constancy of variance.

Table 10: Estimation results for TECH Energy Index

		Effects of extreme oil movements			
	Coef.	Upward		Downward	
ARMA coefficients	μ	0.00049^{**}	(0.00024)	0.00064^{***}	(0.00022)
	θ_1	0.01530^{*}	(0.00922)	0.02036	(00.01500)
	θ_2	0.01790	(0.02169)	0.02216^{*}	(0.01159)
	θ_3	0.07085^{***}	(0.02047)	0.06723^{***}	(0.01347)
Days before the extreme movement date	c_{-5}	0.00223	(0.00433)	0.00071	(0.00336)
	c_{-4}	-0.0021	(0.00330)	0.00158	(0.00184)
	c_{-3}	-0.00023	(0.00325)	0.00096	(0.00238)
	c_{-2}	0.00517	(0.00333)	0.00296^{***}	(0.00068)
	c_{-1}	0.00669^{*}	(0.00332)	-0.01158^{***}	(0.00119)
Extreme movement date	c_0	-0.00055	(0.00334)	-0.00717^{**}	(0.00309)
Days after the extreme movement date	c_1	-0.00225	(0.00329)	0.00613^{**}	(0.00304)
	c_2	-0.00214	(0.00326)	-0.00167	(0.00310)
	c_3	-0.00306	(0.00324)	0.00186	(0.00332)
	c_4	0.00013	(0.00323)	-0.00176	(0.00324)
	c_5	-0.00335	(0.00317)	-0.00390	(0.00339)
Variance equation	w	-0.10478^{***}	(0.01405)	-0.09678^{***}	(0.02908)
	α	-0.04227^{***}	(0.01759)	-0.03991^{***}	(0.01032)
	β	0.98663^{***}	(0.00163)	0.98760^{***}	(0.00328)
	γ	0.13997^{***}	(0.01884)	0.14311^{***}	(0.03998)
Log-likelihood		5324.28		5331.12	
AIC		-5.4722		-5.4792	
$LB(15)$		16.8		17.68	
$LB^2(15)$		16.92		15.88	
ARCH test		17.48		16.35	

Standard deviations are in parentheses. *** Significant at 1%, ** Significant at 5%, * Significant at 10%.

Table 11: GARCH(1,1) estimations

Coeffi	Renewable energy returns				
	SOLAR	WIND	ERIX	SPCGE	TECH
ω	0.00001**	0.00001***	0.00001***	0.00001**	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
α	0.07224***	0.11490***	0.09713***	0.09783***	0.05852***
	(0.00886)	(0.00795)	(0.00606)	(0.01031)	(0.01549)
β	0.91523***	0.84401***	0.87038***	0.88413***	0.93534***
	(0.01128)	(0.00981)	(0.00835)	(0.01169)	(0.01657)
Loglikelihood	7483.57	8300.25	7474.14	7799.54	5311
AIC	−5.2606	−5.8349	−5.2540	−5.4828	−5.4750
$LB^2(12)$	5.284	20.74	9.21	9.72	15.99
ARCH test	5.113	19.42	9.41	9.61	16.48

Standard deviations are in parentheses.*** Significant at 1%, ** Significant at 5%, * Significant at 10%.

Table 12: EGARCH(1,1) estimations

Coeffi	Renewable energy returns				
	SOLAR	WIND	ERIX	SPCGE	TECH
ω	−0.12434***	−0.37975***	−0.26389	−0.13489***	−0.10044***
	(0.00671)	(0.06616)	(0.16516)	(0.00707)	(0.00753)
α	−0.01159	−0.06782***	−0.06840	−0.03864***	−0.03870***
	(0.00707)	(0.01198)	(0.11000)	(0.00881)	(0.00357)
β	0.983370***	0.95500***	0.96657***	0.98304***	0.98697***
	(0.00086)	(0.00758)	(0.02096)	(0.00209)	(0.00093)
δ	0.155920***	0.19103***	0.16703	0.17672***	0.13848***
	(0.01497)	(0.01850)	(0.10735)	(0.01928)	(0.01032)
Loglikelihood	7482.88	8305.8	7482.75	7797.5	5312.96
AIC	−5.2594	−5.8381	−5.2593	−5.4807	−5.4760
$LB^2(12)$	6.559	26.06**	12.94	12.17	19.86
ARCH test	6.15	25.79**	13.19	11.8	20.4

Standard deviations are in parentheses.*** Significant at 1%, ** Significant at 5%, * Significant at 10%.

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