

VOLATILITY SPILLOVERS AMONG ALTERNATIVE ENERGY, OIL AND TECHNOLOGY GLOBAL MARKETS

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Master en Banca y Finanzas Cuantitativas

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ABSTRACT

The purpose of this paper is to investigate the volatility spillovers between oil, alternative energy and technology global markets. For such a study we applied two different methodologies: multivariate GARCH models (BEKK, diagonal, constant conditional correlation and dynamic conditional correlation) and the one recently proposed by Diebold and Yilmaz (2012). In addition, dynamic conditional correlations are used to address some interesting financial problems such as hedge ratios or risk-minimizing portfolio weights. Our empirical results are based on a data set which covers from 2002 to 2015. The Ardour Global Alternative Energy Index, the nearest contract to maturity on the Brent futures contracts and the Dow Jones Technology Titans 30 Index, are considered as the best choices in order to represent the global markets for alternative energy, oil and technology, respectively. The outcomes derived from GARCH models (considering the BEKK model as the benchmark since it assumes a positive definite variance and it is the most general representation of all them) and those obtained from the Diebold and Yilmaz (2012) methodology, show that the strongest evidence for volatility spillovers is found between alternative energy and technology global markets. On average, a long position in alternative energy companies can be hedged with a short position in the Brent crude oil futures market. However, due to the high and positive correlation, which exists between global alternative energy and technology, it is not convenient for investors to hedge an investment in alternative energy companies with a short position in technology companies. Finally, some robustness checks are considered.

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1. INTRODUCTION

Natural resources have usually been the driving factors for the world-wide economy, but in recent decades one additional factor has come on the scene and now it's on the top of our agenda, the alternative and renewable energy.

Global competition has led to strategic concerns due to the emergence of new world powers such as China or Brazil, the high commodity prices and the vulnerability of global supply. Hence, energy security issues (global oil supplies in the face of increased global demand or political insecurity in oil rich countries), coupled with an increased concern about the natural environment (climate change or local air quality issues), are decisive factors behind oil price movements. Thus, these facts underline our triple challenge of dealing with the economic, the socio-political, and the environmental dimensions of the resources allocation problem.

Moreover, these concerns about future oil shortages stem from current estimates that predict world oil production will peak somewhere between 2016 and 2040 (*Hubbert Peak Theory*). Oil is a globally traded commodity and the price of oil is determined by its demand and supply conditions. So, such rapidly increasing demand for oil from emerging market economies and also, oil supply shortages will lead to much higher oil prices in the future and eventually a substitution away from oil to alternative energy sources. In addition, in the short to medium term, the perspectives for oil are complex since the largest consumers of oil are not the countries with the oil largest reserves.

While it is widely accepted that rising oil prices are good for the financial performance of alternative energy companies and also, that rising oil prices should help to spur a greater demand and supply of alternative energy, the truth is that we cannot be sure about that. In fact, there has been relatively little statistical work done to measure just how sensitive the financial performance of alternative energy companies is to changes in oil prices. What we could expect is that rising oil prices could provide a strong stimulus for substituting from petroleum based energy production and moving to alternative based energy sources production. In addition, even though the alternative energy industry may still be small compared to other more established energy industries, there is an undeniable growing role played by renewable sources of energy,

since annual investment increased from \$60 billion in 2000 to a high point approaching \$300 billion in 2011 (International Energy Agency, IEA). Besides, in 2013, new renewable power capacity expanded at its fastest pace to date. Globally, renewable generation was estimated on par with that from natural gas (Renewable Energy Medium-Term Market Report 2014, IEA). For these reasons, investors, consumers, governments and other industries will be seeking alternatives to current energy sources. According to Bloomberg New Energy Finance:

"World clean energy investment rebounded strongly in 2014, boosted by demand for large-scale and rooftop solar photovoltaics on the back of its greatly improved competitiveness, and by the financing of a record \$19.4bn of offshore wind projects. Authoritative annual data, show that global investment in clean energy was \$310bn last year. This was up 16% from a revised \$268.1bn in 2013, and more than five times the figure of \$60.2bn attained a decade earlier, in 2004, albeit still 2% below the all-time record of \$317.5bn reached in 2011. The jump in investment in 2014 reflected strong performances in many of the main centers for clean energy deployment, with China up 32% to a record \$89.5bn, the US up 8% to \$51.8bn (its highest figure since 2012), Japan up 12% to \$41.3bn, Canada up 26% at \$9bn, Brazil up 88% at \$7.9bn, India up 14% to \$7.9bn, and South Africa up 5% at \$5.5bn. Europe, despite the flurry in offshore wind, was a relative dull spot overall, investment there edging 1% higher to \$66bn."

Despite the fact that this bodes well for the industry in the long run, a better understanding of the relationship between oil prices and the financial performance of alternative and clean energy companies is crucial to infer the development that the alternative energy will experience in the next years.

The dynamics shown by the returns and volatilities and also, the correlations and volatility spillovers among the different international markets, will determine investment opportunities and profits that investors can get through diversification and portfolio hedging. Usually, investing internationally has often been a great opportunity for investors looking to increase the total return of their portfolio. The diversification benefits are achieved through the addition of low correlation assets of international markets that help to reduce the overall risk of the portfolio. However, although the benefits of investing internationally are widely accepted, many investors are still hesitant to invest abroad.

However, very little is known about the volatility dynamics of alternative energy stock prices and the possible correlation between the stock prices of alternative energy companies and other relevant financial markets like those regarding oil prices or the stock prices of technology companies. In fact, we believe that alternative and renewable energy sources will play a crucial role in meeting future energy demand. Such an important role depends on many factors, including advances in technology, public acceptance and economic viability. In addition, questions about affordability, sustainability and reliability of the global energy system often boil down to questions about investments. Will market conditions, much influenced by policy, create sufficient opportunities for investment in the regions and sectors where it is needed? Will the available financing be sufficient, on suitable terms, for these opportunities to be realized? And will really investment be channeled towards areas that ameliorate and solve the future shortage in fossil fuels (especially oil) and the problem of climate change? For all these reasons, it will be interesting to study the dynamics of global alternative energy market by measuring if it is more influenced by the oil price movements or on the contrary, by the technology sector, both in terms of giving and receiving volatility spillovers.

As mentioned before, there has been relatively little empirical research done to measure how sensitive the financial performance of alternative energy companies are to changes in other markets, such as those of oil or technology. As far as we know, there are two main researches related to the study of volatility dynamics of the alternative energy sector and its possible correlations and relationship with oil and technology markets. In the first one, Henriques and Sadorsky (2008), the authors investigate the empirical relationship between alternative energy stock prices, technology stock prices, oil prices, and interest rates by estimating a four variable vector autoregression model. Outcomes show how technology stock prices and oil prices each individually Granger cause the stock prices of alternative energy companies. In addition, simulation results show that a shock to technology stock prices has a larger impact on alternative energy stock prices than does a shock to oil prices.

Regarding the second of these main researches, Sadorsky (2011) analyzes the correlations and volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies in the US market by using multivariate GARCH models. These four GARCH models (BEKK, diagonal, constant conditional

correlation and dynamic conditional correlation) are compared and contrasted. The results obtained show that definitely, the stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices in the US market.

As an extension to Sadorsky (2011), this research has the same aim but trying to analyze the volatility spillovers among alternative energy, oil and technology global markets. In addition, in Sadorsky (2011) volatility spillovers are just analyzed using multivariate GARCH models. In the present work we will apply the GARCH methodology and also, another recent econometric procedure introduced by Diebold & Yilmaz (2012) where we use a generalized vector autoregression in which forecast-error variance decompositions are invariant to variable ordering proposed measures of both total and directional volatility spillovers.

This paper is organized as follows. In the following section, we discuss the two econometric methodologies applied. Section 3 describes the data and section 4 presents the empirical results (obtained with both methodologies). Section 5 includes two interesting financial applications. Finally, section 6 contains some robustness checks and section 7 the concluding remarks.

2. ECONOMETRIC METHODOLOGY

2.1 Multivariate GARCH models

Volatility modeling and risk measuring are highly relevant in finance. In fact, since risk is unobservable, several methodologies and modeling procedures have been developed to analyze and to forecast it. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model of Engle (1982) and Bollerslev (1986) has subsequently led to a family of autoregressive conditional volatility models. The success of GARCH models can be attributed largely to their ability to capture several stylized facts of financial returns, such as time-varying volatility, persistence and clustering of volatility, and also, asymmetric reactions to positive and negative shocks of equal magnitude.

In order to investigate the conditional correlations and volatility spillovers between oil prices, the stock prices of alternative energy and technology companies, some multivariate conditional volatility models are applied. In particular, four multivariate GARCH models (BEKK, Diagonal, CCC and DCC) are used to model the volatility dynamics of our data. As in Sadorsky (2011), the BEKK model is used as the benchmark since it assumes a positive definite variance and it is the most general representation. The restricted correlation models (Diagonal, CCC and DCC) are designed to address some of the problems encountered with the BEKK model (which can have a poorly behaved likelihood function, making estimation difficult) and still retain analytical tractability. However, these models are simpler than the BEEK one.

The mean equation used in this paper is represented in equation 1, where r_{it} are the market returns for series i and ε_{it} is the random error term with conditional variance h_{it} . The market information available at time $t - 1$ is denoted as I_{it-1} . Equation 2 specifies the relation between the error term ε_{it} and the conditional variance h_{it} . In addition, equation 3 specifies a GARCH(1,1) process with VARMA terms (Ling and McAleer, 2003). The Ling and McAleer approach for modeling the conditional variances allows large shocks to one variable to affect the variances of other variables. This is a convenient specification which allows for volatility spillovers.

$$r_{it} = m_{i0} + \sum_{j=1}^3 m_{ij} r_{jt-1} + \varepsilon_{it} \quad , \varepsilon_{it} | I_{it-1} \sim N(0, h_{it}) \quad i = 1,2,3 \quad (1)$$

$$\varepsilon_{it} = v_{it} h_{it}^{1/2} \quad , v_{it} \sim N(0,1) \quad (2)$$

$$h_{it} = c_{ii} + \sum_{j=1}^3 a_{ij} \varepsilon_{jt-1}^2 + \sum_{j=1}^3 b_{ij} h_{jt-1} \quad (3)$$

Let r_{it} be the vector for the returns with dimension $(N \times 1)$. The conditional variance for r_{it} is a $(N \times N)$ matrix, represented by H_{it} . The diagonal elements of H_{it} are variance terms and elements outside the diagonal are covariances.

Now, the four multivariate GARCH models applied in this research for volatility modeling are presented in a more detailed manner, so we can understand the idea behind each one of them.

The BEKK model [Baba, Engle, Kraft and Kroner (1990) and Engle and Kroner (1995)] assumes the following structure for the covariance matrix H_t :

$$H_t = C_0' C_0 + \sum_{i=1}^q A_i^* \varepsilon_{t-i} \varepsilon_{t-i}' A_i^{*'} + \sum_{i=1}^p B_i^{*'} H_{t-i} B_i^* \quad (4)$$

where A_i^* and B_i^* are $(N \times N)$ parameter matrixes typically with $q = 1$ and $p = 1$ and C_0 is restricted to be an upper triangular matrix. In the case of two variables ($N = 2$) and $p = q = 1$, the complete representation would be as follows:

$$\begin{aligned} \begin{bmatrix} h_{11,t} & h_{12,t} \\ \cdot & h_{22,t} \end{bmatrix} &= \begin{bmatrix} c_{11}^0 & c_{12}^0 \\ 0 & c_{22}^0 \end{bmatrix}' \begin{bmatrix} c_{11}^0 & c_{12}^0 \\ 0 & c_{22}^0 \end{bmatrix} + \\ \begin{bmatrix} a_{11}^* & a_{12}^* \\ a_{21}^* & a_{22}^* \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1} \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1} \varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} &+ \begin{bmatrix} a_{11}^* & a_{12}^* \\ a_{21}^* & a_{22}^* \end{bmatrix} + \\ \begin{bmatrix} b_{11}^* & b_{12}^* \\ b_{21}^* & b_{22}^* \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11}^* & b_{12}^* \\ b_{21}^* & b_{22}^* \end{bmatrix} & \quad (5) \end{aligned}$$

This representation has been the most popular in the literature. In fact, some studies such as Karolyi (1995) that analyzes several specifications for the variances-covariances matrix conclude that this one is the most appropriate among all those applied. This specification can be considered as a particular case of the VECH model and it even enhances it. In fact, the BEKK model improves VECH and diagonal representations because it practically ensures that H_t will be positive definite. Furthermore, it does not require so many parameters to be estimated as in the VECH model and it is not as restricted as the diagonal representation since it allows for certain relations that the last one would not allow.

The Diagonal VECH model.[Bollerslev, Engle and Wooldridge (1988)]. It is a simpler model that does not allow for dynamic interdependence between volatilities. In this case, A_i and B_i are diagonal matrixes and when dealing with two variables ($N = 2$) and $p = q = 1$, the representation would be as follows:

$$\begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11}^0 \\ c_{12}^0 \\ c_{22}^0 \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}, \varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix} \quad (6)$$

that is,

$$h_{11,t}^2 = c_{11}^0 + a_{11}\varepsilon_{1,t-1}^2 + b_{11}h_{1,t-1}^2 \quad (7)$$

$$h_{12,t} = c_{12}^0 + a_{12}\varepsilon_{1,t-1}, \varepsilon_{2,t-1} + b_{12}h_{12,t-1} \quad (8)$$

$$h_{22,t}^2 = c_{22}^0 + a_{22}\varepsilon_{2,t-1}^2 + b_{22}h_{2,t-1}^2 \quad (9)$$

However, notice that this model assumes that individual conditional variances and covariances only depend on their own lags and lagged squared residuals, with the possibility of missing important information. Moreover, it is still necessary to impose restrictions in order to ensure a positive definite H_t . In such a way, it is a simple model

but it does not ensure the existence of a positive definite variance-covariance matrix in each step, so that it could generate numerical problems.

The CCC or Constant Conditional Correlation model [Bollerslev (1990)].

This model assumes that correlations between each pair of returns are constant, so the volatility model consists only of the equations for the variances. In the case of two variables ($N = 2$) and $p = q = 1$, the representation would be as follows:

$$H_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} \\ \rho_{21} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \quad (10)$$

In this case, H_t is assumed to be positive definite if certain restrictions on the parameters are correctly satisfied. Variance terms, $h_{11,t}$ and $h_{22,t}$ are univariate GARCH processes with $p = q = 1$.

R is the conditional correlation matrix defined as follows:

$$R = \begin{bmatrix} 1 & \dots & \rho_{1N} \\ \dots & \dots & \dots \\ \rho_{N1} & \dots & 1 \end{bmatrix} \quad (11)$$

where ρ_{ij} is the correlation coefficient between variables i and j . Then, the conditional variance matrix H_t is defined as:

$$H_{ij,t} = R_{ij} \sqrt{H_{ii,t}} \sqrt{H_{jj,t}} \quad (12)$$

or equivalently,

$$H_t = \text{diag}(\sqrt{h_{11,t}}, \dots, h_{NN,t}) R \text{diag}(\sqrt{h_{11,t}}, \dots, h_{NN,t}) \quad (13)$$

where *diag* produces a diagonal matrix with the elements in (.) in the main diagonal.

The model can be applied with estimated variances coming from either EWMA (Exponentially Weighted Moving Average) or univariate GARCH schemes. Under both options, each covariance is obtained by multiplying the correlation coefficient between the standardized or non-standardized returns by the product of the standard deviations obtained from the conditional volatility models previously estimated by EWMA or GARCH schemes. In addition, this representation has been very popular among empirical studies because it reduces the conditional correlation matrix to constant correlation coefficients between variables, so the number of parameters to be estimated is small in comparison with other models.

Reasonably, once this model has been estimated it cannot be expected to generate dynamic correlations from the obtained covariances. In fact, the estimation of the covariance is the endpoint when we apply this estimation model.

The DCC or Dynamic Conditional Correlation model. [Engle (2002)]. Engle recently introduced this representation and it allows for dynamic dependencies in the correlations. Again in this model, an EWMA representation can be used to estimate variances of individual returns, or it can be estimated through univariate GARCH models. Engle (2002) generalizes the CCC model to the Dynamic Conditional Correlation model (DCC) and it is estimated in two steps. In the first step, the GARCH parameters are estimated. In the second step, the correlations are estimated.

$$H_t = D_t R_t D_t \quad (14)$$

In the previous equation, H_t is the 3x3 conditional covariance matrix, R_t is the conditional correlation matrix, and D_t is the diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = \text{diag}(h_{11,t}^{1/2}, \dots, h_{33,t}^{1/2}) \quad (15)$$

$$R_t = \text{diag}(q_{11,t}^{-1/2}, \dots, q_{33,t}^{-1/2}) Q_t \text{diag}(q_{11,t}^{-1/2}, \dots, q_{33,t}^{-1/2}) \quad (16)$$

Q_t is a symmetric positive definite matrix.

$$Q_t = (1 - \theta_1 - \theta_2) \bar{Q} + \theta_1 \xi_{t-1} \xi'_{t-1} + \theta_2 Q_{t-1} \quad (17)$$

\bar{Q} is the 3x3 unconditional correlation matrix of the standardized residuals ξ_{ij} . The parameters θ_1 and θ_2 are non-negative with a sum of less than unity. The correlation estimator is,

$$p_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \quad (18)$$

In the previous representations, for the constant conditional correlation (CCC) case, $R_t = R$ and $R_{ij} = \rho_{ij}$ and in the Diagonal model, $\rho_{ij} = 0$ for all i and j . The choice of representing the correlation as a constant, instead of using a dynamic one, affects in a determinant way when we are dealing with financial data.

Finally, all the MGARCH models are estimated by Quasi-Maximum Likelihood estimation (QMLE) using the BFGS algorithm. T-statistics are calculated using a robust estimate of the covariance matrix.

2.2. Diebold & Yilmaz (2012)

Diebold and Yilmaz (2009) firstly introduces a volatility spillover measure or index, based on forecast error variance decompositions from vector autoregressions (VARs). This initial methodology can be applied to analyze spillovers in returns or in volatilities across individual assets, asset portfolios, asset markets, etc,. However, this procedure was based on a Cholesky-factor identification of VARs, so the resulting variance decompositions were dependent on variable ordering. In addition, it just considered total spillovers, (from/to each market i , to/from all other markets added across i) but in any case addresses directional spillovers (from/ to a particular market).

For such reason, Diebold and Yilmaz decide to make an extension of their previous work and they introduced huge improvements in their methodology. Indeed, whereas Diebold and Yilmaz (2009) focuses on total spillover within a simple VAR framework (order-dependent results based on Cholesky factorization), the methodology introduced in 2012 takes into consideration directional spillovers with a generalized VAR model.

Hence, we use the method developed by Diebold and Yilmaz (2012). The starting point of the analysis is the following p -order, 3-variable Vector Autoregressive (VAR) model:

$$r_t = \sum_{i=1}^p \Phi_i r_{t-i} + \varepsilon_t \quad (19)$$

where

$$\varepsilon \sim iid(0, H) \quad (20)$$

is a vector of independently and identically distributed errors.

Any stationary VAR model admits a moving average representation (MA) which is reached after successive substitutions of r_{t-i} in (19). The moving average representation is:

$$r_t = \sum_{i=1}^{\infty} A_i \varepsilon_{t-1} \quad (21)$$

where the $N \times N$ coefficient matrices A_i are estimated by the recursion:

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p} \quad (22)$$

with A_0 being an $N \times N$ identity matrix and with $A_i = 0$ for $i < 0$.

The moving average coefficients (or transformations such as impulse-response functions or variance decompositions) are the key to understanding the dynamics of the system. We rely on variance decompositions, which allow us to parse the forecast error variances of each variable into parts attributable to the various system shocks.

Diebold and Yilmaz (2012) use the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), hereafter KPPS, in which variance decompositions are invariant in terms of the variable ordering. Variance decompositions allow us to assess the fraction of the M -step-ahead error variance in forecasting r_i that is due to shocks to r_j , $\forall j \neq i$ for each i .

- Variance Shares

Assuming own variance shares to be the fractions of the M -step-ahead error variances in forecasting r_i due to shocks to r_i , for $i = 1, 2, 3$ and cross variance shares, or spillovers, to be the fractions of the M -step-ahead error variances forecasting r_i due to shocks to r_j , for $i = 1, 2, 3$, such that $\forall i \neq j$.

Denoting the KPPS M -step-ahead forecast error variance decomposition by $\theta_{ij}^g(M)$, for $i = 1, 2, 3$ we have:

$$\theta_{ij}^g(M) = \frac{((h_{ii})^{1/2})^{-1} \sum_{m=0}^{M-1} (e_i' A_m H e_j)^2}{\sum_{m=0}^{M-1} (e_i' A_m H A_m' e_i)} \quad (23)$$

where H is the variance matrix for the error vector ε , $(h_{ii})^{1/2}$ is the standard deviation of the error term for the i th equation, and e_i is the selection vector, with one as the i th element and zeros otherwise. In the generalized VAR framework, the shocks to each variable are not orthogonalized; therefore, the sum of each row of the variance decomposition matrix does not add to unity:

$$\left(\sum_{j=1}^3 \theta_{ij}^g(M) \neq 1\right) \quad (24)$$

In this case, dividing it by the row sum normalizes each element of the decomposition matrix:

$$\tilde{\theta}_{ij}^g(M) = \frac{\theta_{ij}^g(M)}{\sum_{j=1}^3 \theta_{ij}^g(M)} \quad (25)$$

where, by construction,

$$\sum_{j=1}^3 \tilde{\theta}_{ij}^g(M) = 1 \quad (26)$$

and

$$\sum_{i,j=1}^3 \tilde{\theta}_{ij}^g(M) = 3 \quad (27)$$

- Total Spillovers

Using the volatility contributions from the KPPS variance decomposition, we can construct a total volatility spillover index:

$$S^g(M) = \frac{\sum_{i \neq j} \tilde{\theta}_{ij}^g(M)}{\sum_{i,j=1}^3 \tilde{\theta}_{ij}^g(M)} \cdot 100 = \frac{\sum_{i \neq j} \tilde{\theta}_{ij}^g(M)}{3} \cdot 100 \quad (28)$$

This index captures the contribution of spillovers of volatility shocks across the three markets to the total forecast error variance.

-Directional Spillovers

Although it is sufficient to study the total volatility spillover index to understand how much of shocks to volatility spill over across markets, the generalized VAR approach enables us to examine the direction of volatility spillovers across markets. Specifically, the directional volatility spillovers received by market i from all other markets j are defined as follows:

$$S_{i\cdot}^g(M) = \frac{\sum_{i \neq j}^3 \tilde{\theta}_{ij}^g(M)}{\sum_{j=1}^3 \tilde{\theta}_{ij}^g(M)} \cdot 100 \quad (29)$$

In a similar fashion, the directional volatility spillovers transmitted by market i to all other markets j are defined as:

$$S_{\cdot i}^g(M) = \frac{\sum_{i \neq j}^3 \tilde{\theta}_{ji}^g(M)}{\sum_{j=1}^3 \tilde{\theta}_{ji}^g(M)} \cdot 100 \quad (30)$$

One can think of a set of directional spillovers as providing a decomposition of total spillovers into those coming from (or to) a particular source.

-Net Spillovers

The net directional volatility spillover provides information on whether a market is a receiver or a transmitter of volatility in net terms. We obtain the net spillover from market i to all other markets j by subtracting equation (30) from equation (29). Thus, the net directional volatility spillover is given by the following:

$$S_i^g(M) = S_{\cdot i}^g(M) - S_i^g(M) \quad (31)$$

-Net Pairwise Spillovers

To examine the net pairwise volatility spillover between markets i and j , we compute the difference between the gross volatility shocks transmitted from market i to market j and gross volatility shocks transmitted from j to i :

$$S_{ij}^g(M) = \left(\frac{\tilde{\theta}_{ij}^g(M)}{\sum_{k=1}^3 \tilde{\theta}_{ik}^g(M)} - \frac{\tilde{\theta}_{ji}^g(M)}{\sum_{k=1}^3 \tilde{\theta}_{jk}^g(M)} \right) \cdot 100 \quad (32)$$

3. DATA

The data for this study includes the daily closing prices in US dollars of the **Ardour Global Alternative Energy Index (AE)**, the nearest contract to maturity on the **Brent crude oil futures contract (OIL)** and the **Dow Jones Technology Titans 30 Index (TECH)**.

The **Ardour Global Alternative Energy Index (Extra Liquid)** includes a fixed number of 30 stocks which are capitalization weighted, adjusted for free float. In fact, it is a compilation of global alternative energy stocks that are principally engaged in the business of alternative energy. This index comprises public companies engaged in five primary sectors: a) Enabling Technologies, b) Environmental Technologies, c) Environmental Efficiency, d) Alternative Energy Sources, and e) Distributed Generation. Constituents include the thirty largest and most actively traded stocks in the Ardour Global Alternative Energy Composite Index. All companies contained in the Ardour Global Alternative Energy Index (Extra Liquid) are categorized as being “principally” engaged in the global alternative energy industry. For the purposes of this index, a principally engaged company must derive 50% or more of its annual revenues from its participation in the alternative energy sector.

ICE Brent futures and options are traded at ICE Futures Europe, ICE’s London based futures exchange and executed on the ICE Web trading platform, which is distributed in more than 70 countries. In 2012, ICE Brent became the world’s largest crude oil futures contract in terms of volume and ICE Brent market share has almost doubled since 2008. Approximately two-thirds of the world’s traded crude oil uses the Brent complex, which includes ICE Brent futures with its deep liquidity and far-reaching forward curve, as a price benchmark. Many national oil producers and other participants around the world price crude at a differential to Brent, depending on the crude grade. Factors such as Brent’s accessibility and reach as a seaborne crude, production, adaptation to changing global economics in the oil market, stability and geographic location have consolidated Brent’s global benchmark position. It has also contributed to physical participants, such as international airlines and oil producers in Asia, adopting Brent as a primary hedging tool. In addition to the extensive usage of Brent as both a pricing benchmark and a hedging tool for global crude prices, Brent’s

global relevance is also proved and supported by comparing historical changes in key spreads such as WTI, LLS, Mars, Brent and Dubai.

The **Dow Jones Technology Titans 30 Index** represents the leading companies in the global Technology sector. The index includes 30 stocks selected based on rankings by float-adjusted market capitalization, revenue and net profit. In addition, it covers the Technology Supersector of proprietary classification system described at www.djindexes.com. This Index was first calculated on February 12, 2001. There are no companies included in both AE and TECH.

The sample period for the data set covers January 2002 to April 2015. All this data is collected from Thomson Reuters Datastream. Other indexes were considered, but these were the best affordable options. See robustness check section for further details.

First, some plots of the raw data show the dynamics experienced by each one of the three global markets in Figures 1 to 3.

Figure 1. Raw Data Plot for AE

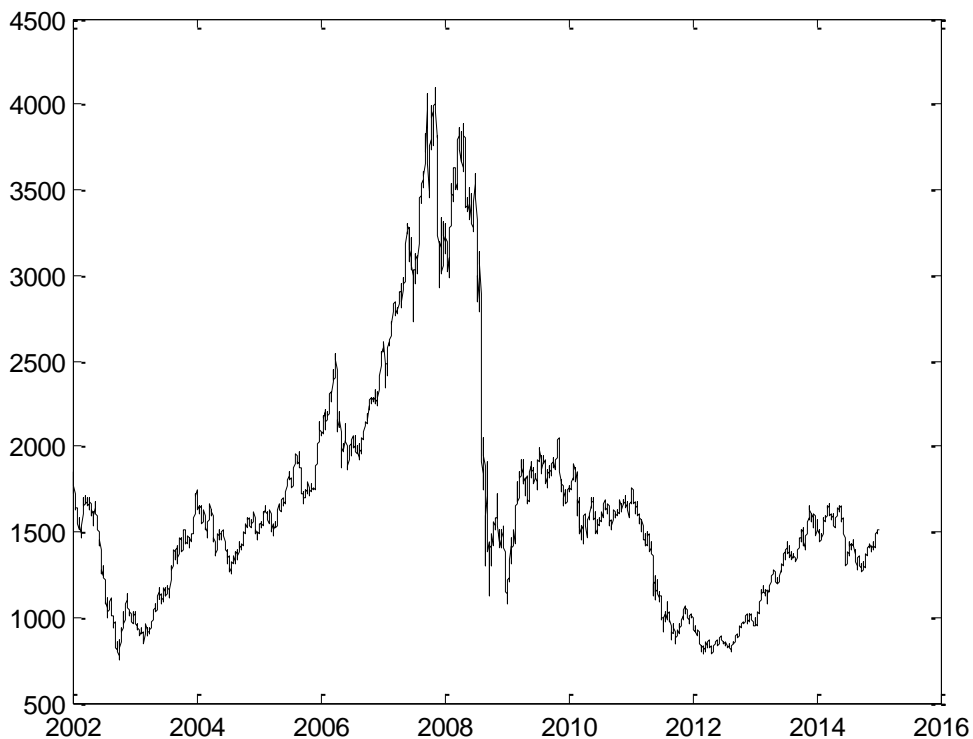


Figure 2. Raw Data Plot for OIL

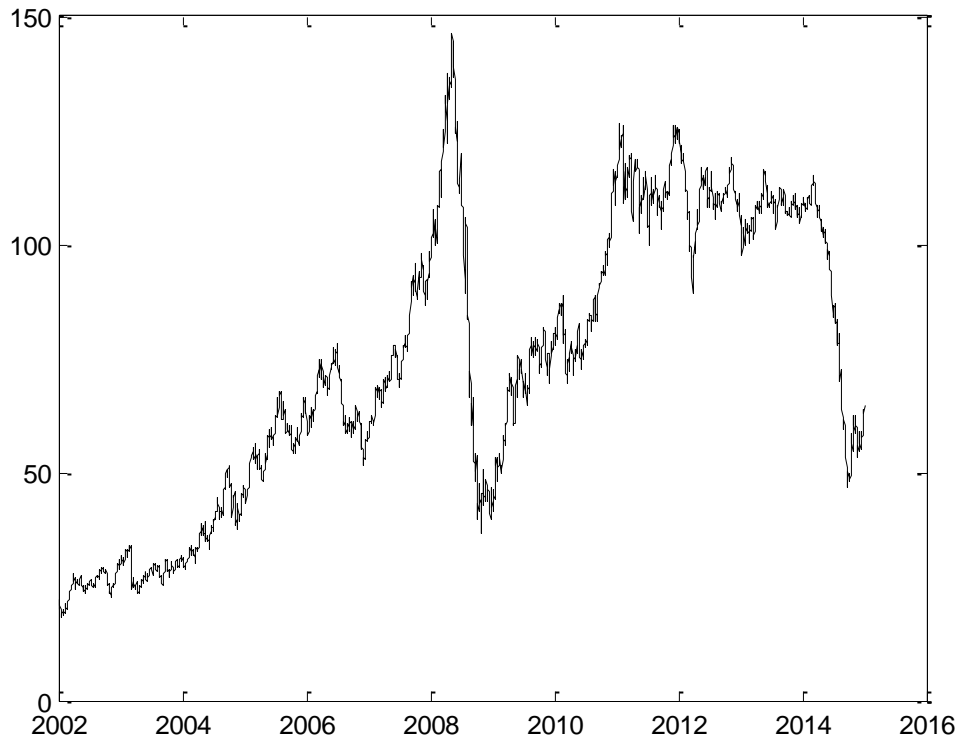
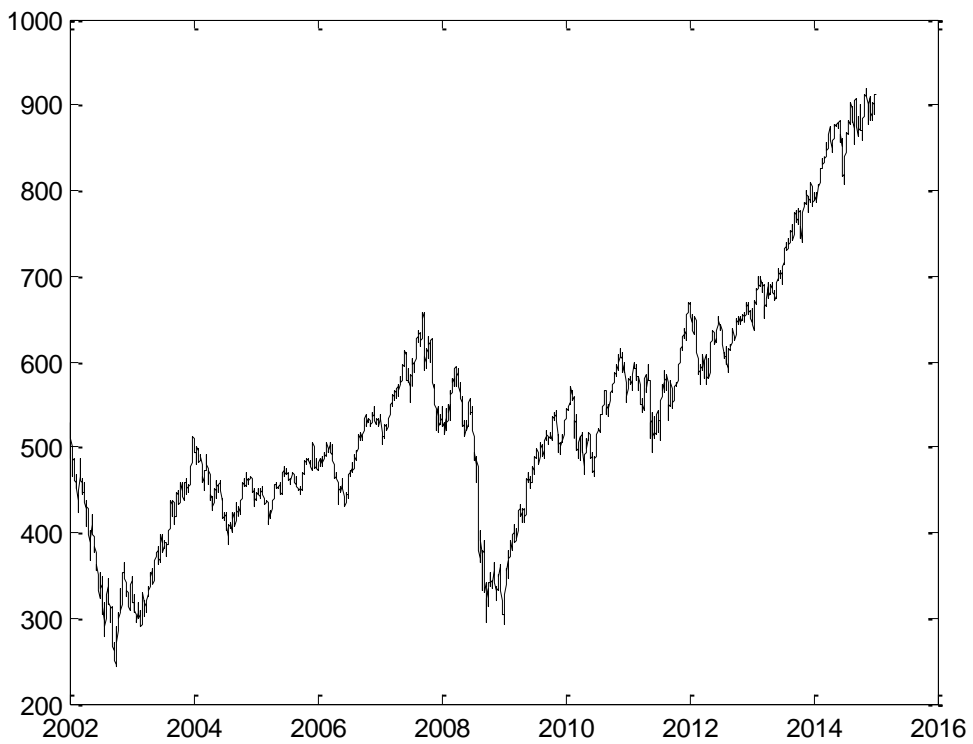


Figure 3. Raw Data Plot for TECH



Before the second half of 2008 the three sectors show relatively the same pattern, showing a huge fall on prices at the beginning of the recent Financial Crisis. The recession of 2008-2009 had a significant impact on the stock prices of alternative energy and technology companies and also, on the oil prices, which suffered a steep drop. Moreover, AE and TECH variables tend to move together at the beginning of the sample period since both show a common drop in 2003 and a subsequent rise after that. From 2009-2010 the three sectors do not show a clear common pattern, but they experienced different cyclical movements up to now.

In addition, for each of the data series, continuously compounded daily returns are calculated as $100 * (p_t/p_{t-1})$ where p_t is the daily closing price. A summary statistics for the returns are provided in Table 1.

Table 1. Summary statistics for daily returns

	Alternative Energy	Oil	Technology
Mean	-0.0398	0.0340	0.0181
Median	0.0692	0.0228	0.0681
Maximum	14.2012	12.7066	9.5422
Minimum	-12.4123	-10.9455	-8.4052
Std. Dev.	1.7785	2.0701	1.3147
Skewness	-0.3574	-0.0688	0.0736
Kurtosis	10.6297	6.1118	8.2987

For each of the series, the mean and the median values are close to zero and also, the standard deviation values are higher than those corresponding to the mean. Moreover, the three series show a scanty amount of skewness and a larger amount of kurtosis so the returns of the three variables are not normally distributed.

Unconditional correlations in Table 2 present similar results from the ones obtained by Sadorsky (2011), which implies a strong positive correlation between AE and TECH. The unconditional correlation between AE and OIL is positive but the value is less than a half of the unconditional correlation between AE and TECH. Regarding

the unconditional correlation between OIL and TECH, it can be seen that it's the lowest one.

Table 2. Correlations between daily returns

	Alternative Energy	Oil	Technology
Alternative Energy	1	0.3076	0.7406
Oil	0.3076	1	0.1884
Technology	0.7406	0.1884	1

The correlations between the squared daily returns show a similar pattern as for the correlations between the returns in Table 3. Again, the correlation between AE and TECH is positive and larger than the one between AE and OIL.

Table 3. Correlations between daily squared returns

	Alternative Energy	Oil	Technology
Alternative Energy	1	0.3884	0.6238
Oil	0.3884	1	0.2614
Technology	0.6238	0.2614	1

In addition, time series graphs of the squared daily returns are computed and they show how volatility has changed across time. These graphs appear in Figures 4 to 6.

Figure 4. Squared daily returns for AE

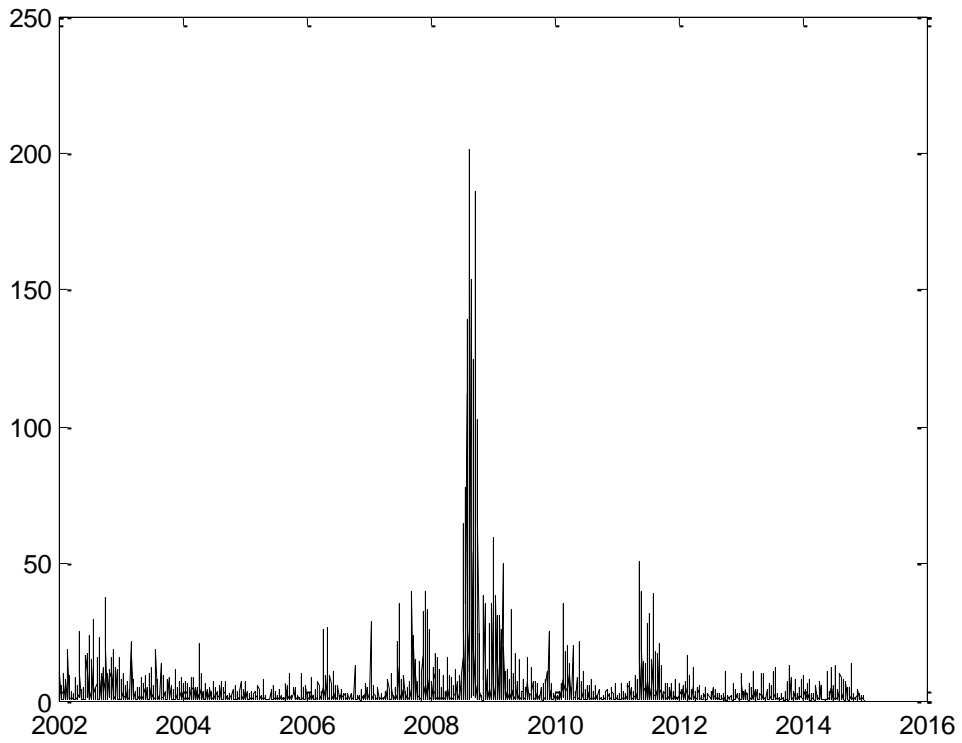


Figure 5. Squared daily returns for OIL

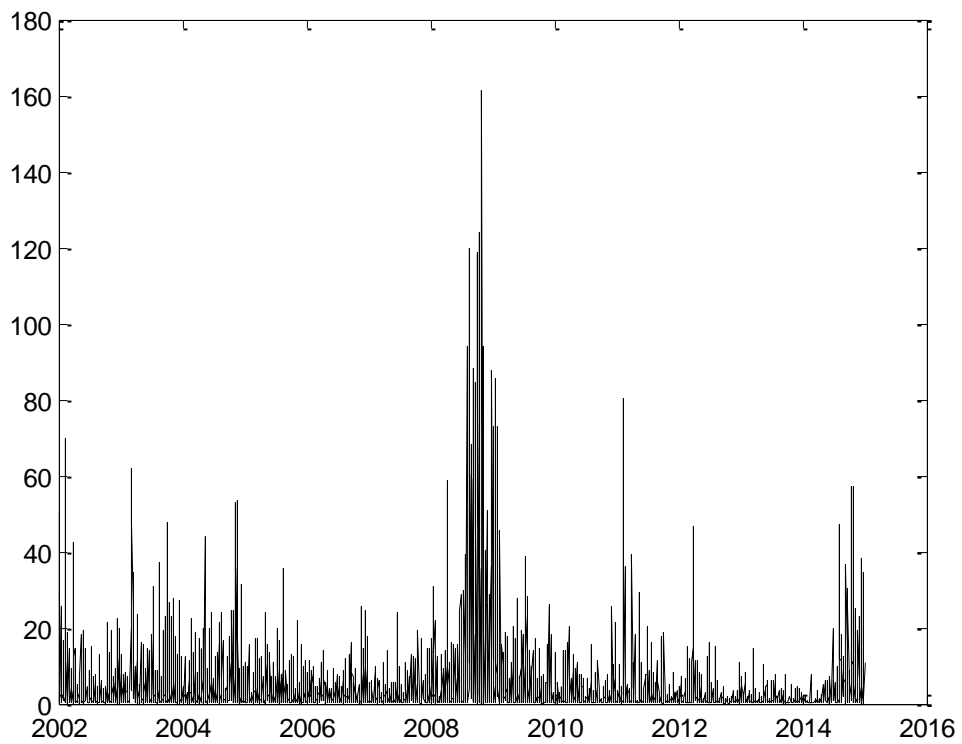
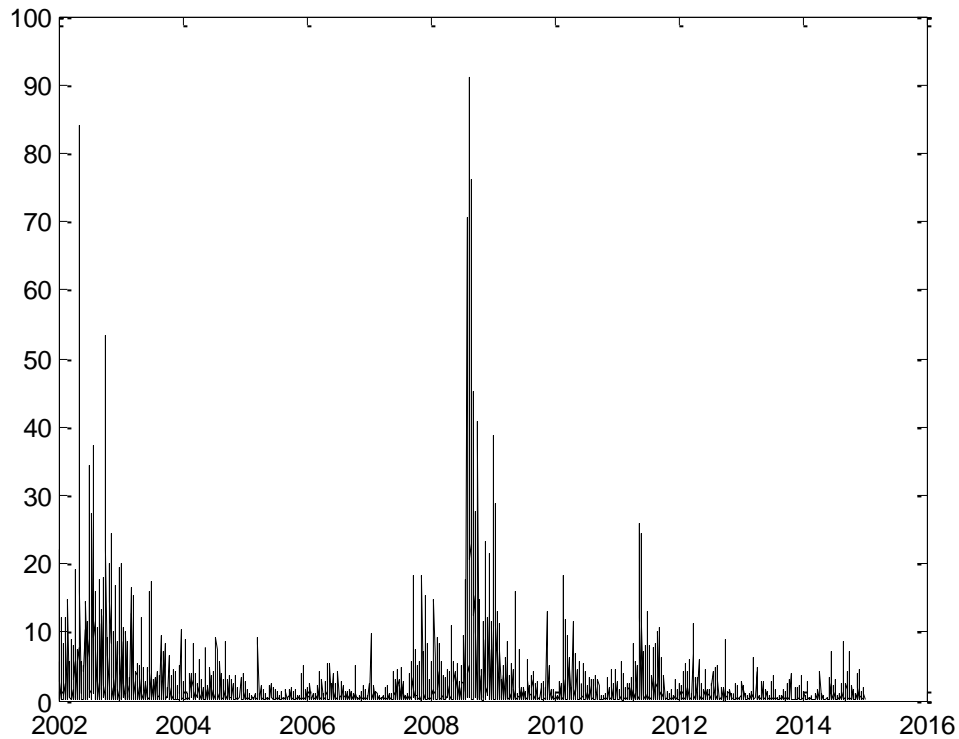


Figure 6. Squared daily returns for TECH



The three plots display clear episodes of volatility clustering between September 2008 and September 2009 with the beginning of the Global Financial Crisis. In addition, TECH shows some large spikes in volatility in 2002-2003 in response to the bursting of the technology stock market bubble. During 2003-2004 OIL also reflects considerable jumps in volatility.

According to the second part of the sample period, once the Global Financial Crisis have been started, the three graphs present another pronounced volatility clustering between 2011-2012. Finally, looking at the second graph corresponding to the oil market, it is also evident that there have been relevant increases in volatility from 2014 up to now due to the huge fluctuations in the prices of Brent.

4. EMPIRICAL RESULTS

4.1 MGARCH models methodology

First, we will present the results obtained from multivariate GARCH models. This methodology follows two steps. A vector autoregression (VAR) with one lag is applied to model the returns, which is compatible with the idea of possible autocorrelations and cross-autocorrelations in returns. VAR length is selected according to the AIC and SIC criterion. Then, a multivariate GARCH model is used to model the time varying variances and covariances. For restricted correlation models, that is, Diagonal, CCC and DCC models, the conditional variance is assumed to have a VARMA-GARCH (1,1) structure (Ling & McAleer, 2003).

Table 4 contains the results derived from both mean and variance models. As in Sadorsky (2011), the BEKK model is considered the benchmark since it assumes a positive definite variance and it is the most general representation and it is compared to the other three restricted correlation models (diagonal, constant conditional correlation and dynamic conditional correlation). Models are estimated using QMLE and variable order is AE (1), OIL (2) and TECH (3). In the variance equations, c denotes the constant terms, a denotes the ARCH terms and b denotes the GARCH terms. In the mean equation m_{13} represents the effect of a one period lag TECH returns on current period AE returns. The coefficient a_{13} for example represents the short-term volatility spillover from TECH to AE while b_{13} represents the long-term volatility spillover from TECH to AE. In addition, in brackets next to the parameter estimates are the corresponding t-statistics and ** indicates significance at 5 %.

Table 4. MGARCH parameter estimates

	BEKK		DIAGONAL		CCC		DCC	
	Coeff	T stat	Coeff	T stat	Coeff	T stat	Coeff	T stat
Mean								
m₁₀	0.0607***	3.76	0.0741***	3.22	0.0716***	3.28	0.0687***	3.29
m₁₁	0.0853***	6.63	0.0908***	4.05	0.1034***	5.99	0.0818***	3.73
m₁₂	0.0222**	2.26	0.0261**	2.18	0.0235**	2.27	0.0210	1.85
m₁₃	0.0345**	2.29	0.0572**	2.07	0.0207	1.10	0.0354	1.26
m₂₀	0.0413	1.48	0.0439	1.44	0.0055**	2.04	0.0512	1.81
m₂₁	-0.0056	-0.23	0.0128	0.47	0.0190	0.95	0.0064	0.30
m₂₂	-0.0574***	-3.81	-0.0607***	-3.18	-0.0595***	-3.33	-0.0586***	-3.27
m₂₃	0.0561	1.71	0.0415	1.18	0.0365***	3.96	0.0388	1.50
m₃₀	0.0625***	5.09	0.0515***	3.34	0.0605***	3.96	0.0635***	4.14
m₃₁	0.0190**	2.24	0.0167	1.01	0.0287***	2.72	0.0166	1.08
m₃₂	-0.0019	-0.26	-0.0448	-0.58	-0.0043	-0.56	-0.0028	-0.33
m₃₃	0.0625***	4.94	0.0722***	3.04	0.04188***	2.80	0.0645***	3.03
Variance								
c₁₁	0.1848***	10.16	0.0413***	5.17	0.0647***	4.25	0.0424***	5.00
c₂₁	0.0324	1.58						
c₂₂	0.1156***	7.21	0.0181***	3.13	0.0273***	3.05	0.0197***	3.30
c₃₁	0.0646***	5.12						
c₃₂	0.0306**	2.24						
c₃₃	0.0570***	5.61	0.0129***	4.32	0.0093	1.83	0.0156***	5.96
a₁₁	0.2891***	13.55	0.0759***	3.89	0.1048***	8.15	0.0649***	5.58
a₁₂	0.0100	0.49	0.0087	1.36	0.0048	0.79	0.0129**	2.14
a₁₃	0.0612***	4.26	0.0009	0.09	-0.0742***	-6.07	-0.0059	-0.41
a₂₁	0.0128	1.40	0.0338	3.58	0.0567***	4.34	0.0512***	3.73
a₂₂	0.1749***	17.61	0.0391***	7.80	0.0390***	7.26	0.0395***	8.50
a₂₃	0.0024	0.34	-0.0512***	-4.49	-0.0945***	-5.56	-0.0697***	-4.37
a₃₁	-0.0816***	-2.85	0.0055	0.79	-0.0181**	-2.26	0.0333***	4.65
a₃₂	0.0345	1.32	-0.0016	-0.40	-0.0066	-1.41	-0.0029	-0.68
a₃₃	0.1622***	7.63	0.0670***	6.89	0.0881***	7.55	0.0260***	2.94
b₁₁	0.9478***	129.01	0.9043***	129.22	0.8145***	25.11	0.9127***	52.29
b₁₂	0.0005	0.09	0.2953	0.13	-0.0278	-0.79	-0.0107	-1.19
b₁₃	-0.0165***	-3.97	0.1858	0.12	0.1852***	3.65	0.0145	0.75
b₂₁	-0.0006	-0.29	2.4939	1.38	-0.0989	-1.92	-0.0298	-1.42
b₂₂	0.9828***	528.38	0.9541***	171.83	0.9433***	112.98	0.9551***	179.82
b₂₃	0.0003	0.23	5.5260	1.38	0.2986***	3.28	0.0345	1.29
b₃₁	0.0233***	2.82	1.0211	1.29	0.0533**	2.21	-0.0458***	-4.39
b₃₂	-0.0135	-1.80	3.5369	1.32	0.0854**	2.44	0.0038	0.75
b₃₃	0.9862***	181.01	0.9190***	98.36	0.8499***	32.13	0.9762***	80.90
ρ₂₁					0.2626***	17.07		
ρ₃₁					0.7200***	91.87		
ρ₃₂					0.1580***	9.89		
θ₁							0.0236***	7.41
θ₂							0.9724***	241.70
Log L	-16845,24		18401,48		-17013,94		-16802,06	
AIC	9727		10622		9824		9702	
SIC	9791		10680		9888		9764	

Variable order is AE (1), OIL (2) and TECH (3). In brackets, next to the parameter values estimates are the corresponding t-statistics. ** indicates significance at 5%.

Regarding the VAR structure for returns, except for the constants (m_{i0}) and (m_{ii}) own terms, which of course, do not provide us with relevant ideas, there is not one cross- parameter that was significant at the same time in the four models.

In our study for the global market there is not such statistically significant parameter common in the four models. However, since we are considering the BEKK model as the benchmark, we can see that both m_{13} and m_{31} are positive and significant at 5%. This result is important in establishing a positive relationship between current period AE returns and last period TECH returns and vice versa. Hence, for the global market scenario it can be seen that there is a bidirectional spillover in terms of returns between AE and TECH. In other words, current period AE returns are influenced by last period TECH returns and vice versa.

In addition, parameters m_{13} and m_{31} are also statistically significant at 5% and at 1% in the Diagonal and CCC models, respectively. Furthermore, there is another interesting result corresponding to the m_{12} parameter. This last mentioned coefficient is statistically significant at 5% in all models except for one, the DCC. Thus, this will indicate that Alternative Energy could also depend on Oil but in a weaker way.

According to the variance model, firstly we will examine the own conditional effects, for GARCH, $b(\cdot)$ and ARCH, $a(\cdot)$ schemes, which have a key role in explaining conditional volatility.

On the one hand, regarding GARCH parameters that measure long-term persistence in volatility, we focus on all the estimated b_{ii} elements. For example, b_{11} element refers to the GARCH term in the AE equation, while b_{22} refers to the GARCH term in the OIL equation and finally, b_{33} refers to the GARCH term in the TECH equation. All these estimated coefficients are statistically significant at the 1% level for the four models and also, they show similar values in each of the MGARCH models. In the case of the BEKK model, TECH shows the most amount of long-term persistence in volatility, followed by OIL and AE.

On the other hand, own conditional ARCH effects, a_{ii} which measure short-term persistence in volatility are also decisive in explaining conditional volatility. As in Sadorsky (2011) it can be checked how all the estimated a_{ii} coefficient values are smaller than their respective estimated b_{ii} values, which means that own volatility long-

run persistence effects (GARCH) is larger than short-run persistence effects (ARCH). In addition, they are also statistically significant at the 1% level for the four models. The results obtained in the BEKK model show that AE presents the most amount of short-term persistence followed by OIL and TECH.

As we mentioned before, BEKK model is going to be the benchmark since the other three models (Diagonal, CCC and DCC) are considered more restricted. Thus, we will analyze the possible evidences of volatility spillovers shown by the BEKK model and then, we will focus on the other MGARCH models. Hence, looking at BEKK results, it can be seen that they follow the same line as the one introduced by Sadorsky (2011). For short-term volatility persistence there is evidence of volatility spillovers between AE and TECH (a_{13}) and between TECH and AE (a_{31}). There is also evidence of long-term persistence volatility spillovers between AE and TECH (b_{13}) and between TECH and AE (b_{31}). In fact, all this estimated coefficients are statistically significant at 1% and they present both negative and positive values and relatively of the same order. Considering the full suite of models again there is evidence of inter-sector spillover effects between AE and TECH and TECH and AE both in short and long terms. In the case of the CCC model, parameters a_{13}, a_{31}, b_{13} and also, b_{31} are statistically significant. The DCC model also provides evidence in this same line, so a_{31} and b_{31} appear to be statistically significant at 1%, showing once again spillover effects between TECH and AE. In addition, the three restricted correlation models (Diagonal, CCC and DCC) show that for short-term volatility persistence there is evidence of volatility spillovers between AE and OIL and also, between TECH and OIL a_{21} and a_{23} so oil prices could be influenced by both the stock prices of Alternative Energy and Technology companies.

On balance, in our proposal for the Global Market, the strongest evidence for volatility spillovers is the same as Sadorsky found for the US Market. Therefore, contrary to what we might initially expect, there is closer relationship between AE and TECH than between AE and OIL. Shocks to Technology stock prices have a greater impact on the stock prices of Alternative Energy companies than does a shock to Oil prices. This result is crucial when analyzing the future expectations of Alternative and Clean energy in terms of investment decisions and hedging strategies.

Table 4 shows correlations between OIL and AE (ρ_{21}), TECH and AE (ρ_{31}) and TECH and OIL (ρ_{32}) and they are each positive and statistically significant at 1% level. As in Sadorsky (2011) the highest correlation is found between TECH and AE (0.7200) and the second highest is between OIL and AE (0.2626). TECH and OIL correlation (0.1580) presents the lowest value. For the DCC model, the estimated coefficients on θ_1 and θ_2 are each positive and statistically significant at the 1% level. These estimated coefficients sum to a value, which is less than one, meaning that the dynamic conditional correlations are mean reverting.

Furthermore, the AIC and SIC criteria show that the DCC model is the best model which shows evidence of volatility spillovers but not in a bidirectional way, but in a unidirectional one, from AE to TECH. In addition, both AIC and SIC information criteria rank the BEKK model as the second best with results very close to those obtained in the DCC model. Moreover, if the model is adequate, the standardized residuals should be serially uncorrelated (if the mean model is chosen correctly), and their squares should be as well (if the variance model is chosen correctly). The first can be tested with Ljung-Box (1978) and the second with the McLeod-Li (1983). In Table 5 the diagnostic tests for the standardized residuals and standardized squared residuals are presented. The four models show no evidence of serial correlation at 10% level and so they fit very well to our data.

Table 5. Diagnostic tests for standardized residuals.

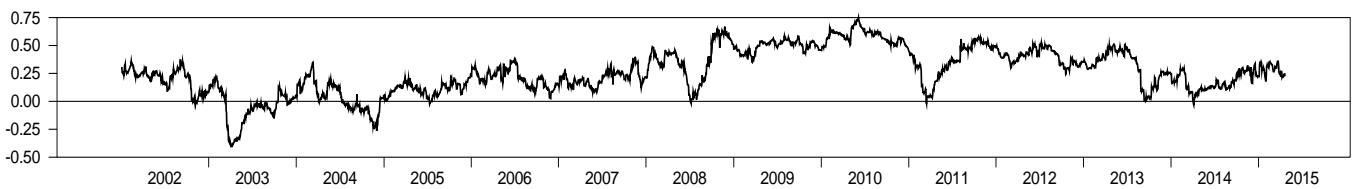
	<i>BEKK</i>			<i>DIAG</i>			<i>CCC</i>			<i>DCC</i>		
	AE	OIL	TECH	AE	OIL	TECH	AE	OIL	TECH	AE	OIL	TECH
Q(20) r	18.89	16.42	14.36	15.56	16.82	13.04	16.83	15.77	14.21	19.69	16.84	14.58
p-value	0.5291	0.6901	0.8120	0.7437	0.6648	0.8755	0.6639	0.7309	0.8194	0.4776	0.6634	0.7998
Q(20) r²	18.14	26.85	28.10	10.71	21.88	20.44	29.36	21.75	35.22	19.25	20.41	23.14
p-value	0.5779	0.1395	0.1071	0.9534	0.3470	0.4307	0.0809	0.3541	0.0190	0.5055	0.4328	0.2821

Dynamic conditional correlations

The DCC model is used to construct dynamic conditional correlations. Figure 7 shows time-varying conditional correlations from such a model. Thus, it can be seen how dynamic conditional correlations considerably vary from the constant conditional correlations ($\rho_{21} = 0.2626$, $\rho_{21} = 0.7200$ and $\rho_{32} = 0.1580$). Besides, dynamic conditional correlations can provide much more useful information than what the constant correlations can do.

Figure 7. Time-varying conditional correlations from the DCC model

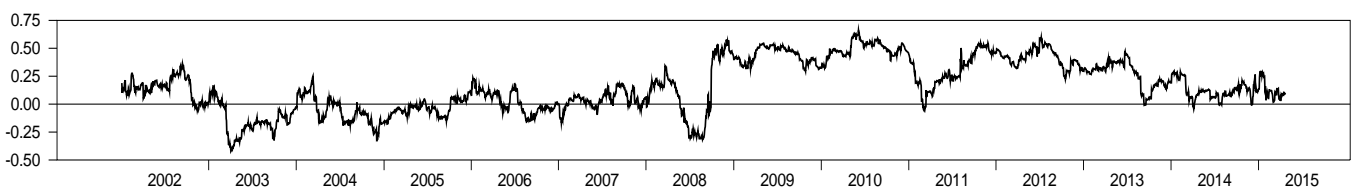
AE and OIL



AE and TECH



OIL and TECH



Until 2008 we can easily appreciate that graphs 1 and 3, that is, AE-OIL and OIL-TECH conditional correlations present relatively a similar pattern. In fact, both conditional correlation dynamics vary in a range between -0.5 and 0.5. The second graph regarding AE-TECH dynamic conditional correlation presents only positive values and in most of the cases, larger than 0.5. This means that there is little scope for portfolio diversification between these two sectors. The AE and OIL conditional correlation plot shows negative values at the beginning of the sample period, between 2003-2004 but after that, it has positive values between 0 and 0.5. OIL and TECH conditional correlation plot presents a similar pattern than AE and OIL reaching also lower values in 2003 and 2004.

However, the three pair of conditional correlations present an inflection point in the late of 2008 with the arrival of the recent Financial Crisis. Thus, since 2008 there is an evident upward trend in each pair of correlations that is maintained up to 2011, year in which a fall occurs in the three of the dynamic graphs. In addition, the dynamic correlation between AE and OIL reached very low values in 2003 and surpass the 0.5 value for the first time in December of 2008. Then, since 2009 it experienced a slight downward trend up to April 2015, with a dynamic conditional correlation of about 0.25. The dynamic conditional correlation between AE and TECH reaches low values in the second half of 2008, about 0.35. Then, it experienced its highest values at the end of 2008 of about 0.8 and also, at the end of 2011 by reaching a value closed to 0.9. Now, during 2015 AE-TECH dynamic conditional correlation is about 0.7. Finally, regarding the last graph between OIL and TECH it presents its lower values in 2003 and it attains the 0.5 value at the end of 2008. Since the end of the sample period, from 2014 up to April 2015 the correlation is close to 0.

4.2 Diebold and Yilmaz (2012) methodology

Now, we will examine the evidence of volatility spillovers among these three global markets (Alternative Energy, Oil and Technology) by using the methodology introduced by Diebold and Yilmaz 2012.

Firstly, we will make some comments related to the management of the data. Then, we present an initial analysis of the data with descriptive statistics and finally, we will analyze spillover dynamics according to this methodology. Spillover dynamics will be studied by examining rolling-sample total spillovers, rolling-sample directional spillovers, rolling-sample net directional spillovers and rolling-sample net pairwise spillovers.

- *Some comments about the data*

Following Diebold and Yilmaz (2012) methodology, we will examine daily volatilities of the three sectors: AE, OIL and TECH. The data sample is exactly the same one used with the GARCH methodology. Thereby, daily returns are again calculated as the change in log prices and multiplying by 100 but daily volatilities have to be computed, since we have not dealt with them until now.

We opted for calculating daily volatilities with a usual estimator, squared returns. Consider a time series of returns r_{t+i} and $i = 1, \dots, T$, and the sample variance, σ^2 :

$$\hat{\sigma}^2 = \sqrt{\frac{1}{T-i} \sum_{i=1}^T (r_{t+i} - \mu)^2} \quad (33)$$

where r_{t+i} is the return at time $t + i$, and μ is the average return of a day, and $\sigma = \sqrt{\sigma^2}$ is the unconditional volatility for the period 1 to T. Considering that the average return on a reduced period of time (as the time between two transactions from one day to the next one) is very small, the estimator for the volatility is defined as follows:

$$\hat{\sigma}^2 = \sqrt{252} \sqrt{\frac{1}{T-i} \sum_{i=1}^T r_{t+i}^2} \quad (34)$$

In order to annualizes the volatility we multiply it by the squared root of 252, since we are dealing with data based on a trading year. Next, the plots for the volatility dynamics corresponding to the three sectors are presented in Figure 8. In addition, some descriptive statistics were provided in Table 6.

Figure 8: Daily Volatilities - Annualized Std. Deviation % (Alternative Energy; Oil; Technology)

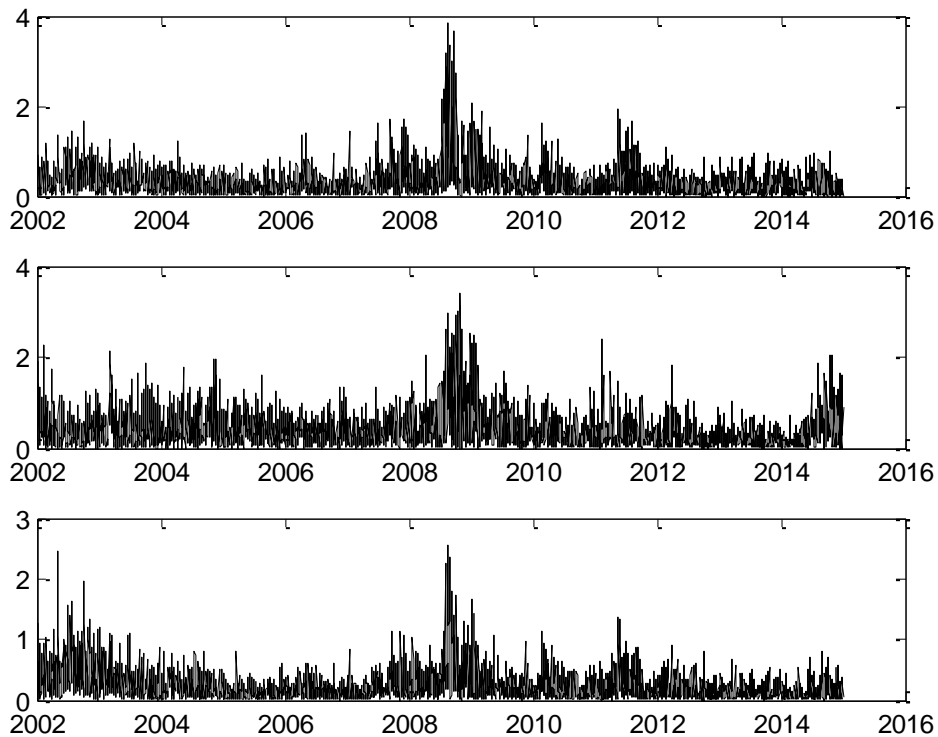


Table 6: Volatility Summary Statistics

	Alternative Energy	Oil	Technology
Mean	0.3315	0.4003	0.2417
Median	0.2449	0.2885	0.1625
Maximum	3.8265	3.4238	2.5711
Minimum	0	0	0
Std. Deviation	0.3460	0.3885	0.2590
Skewness	3.1740	2.1002	2.5478
Kurtosis	20.6054	9.8059	13.5524

The previous results provide us some interesting ideas. Oil prices have been the most volatile followed by Alternative Energy and Technology sectors. Moreover, the three sectors present similar volatility patterns. In general, they show higher volatility levels at the beginning of the recent crisis, that is, between 2008 and 2010, displaying huge jumps in 2009. Notice that a pattern of volatility clustering is evident for each one of the three sectors. Thus, up to 2008 there was no a common trend but after 2008, there is a slight upward common trend. We can observe two peaks both at 2010 and 2012, which of course are more evident in the case of Alternative Energy and Oil sectors than in Technology, since this last one is less volatile and not highly persistent. In addition, at the end of the sample period during the first months of 2015, the Oil sector again has been reaching higher volatility levels.

- *Unconditional Patterns: The Full-Sample Volatility Spillover Table*

In this section we provide a full-sample analysis of the three sectors volatility spillovers in Table 7. Following Diebold and Yilmaz (2012), the entry ij^{th} is the estimated contribution to the forecast error return and variance of sector i coming from innovations in sector j . Thus, the off-diagonal column sums (labeled "Contribution to others") or row sums (labeled "Contribution from others") are the "to" and "from" directional spillovers, and the "from minus to" differences are the net volatility spillovers. In addition, the total volatility spillover measure appears in the lower right corner of the spillover table. In fact, this total volatility spillover index is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including diagonals (or row sum including diagonals), expressed as a percentage. As Diebold and Yilmaz (2012) well explained, volatility spillovers displayed in Table 7 provides a kind of "input-output" decomposition of the total volatility spillover measure.

Table 7. Volatility Spillover Table

	Alternative Energy	Oil	Technology	Directional FROM others
Alternative Energy	61.9	7.9	30.3	38
Oil	16.5	72.7	10.8	27
Technology	34.5	6.3	59.3	41
Directional TO others	51	14	41	106
Directional including own	113	87	100	Total Spillover Index (106/300): 35.33%

The results are based on a vector autoregression of order 1 and on a generalized variance decomposition of 10-day-ahead volatility forecast errors.

The total volatility spillover index among the three global markets is equal to 35.3% which indicates that slightly more than a third of the total variance of the forecast errors during the sample is explained by shocks across global markets, whereas the remaining 64.67% is explained by idiosyncratic shocks.

In addition, regarding the previous table from the "Directional to others" row, gross directional volatility spillovers amount to others from both Alternative Energy and Technology are much more higher than in the case of Oil. In addition, from the "Directional from others" column, gross directional volatility spillovers amount from others show similar outcomes, although Oil continues to be the one with the lowest. So, initially the results obtained according to the Diebold and Yilmaz (2012) methodology provide us concise and similar evidences to the ones of the BEKK model.

Regarding pairwise directional spillovers (the off-diagonal elements of the upper-left 3×3 sub-matrix), the highest observed pairwise volatility spillover is from TECH to AE (34.5%). In return, the pairwise volatility spillover from AE to TECH (30.3%) is second highest. In fact, the results in Tables 7 follow the same line of the MGARCH models and the conclusions discussed by Sadorsky (2011) for the case of U.S.A. Thus, AE and TECH show a positive relationship in terms of volatilities, from AE to TECH and also, from TECH to AE. So, definitely, they are influenced by each other. In such a way, AE and TECH volatility spillovers in both directions with respect to the OIL sector show lower figures, so they seem to be less influenced by the Brent price movements.

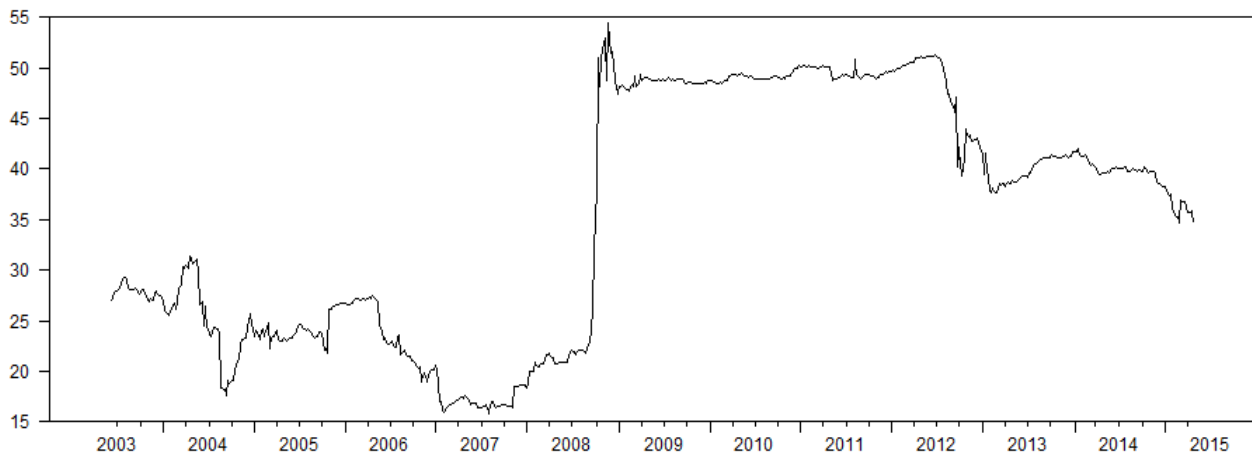
In terms of the directional spillovers to others throughout the full sample, our results suggest that volatility in AE contributed the most to the other markets' forecast error variance (51 points), followed by TECH (41 points) and OIL (14 points). As for the directional spillovers received from others, Technology global market appears to be the sector that received the highest percentage of shocks from the other two sectors (41 points) but Alternative Energy remains closely (38 points) and followed by Oil (27 points).

Finally, net directional spillovers were calculated by the difference between the column-wise sum ("Contribution to others") and the row-wise sum ("Contribution from others"). AE ($51-38 = 13$ points) is a net transmitter of volatility to other markets, TECH ($41-41 = 0$ points), which is neutral, since it receives the same volatility amount as it transmits to the others and OIL, which is definitely the leading net receiver of volatility ($14-27 = -13$ points).

- *Conditioning and Dynamics I: The Rolling- Sample Total Volatility Spillover Plot*

The static full-sample analysis of volatility spillovers in Table 7, although it provides a useful summary of the "average" volatility spillovers behavior, it doesn't address the issue of capturing cyclical movements. To gain further insights into the dynamics of the total volatility spillovers, we now estimate them using a 200-day rolling-sample window with a step horizon of 10 days as Diebold and Yilmaz (2012) proceed in their research. We assess the extent and nature of spillover variation over the time, via the corresponding time series of spillover indexes, which we examine graphically in Figure 9.

Figure 9. Total Volatility Spillover, Three Global Markets (200-day rolling window)



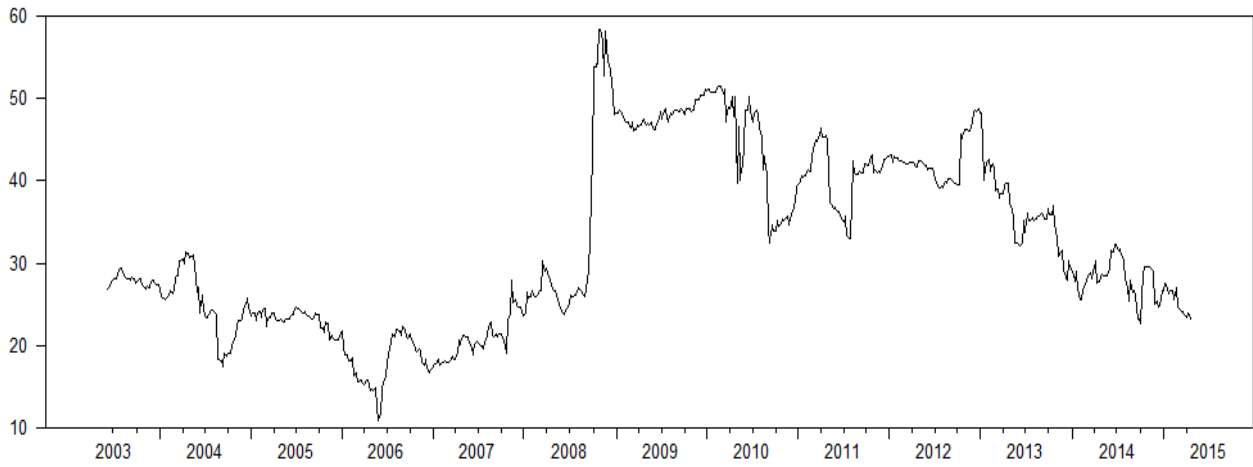
The x-axis represents the period of time and the y-axis measures the level of volatility expressed as a percentage.

In Figure 9 we can identify two different periods, before and after the Global Financial Crisis of 2007-2008. In addition, it can be seen that it initially starts with a value around 27%, which was due to the remaining effects of the tech bubble which started at 2000. Then, volatility spillover experienced a gradual decreasing trend up to the late of 2007 or the beginning of 2008. After that, the spillover plot is obviously determined by the recent Financial Crisis. In addition, the spillover index reached values that surpass the 50%. Finally, regarding the higher volatility levels reached in 2009-2010 during this recent crisis, they were the result of:

- July-August 2007: Credit crunch
- September- December 2008: Collapse of Lehman Brothers
- First half of 2009: European contagion and the effects on global economy.

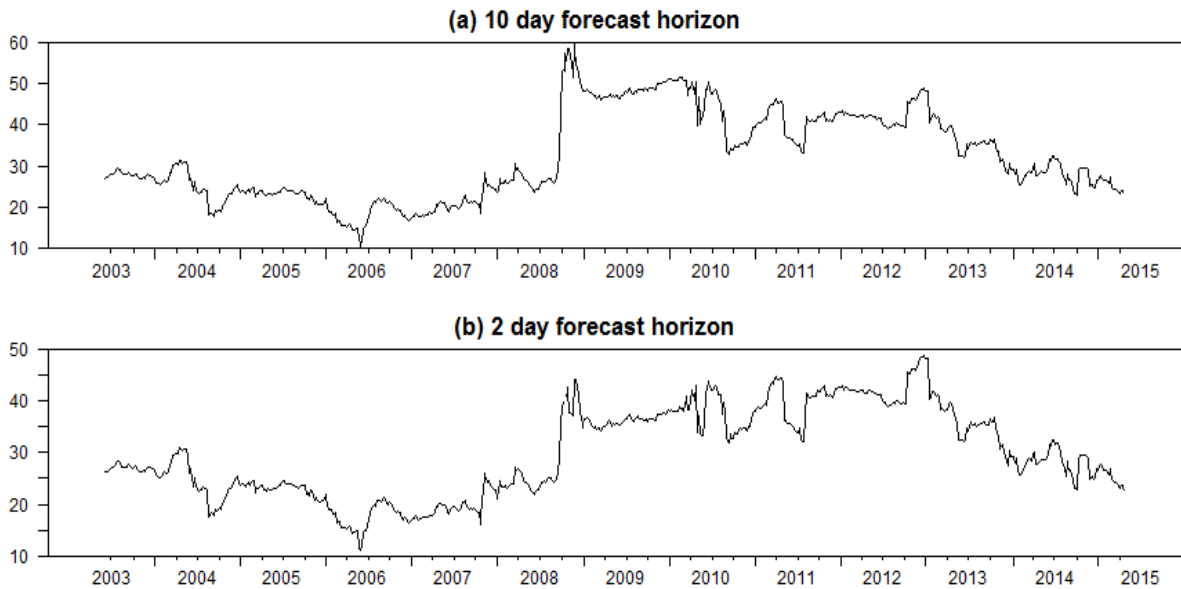
Moreover, we also perform some changes in this rolling-sample analysis in order to check for the robustness with respect to the rolling window width and the chosen forecast horizon. Figure 10 shows volatility spillover plots produced using a shorter 75-day rolling window width. In addition, in Figure 11 we use the original 10-day forecast horizon in panel 2a and a shorter 2-day horizon in panel 2b for a 75-day rolling window width. Thus, these results appear largely robust to all variations. The reduced smoothing due to the shorter window width lets us track movements in volatility spillovers with greater resolution and details.

Figure 10. Total Volatility Spillover, Three Global Markets (75-day rolling window)



The x-axis represents the period of time and the y-axis measures the level of volatility expressed as a percentage.

Figure 11. Total Volatility Spillover, Three Global Markets (10-day and 2-day forecast horizon)



The x-axis represents the period of time and the y-axis measures the level of volatility expressed as a percentage.

- *Conditioning and Dynamics II: Rolling- Sample Gross Directional Volatility Spillover Plots*

Although the previous analysis provides a general overview of total volatility dynamics, it doesn't take into account directional spillover information. As we have mentioned before, this information is contained in the " Directional to others" row and the "Directional from others" column. The purpose of this section is to analyze this row and column in a dynamic way. In Figures 12, 13 and 14, we present the directional volatility spillovers from each of the three sector to the others, that is, "Directional to others" row in Table 7.

Figure 12. Volatility Spillover from AE to others

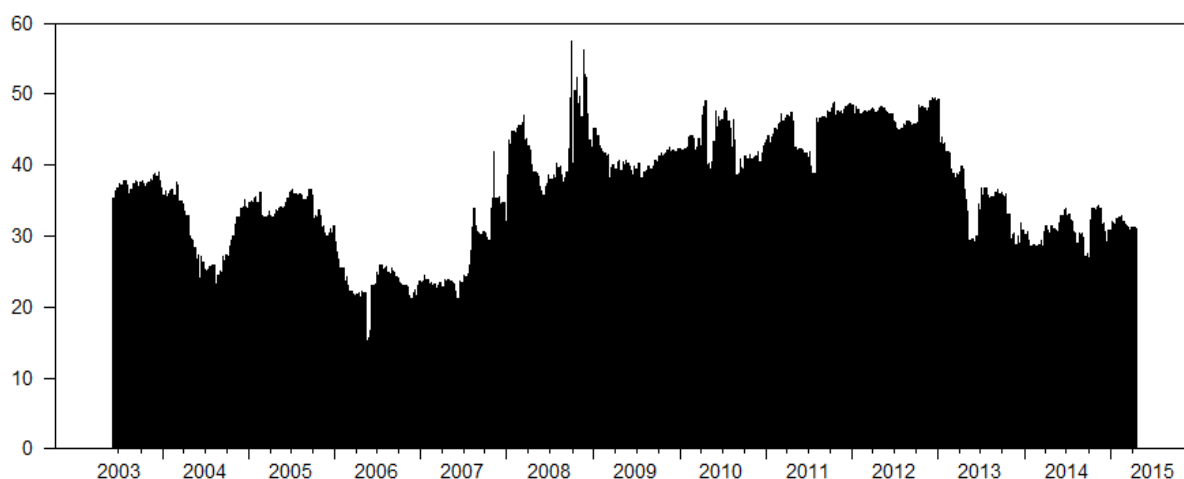


Figure 13. Volatility Spillover from OIL to others

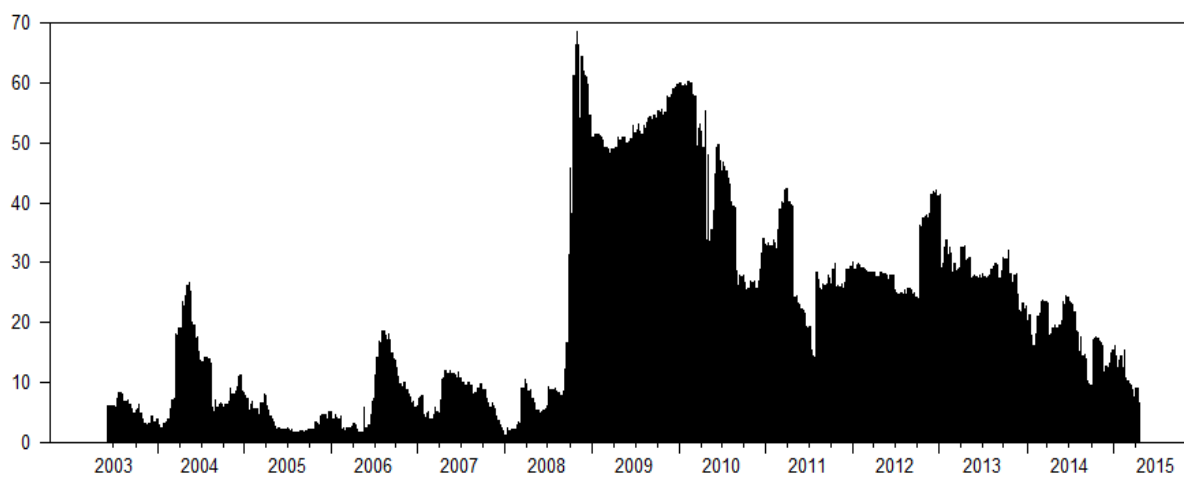
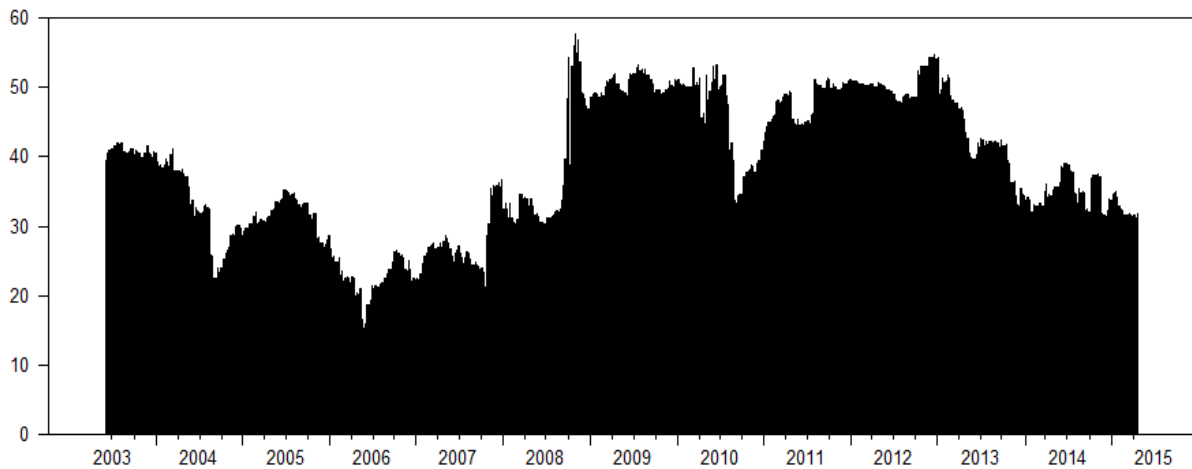


Figure 14. Volatility Spillover from TECH to others



The three plots above follow a different pattern. Nevertheless, in general terms spillovers for the three markets are lower before the start of the recent Financial Crisis and much more higher after that. In fact, this dynamic is very clear in the case of Oil, whose directional spillovers were in most of the cases below 20% before mid-2008 and then, during the Crisis and volatile times, directional spillovers increased up to 70%. In addition, the Alternative Energy market also goes from a 35% of volatility on average before mid-2008 and then, during the first years of the Financial Crisis (2008-2009) it has reached higher levels, around 50-60%.

Finally, the Technology market also presents higher directional spillovers to the others sectors during the post-crisis period than during pre-crisis years. Technology market is perhaps that one in which the difference before and after the Financial Crisis is not as significant as in the other two global markets.

Next, we will present Figures 15, 16 and 17, which represent the directional volatility spillovers from others to each of the three sectors; they correspond to the "Directional from others" column in Table 7.

Figure 15. Volatility Spillover from others to AE

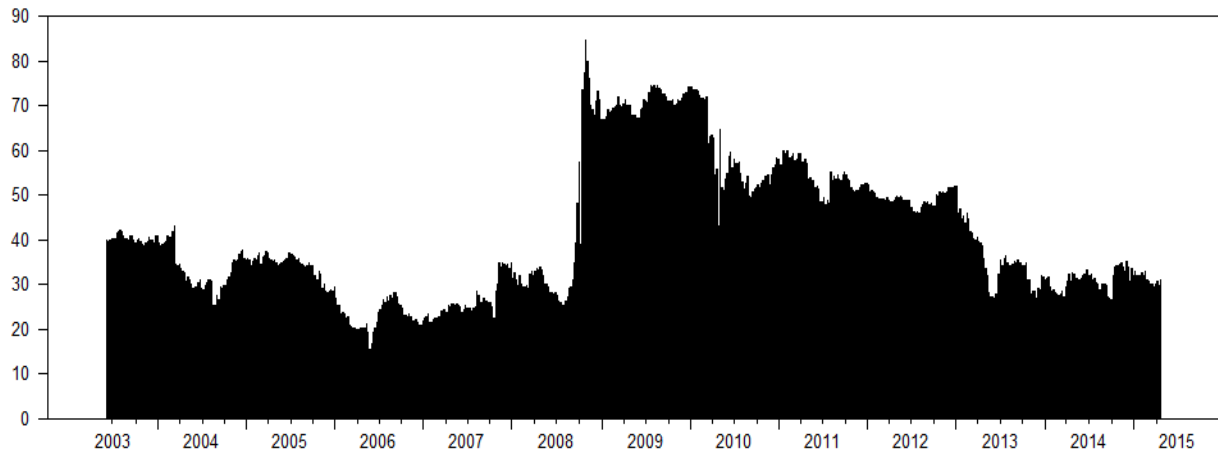


Figure 16. Volatility Spillover from others to OIL.

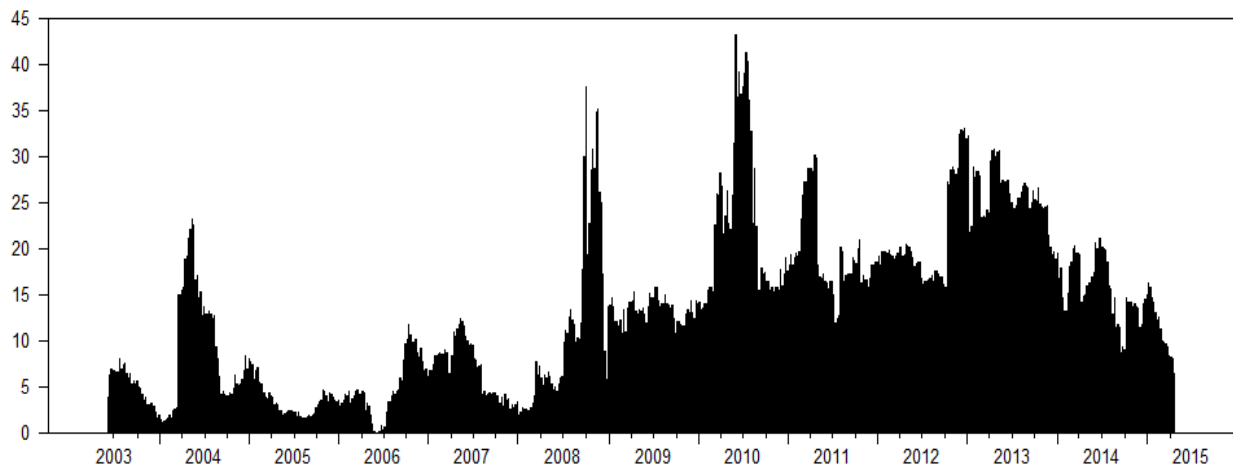
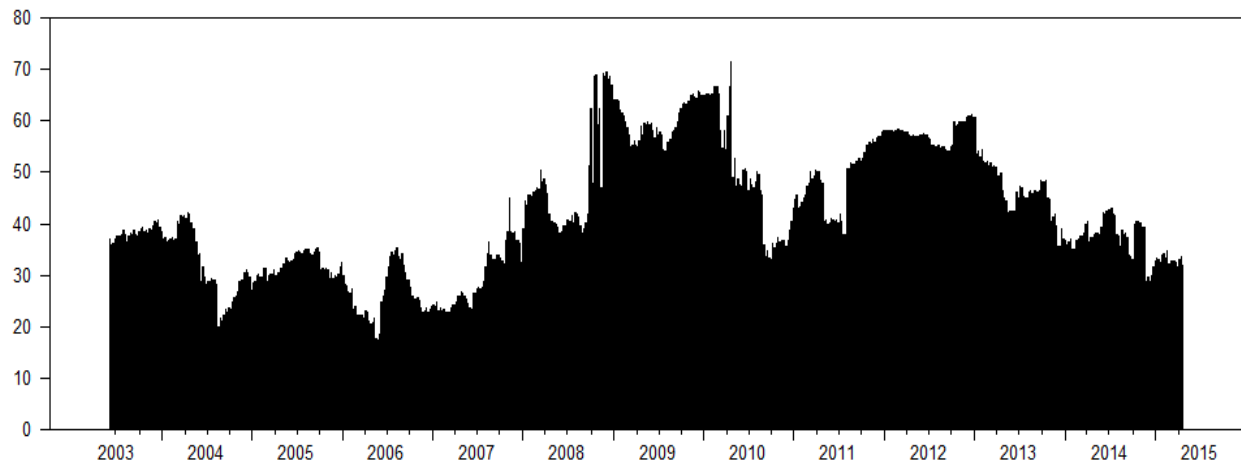


Figure 17. Volatility Spillover from others to TECH.



As with the directional spillovers to others, the spillovers vary greatly over the sample period. One can quickly check that Oil market is certainly that one which receives lower volatility spillovers from the other two markets before the Financial Crisis but the spillovers considerably increase during the post-crisis period. Regarding Alternative Energy and Technology markets, they receive greater spillovers in the period before the Crisis than Oil. However, although the intensity of volatility spillovers is also higher after the beginning of the Crisis, they don't suffer a huge and pronounced change from the pre to the post-crisis period as Oil does.

- *Conditioning and Dynamics III: Rolling- Sample Net Directional Volatility Spillover Plots*

So far, we have discussed the gross volatility spillover plots. However, this methodology provides us with a very useful measure in terms of net directional spillovers. Hence, we will present additional plots, Figures 18, 19 and 20. These plots correspond to the net directional spillover, that is, the difference between the "Contribution from" column sum and the "Contribution to " row sum. Besides, net pairwise spillovers for each one of the possible combinations of the three sectors are calculated and presented in Figures 21, 22 and 23.

Figure 18. Net Volatility Spillovers: Alternative Energy

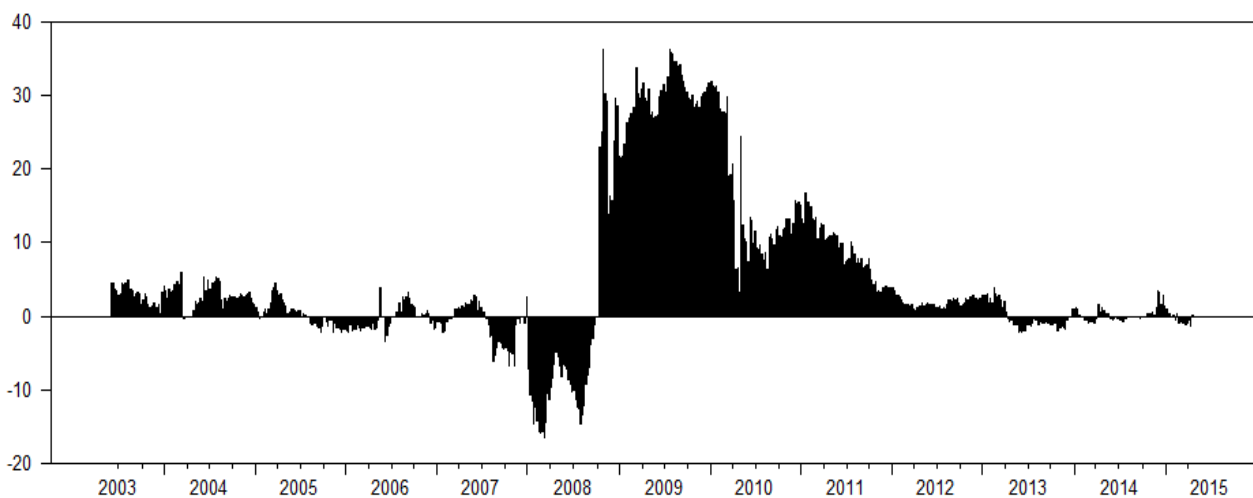


Figure 19. Net Volatility Spillovers: Oil

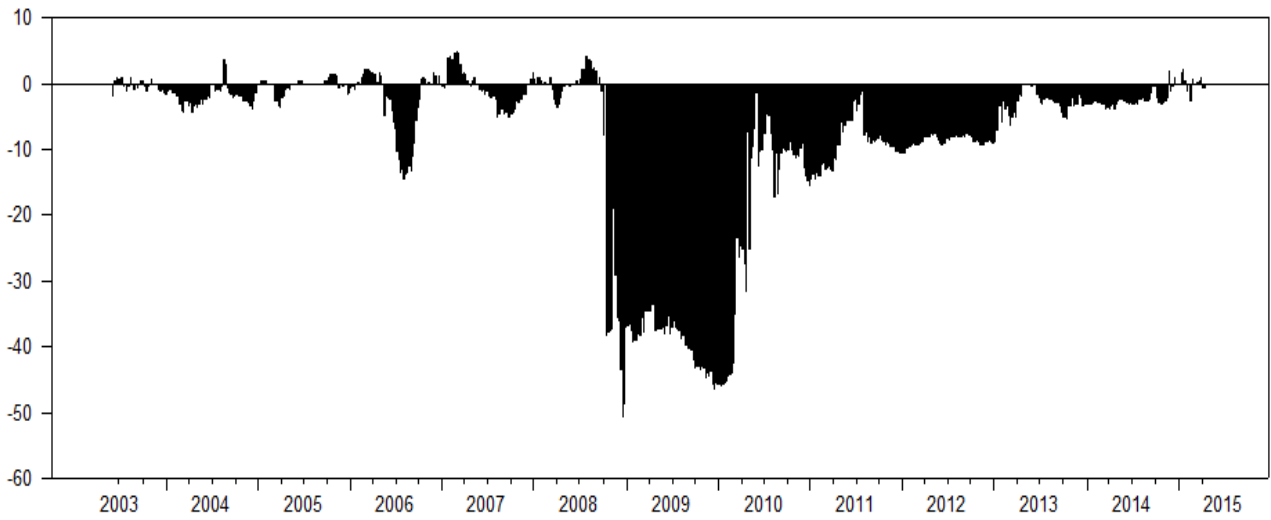


Figure 20. Net Volatility Spillovers: Technology

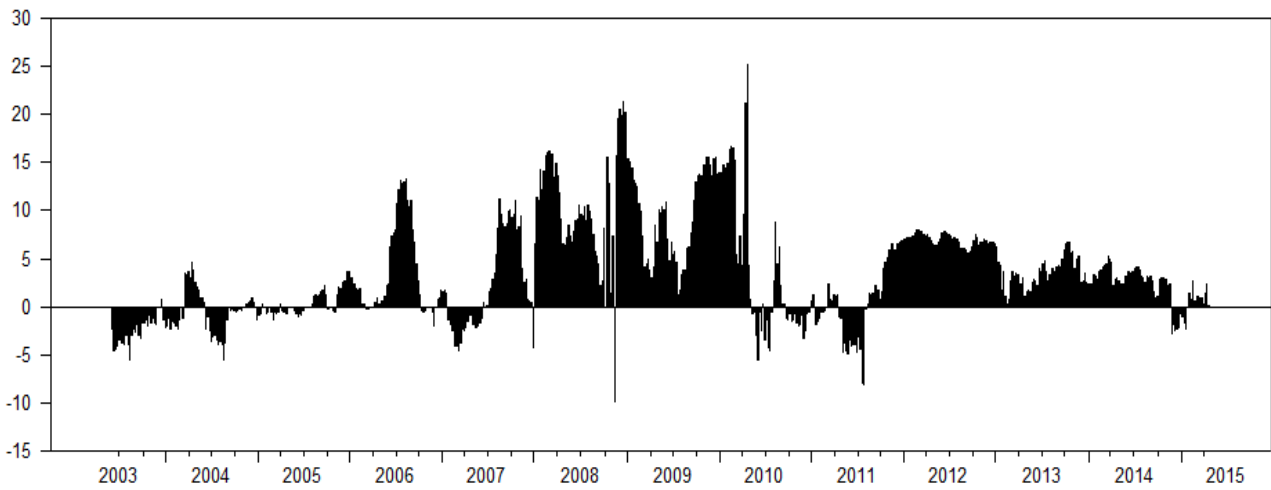


Figure 21. Net Pairwise Volatility Spillovers: Alternative Energy - Oil

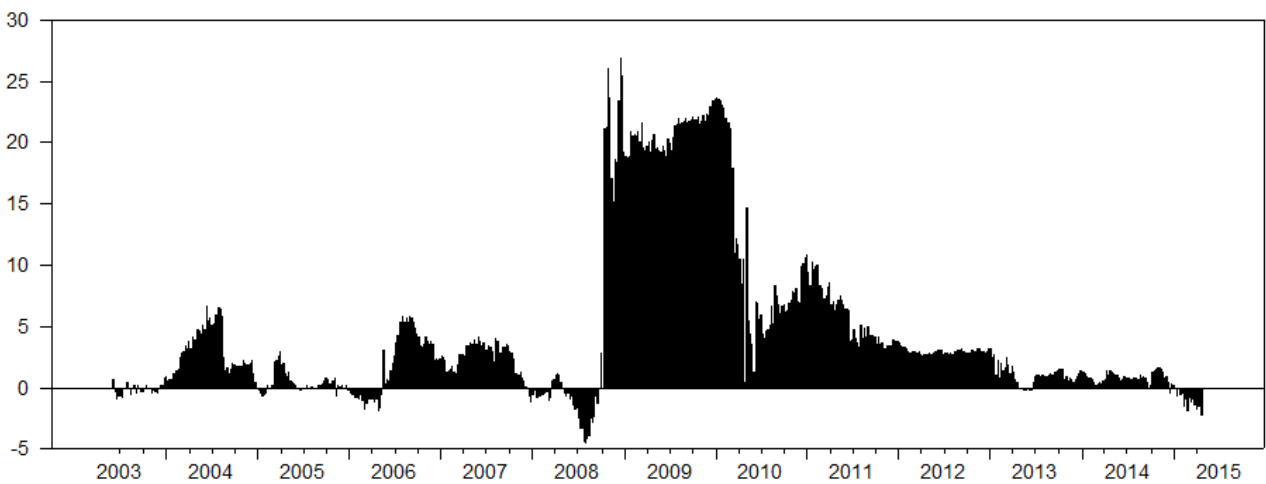


Figure 22. Net Pairwise Volatility Spillovers: Alternative Energy - Technology

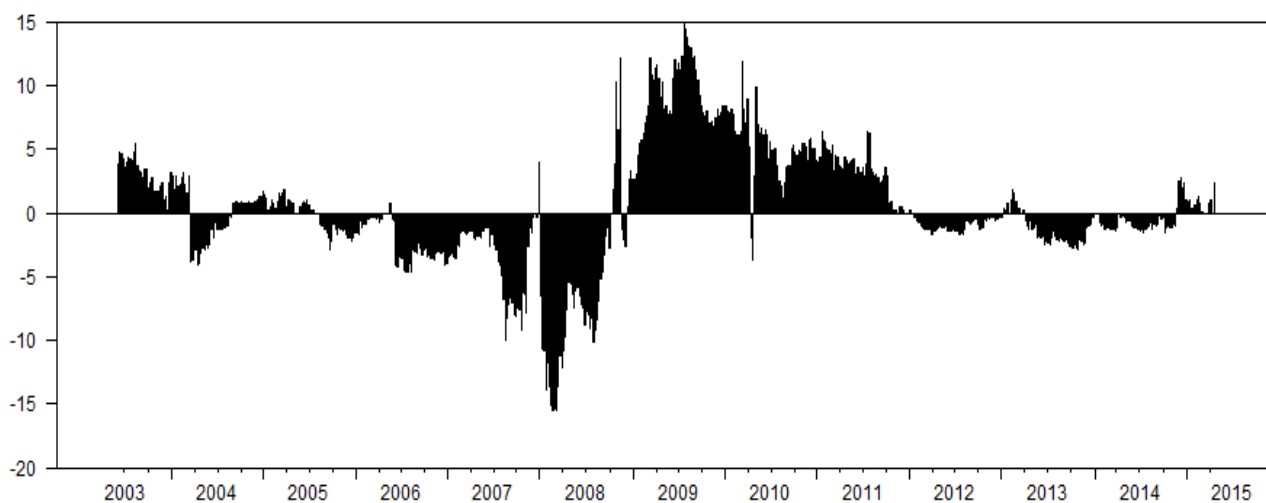
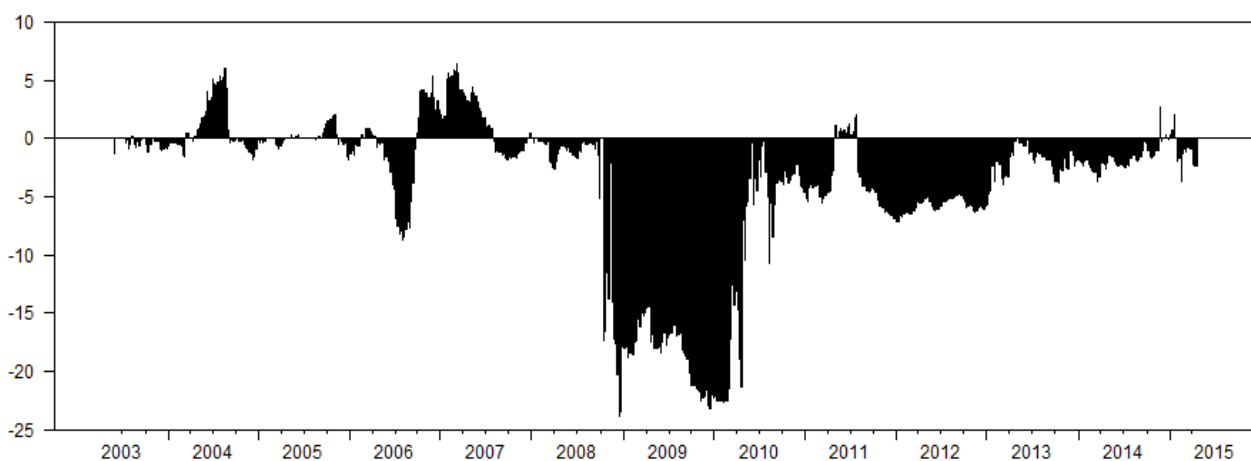


Figure 23. Net Pairwise Volatility Spillovers: Oil - Technology



Until the recent global crisis, in general terms net volatility spillovers from/to each of the three markets do not exceed the 10% mark. Moreover, until 2007, all three markets were relatively both the giving and receiving ends of volatility transmissions. However, although the general patterns show that things dramatically changed since January 2008, there are few exceptions. In fact, Figure 20, which displays the net volatility spillovers related to the global Technology market, shows that in 2006, this market reflect a peak of volatility, surpassing the 10% level.

Figure 18 shows that during the first part of the sample period, from 2003 up to the mid-2005, Alternative Energy global market was a net transmitter. Then, from mid-

2005 to mid-2008, Alternative Energy global market was a net receiver. After the beginning of the crisis up to 2011, Alternative Energy changed its role and it clearly became a net transmitter. Alternative Energy global market was transmitting volatility to both Oil and Technology sectors (see Figures 21 and 22).

From 2013 up to now, it seems that the Alternative Energy global market is receiving volatility spillovers from the other two markets but the intensity of volatility has significantly decreased.

The second net volatility spillover plot refers to Oil dynamics. In general, we could say that Oil is clearly the dominant net receiver but there are some episodes in which Oil was transferring volatility to the other markets. We refer to the period between the late 2006 and the beginning of 2007 and also, during the beginning of 2008. In addition, during the last months of the sample period, Oil is a net transmitter of volatility (see Figures 21 and 23).

Finally, regarding Figure 20, which reflects the net volatility spillover dynamics of the Technology global market, in general terms, this market can be considered as a net transmitter of volatility rather than a net receiver. However, as it happened with the oil market there are some individual episodes during which technology is a net receiver. We can point out the period between 2003 and 2004, the late of 2006 and the beginning of 2007 and also, between 2010 and 2011.

5. SOME APPLICATIONS: HEDGING AND PORTFOLIO WEIGHTS

Estimating the time-varying covariance matrix is crucial for portfolio selection, asset allocation and risk management. In this section, we propose some interesting financial applications that prove the relevance of calculating such covariance matrices. Hence, we applied our results to two essential financial problems. Both applications will provide useful information for investors involved in the Alternative Energy industry.

First, we will consider the problem of estimating a dynamic risk-minimizing hedge ratio using multivariate GARCH models. In particular, by applying the methodology introduced by Kroner and Sultan (1993), conditional volatility estimates can be used to construct hedge ratios. Thus, a long position in a given asset (asset i) can be hedged with a short position in another asset (asset j). The hedge ratio between asset i and asset j is:

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}} \quad (35)$$

For our purpose and by using the DCC model, we have computed the hedge ratios and so, their dynamics have been represented in Figures 24, 25 and 26. In addition, we provide summary statistics for each one of the hedge ratios (long/short) in Table 8.

Figure 24. Time-varying hedge ratios (DCC model) - AE

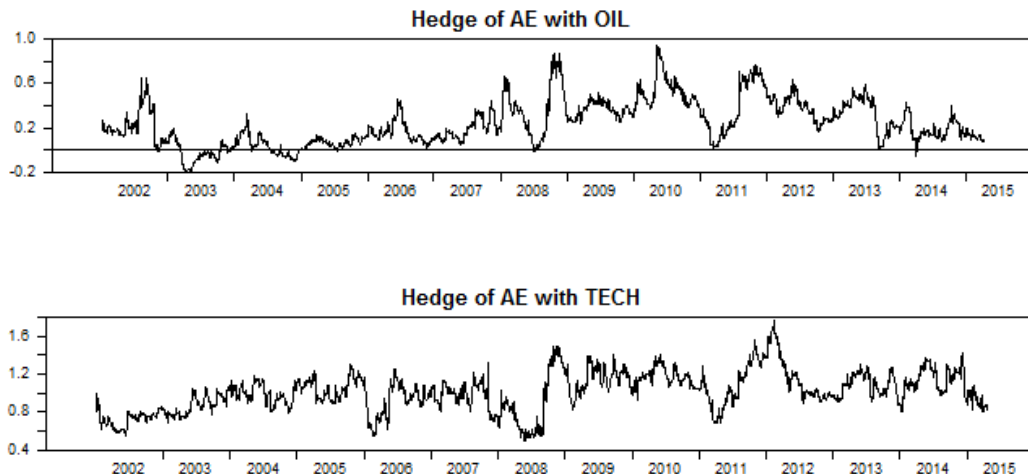


Figure 25. Time-varying hedge ratios (DCC model) - OIL

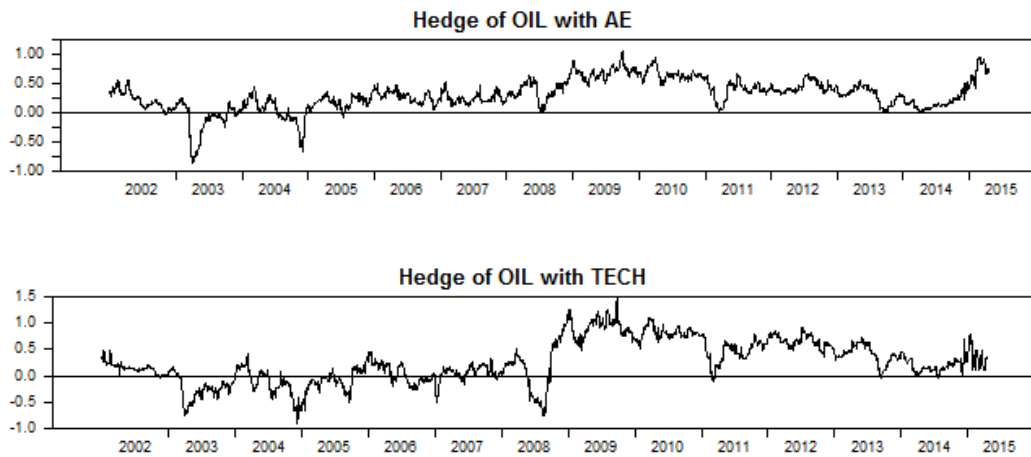


Figure 26. Time-varying hedge ratios (DCC model) - TECH

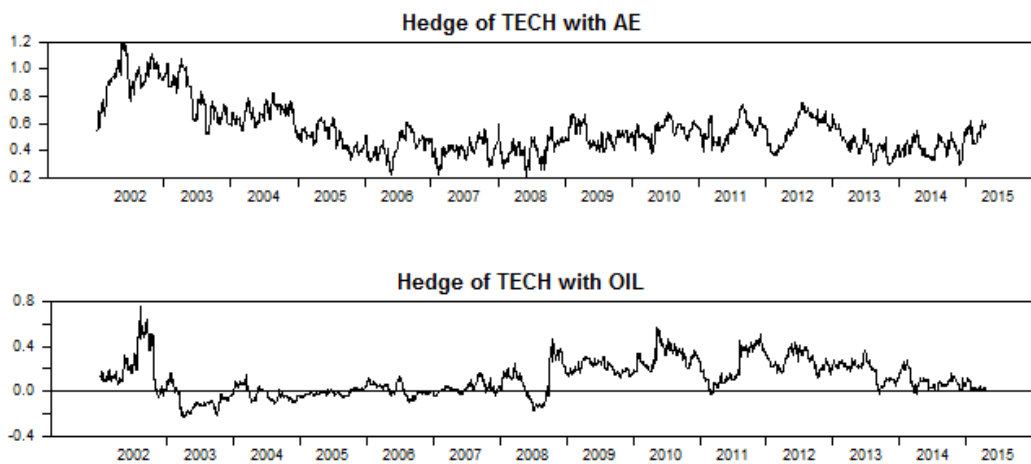


Table 8. Hedge ratio (long/short) summary statistics

	Mean	St. Dev	Min	Max
AE/OIL	0.24	0.21	-0.19	0.94
AE/TECH	1.01	0.21	0.48	1.76
OIL/AE	0.31	0.27	-0.87	1.07
OIL/TECH	0.26	0.41	-0.94	1.46
TECH/AE	0.55	0.18	0.21	1.19
TECH/OIL	0.11	0.16	-0.24	0.76

For most of the hedge ratios, computed from the DCC model, the graphs show considerable variability since the beginning of the recent Financial Crisis. Hence, for many of the hedge ratios it is also the case that the maximum value is achieved at the beginning of the Financial Crisis or some years later. In fact, in Figure 24, the AE with OIL hedge has its maximum value at mid-2010 and the AE/ TECH hedge has its highest value in the late of 2011 and the beginning of 2012. In the case of the Figure 25, which shows the hedge ratios of OIL with respect to AE and TECH, it can be seen that in both cases (Hedge of OIL with AE/Hedge of OIL with TECH) the maximum values are attained in the late of 2009 and the beginning of 2010.

However, looking at Figure 26, which shows TECH/AE and TECH/OIL hedge ratios, we can see that the highest values for these hedge ratios were recorded near the beginning of the sample period, in the pre-crisis period. In such a way, it was not convenient for investors to hedge TECH with short position in AE or OIL during the initial years of the sample period.

In addition, in Table 8 we can see that the average value of the hedge ratio between AE and OIL is 0.24 while the average value of the hedge ratio between AE and TECH is 1.01. The average value of the hedge ratio between OIL and TECH is 0.26, which is higher than the hedge between AE and OIL. These results reflect that a \$1 long position in AE can be hedged for 24 cents with a short position in the Oil market. Similarly, a \$1 long position in OIL can be hedged for 26 cents with a short position in the TECH index. In addition, as expected from what we obtained from the dynamic conditional correlation analysis, it is not convenient to hedge AE with a short position in TECH. Notice that four of the hedge ratios record maximum values in excess of unity.

Secondly, we consider the problem of calculating the optimal fully invested portfolio holding subject to a no-shorting constraint. This application is illustrative of the types of problems faced by portfolio managers when deriving their optimal portfolio holdings. In order to avoid forecasting expected returns, we assume here that the expected returns are zero, making the problem equivalent to estimating the risk-minimizing portfolio weights. In such a way, following Kroner and Ng (1998), the conditional volatilities from MGARCH models can be used to construct optimal portfolio weights:

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}} \quad (36)$$

$$w_{ij,t} = \begin{cases} 0, & \text{if } w_{ij,t} < 0 \\ w_{ij,t}, & \text{if } 0 \leq w_{ij,t} \leq 1 \\ 1, & \text{if } w_{ij,t} > 1 \end{cases} \quad (37)$$

In constructing portfolio weights between two assets, $w_{ij,t}$ is the weight of the first asset in a one dollar portfolio of two assets (asset i , asset j) at time t , $h_{ij,t}$ is the conditional covariance between assets i and j and $h_{jj,t}$ is the conditional variance of asset j . The weight of the second asset is $1 - w_{ij,t}$. In such a way, we have provided summary statistics for portfolio weights computed from the DCC model which are reported in Table 9.

Table 9. Portfolio weights summary statistics

	Mean	St. Dev	Min	Max
AE/OIL	0.61	0.19	0.05	1.03
AE/TECH	0.05	0.34	-0.66	1.34
OIL/TECH	0.23	0.16	-0.06	0.96

The average weight for the AE/OIL portfolio is 0.61, indicating that for a \$1 portfolio, 61 cents should be invested in AE and 39 cents invested in OIL. The average weight for the AE/TECH portfolio indicates that 5 cents should be invested in AE and 95 cents invested in TECH. Finally, the average weight for the OIL/TECH portfolio indicates that 23 cents should be invested in OIL and 77 cents invested in TECH.

6. ROBUSTNESS CHECKS

In this section we consider several robustness checks. Firstly, we propose to study volatility spillovers with another type of data coming from ETFs. Secondly, we investigate another alternative for our global market volatility spillovers research by considering different indexes from those ones previously used for representing the Alternative Energy and Technology markets.

6.1. ETFs

Why ETF's? Exchange Traded Funds are hybrid investment instruments between funds and shares so, they combine the diversification offered by a portfolio fund portfolio with the flexibility of being able to enter and leave the fund with a simple trading operation on the stock exchange. As we commented at the beginning, our final objective is to analyze volatility spillovers among these three markets in order to have a better understanding of the financial performance of alternative energy companies and provide useful information for investors. In fact, this could be the key to encourage the development of the alternative energy industry in the forthcoming years. In such a way, the idea of extending the proposal with ETFs comes because when analyzing investment strategies or hedging ratios, it is easier for investors if they invest and they make use of ETFs (after all, they replicate certain indexes) rather than doing so directly in the indexes. Some of the most important characteristics of this products are accessibility (easy access for investors); flexibility (you can buy or sell at any time); transparency (ETFs usually replicate very well known indexes), liquidity (ETFs can be bought and sold at any time) and strength (these products are already established in international markets). Therefore, there are relevant benefits derived from the investment in ETFs instead of investing in the indexes.

Thus, we found that both **The Market Vectors Global Alternative Energy ETF (GEX)** and **The iShares Global Tech ETF (IXN)** were the most adequate ETFs representing Alternative Energy and Technology global markets, respectively. The data for these ETFs were also collected from Thomson Reuters Datastream and the sample period for this data set covers May 2007 to May 2015. Again, in the case of Oil, we use

the nearest contract to maturity on the Brent crude oil futures for the corresponding time period.

6.2. The S&P Global Clean Energy Index and The DJ Global Technology Index.

The aim of this proposal is to contrast the results that we will get when we consider other indexes for both Clean Energy (CE from now on) and Technology, in which the US market had a lower weight. In such a way, we can check if the obtained outcomes with the Ardour Global Alternative Energy Index and the Dow Jones Technology Titans 30 Index are unbiased or not due to the strong presence of the US market in those indexes. Thus, we can conclude if our results are very similar from those obtained by Sadorsky (notice he made his study just for the US market) due to the high number of US company components in both indexes or on the contrary, our results are not influenced by such fact. Hence, we considered that for such purpose both **The S&P Global Clean Energy Index (SPGTCED)** and **The Dow Jones Global Technology Index (WITEC)** were the most appropriate indexes representing Clean Energy and Technology sector, respectively. In fact, in the S&P Global Clean Energy Index the US market representation is 22.9% whereas in the Ardour Global Alternative Energy Index is higher, 65.97%. In the case of the global Technology sector, in the Dow Jones Global Technology Index the US market represents the 48.74% out of the total whereas in the Dow Jones Technology Titans 30 Index, the US market presents a higher percentage, 76.78%.

The data for these two indexes were both collected from Thomson Reuters Datastream and Google Finance. The sample period for this data set covers November 2003 to May 2015. Again, in the case of Oil we use the nearest contract to maturity on the Brent crude oil futures for the corresponding time period.

6.3. Empirical results

Now, we will provide the results derived from both proposals when we apply MGARCH models and the recent methodology of Diebold and Yilmaz coupled with the two financial applications discussed in the previous section.

Table 10 contains the MGARCH parameter estimates for ETFs data coupled with Table 11 in which the diagnostic tests for the standardized residuals and standardized squared residuals are presented. Again, in Table 10 models are estimated using QMLE and variable order is AE (1), OIL (2) and TECH (3). In the variance equations, c denotes the constant terms, a denotes the ARCH terms and b denotes the GARCH terms.

In addition, Table 12 provides the results obtained from the Diebold and Yilmaz (2012) methodology. Moreover, the outcomes derived from the two financial applications, hedge ratios and portfolio weights are presented in Tables 13 and 14.

Similarly, in Table 15 we present the MGARCH parameter estimates obtained for the S&P Global Clean Energy Index and the Dow Jones Global Technology Index. As in the previous case, Table 16 shows the diagnostic tests for the standardized residuals and standardized squared residuals. In addition, in Table 17 we provide the outcomes from the Diebold and Yilmaz (2012) methodology applied for this proposal. Finally, time-varying hedge ratios computed from DCC model and the required invested portfolio holdings are presented in Table 18 and 19, respectively.

Only the most relevant results have been included in order to save space but they are available by the author upon request.

Table 10. MGARCH parameter estimates (ETFs)

	BEKK		DIAGONAL		CCC		DCC	
	Coeff	T stat	Coeff	T stat	Coeff	T stat	Coeff	T stat
Mean								
m₁₀	0.0603**	2.18	0.1009***	3.04	0.0586	1.77	0.0692**	2.09
m₁₁	-0.0163	-0.58	0.0023	0.07	-0.0004	-0.01	-0.0141	-0.46
m₁₂	-0.0034	-0.21	-0.0127	-0.65	-0.0054	-0.25	-0.0093	-0.47
m₁₃	0.0292	0.65	0.0273	0.55	0.0445	0.90	0.0379	0.81
m₂₀	0.0199	0.60	0.0263	0.83	0.0216	0.70	0.0350	1.06
m₂₁	0.0273	1.19	0.0437	1.60	0.0412	1.49	0.0367	1.43
m₂₂	-0.0734***	-3.43	-0.0693***	-2.97	-0.0729	-2.98	-0.0733***	-3.24
m₂₃	0.0519	1.34	0.0389	0.88	0.0654	1.49	0.0547	1.25
m₃₀	0.0793***	4.30	0.0497**	2.17	0.0653***	3.12	0.0775***	3.66
m₃₁	-0.0169	-1.12	-0.0179	-0.94	-0.0120	-0.62	-0.0200	-1.20
m₃₂	-0.0035	-0.34	0.0034	0.27	-0.0020	0.15	-0.0019	-0.15
m₃₃	0.0122	0.43	-0.0036	-0.12	0.0056	0.17	0.0151	0.51
Variance								
c₁₁	0.2120***	7.66	0.0597***	3.94	0.0225	0.79	0.0499***	4.74
c₂₁	0.0445	1.77						
c₂₂	0.1014***	5.12	0.0197***	3.00	0.0201**	2.10	0.0276***	3.39
c₃₁	0.0966***	4.19						
c₃₂	0.0166	0.66						
c₃₃	0.0779***	5.96	0.0248***	4.70	0.0218**	1.95	0.0182***	4.32
a₁₁	0.3302***	13.50	0.1122***	6.19	0.1242***	7.04	0.0647***	4.30
a₁₂	0.0321	1.51	0.0239	1.84	0.0211	1.30	0.0338***	2.95
a₁₃	0.0974***	6.14	-0.0569**	-2.18	-0.1611***	-5.66	-0.0098	-0.37
a₂₁	0.0412***	2.77	0.0600***	4.25	0.0647***	4.39	0.0645***	3.87
a₂₂	0.1743***	12.97	0.04323***	6.39	0.0482***	6.10	0.0494***	5.88
a₂₃	-0.0040	-0.38	-0.08578***	-4.53	-0.1161***	-5.11	-0.0889***	3.00
a₃₁	-0.1515***	-3.33	0.0302***	7.66	0.0015	0.15	0.0420***	5.48
a₃₂	0.0137	0.39	-0.0075	-1.32	-0.0360***	-4.36	-0.0040	-0.65
a₃₃	0.1484***	5.76	0.0522***	5.00	0.0804***	4.63	0.0155	1.18
b₁₁	0.9349***	94.99	0.8932***	68.87	0.6626***	6.12	0.9199***	43.22
b₁₂	-0.0000	-0.00	-1.3051	-0.48	-0.1824	-1.84	-0.0692***	-4.62
b₁₃	-0.0281***	-4.79	-0.8496	-0.43	0.7264***	2.57	0.0493	1.20
b₂₁	-0.0055	-1.47	-0.5647	-0.23	-0.0931	-1.17	-0.0054	-0.18
b₂₂	0.9844***	380.40	0.9471***	122.78	0.9204***	48.99	0.9383***	82.59
b₂₃	0.0054**	2.01	-1.0342	-0.22	0.2869***	1.52	0.0085	0.19
b₃₁	0.0469***	2.72	-0.2591	-0.46	0.1396***	1.68	-0.0358***	2.77
b₃₂	-0.0212**	-2.12	-0.7200	-0.48	0.1547**	2.35	-0.0054	-0.66
b₃₃	0.9863***	115.56	0.9001***	77.79	0.6747***	5.20	0.9736***	43.61
ρ₂₁					0.3659***	20.89		
ρ₃₁					0.7537***	85.69		
ρ₃₂					0.3304***	17.87		
θ₁							0.0302***	75.64
θ₂							0.9635***	179.41
Log L	-10554.74		-11598.91		-10607.45		-10523.83	
AIC	10.149		11.147		10.200		10.119	
SIC	10.247		11.236		10.297		10.213	

Variable order is AE (1), OIL (2) and TECH (3). In brackets, next to the parameter values estimates are the corresponding t-statistics. ** indicates significance at 5%.

Table 11. Diagnostic tests for standardized residuals (ETFs)

	<i>BEKK</i>			<i>DIAG</i>			<i>CCC</i>			<i>DCC</i>		
	AE	OIL	TECH	AE	OIL	TECH	AE	OIL	TECH	AE	OIL	TECH
Q(20) r	26.17	18.26	17.14	25.59	17.30	17.38	25.29	16.89	16.62	28.65	17.53	32.80
p-value	0.1603	0.5702	0.6438	0.1796	0.6333	0.6281	0.1906	0.6602	0.6776	0.0949	0.6186	0.6179
Q(20)r²	14.91	32.01	27.38	8.42	28.92	25.99	51.06	27.92	69.20	19.32	17.54	32.80
p-value	0.7818	0.0432	0.1250	0.9887	0.0894	0.1663	0.0002	0.1113	0.0000	0.5014	0.6179	0.0354

Table 12. Volatility Spillover Table (ETFs)

	Alternative Energy	Oil	Technology	Directional FROM others
Alternative Energy	55.6	13.5	30.9	44
Oil	25.3	55.1	19.6	45
Technology	41.5	14.3	44.3	56
Directional TO others	67	28	51	145
Directional including own	122	83	95	Total Spillover Index (145/300): 48.3%

The results are based on a vector autoregression of order 1 and on a generalized variance decomposition of 10-day-ahead volatility forecast errors.

Table 13. Hedge ratio (long/short) summary statistics (ETFs)

	Mean	St. Dev	Min	Max
AE/OIL	0.42	0.21	-0.08	1.04
AE/TECH	1.23	0.21	0.63	0.83
OIL/AE	0.35	0.17	-0.08	0.97
OIL/TECH	0.47	0.32	-0.73	1.40
TECH/AE	0.47	0.09	0.15	0.72
TECH/OIL	0.23	0.16	-0.26	0.69

Table 14. Portfolio weights summary statistics (ETFs)

	Mean	St. Dev	Min	Max
AE/OIL	0.43	0.21	-0.03	1.00
AE/TECH	-0.22	0.21	-1.03	0.5
OIL/TECH	0.25	0.15	-0.07	0.73

Table 15. MGARCH parameter estimates (The S&P Global Clean Energy & The DJ Global Technology Indexes)

Mean	BEKK		DIAGONAL		CCC		DCC	
	Coeff	T stat	Coeff	T stat	Coeff	T stat	Coeff	T stat
m₁₀	0.0740***	4.08	0.0666***	3.16	0.0783***	3.26	0.0780***	3.56
m₁₁	0.1317***	8.53	0.1405***	7.08	0.1359***	6.79	0.1295***	6.69
m₁₂	0.0399***	4.12	0.0370***	3.19	0.0327***	2.46	0.0403***	3.17
m₁₃	0.0052	0.27	0.0159	0.75	0.0323	1.28	0.0078	0.40
m₂₀	0.0575	18.64	0.0481	1.69	0.0605***	2.06	0.0718***	2.45
m₂₁	0.0518***	2.91	0.0435**	-2.23	0.04401**	2.25	0.0469**	2.24
m₂₂	-0.0513***	-3.16	-0.0628***	-3.42	-0.0583***	-3.02	-0.0480**	-2.42
m₂₃	0.0092	0.39	-0.0089	-0.32	-0.0006	-0.02	-0.0044	0.15
m₃₀	0.0552***	3.17	0.0567***	3.87	0.0741***	5.00	0.0579***	3.65
m₃₁	-0.0051	-0.51	-0.0103	-0.94	-0.0070	-0.61	-0.0093	-0.92
m₃₂	-0.0053	-0.61	-0.0038	-0.46	-0.0096	-1.10	-0.0058	-0.69
m₃₃	0.0963***	5.92	0.1068***	5.35	0.1015***	4.94	0.0969***	4.38
Variance								
c₁₁	-0.1307***	-7.89	0.0367***	4.49	0.0054	0.16	0.0535***	3.68
c₂₁	-0.0209	-0.66						
c₂₂	-0.1029***	-4.46	0.0180***	2.72	0.0072	0.55	0.0220***	3.01
c₃₁	-0.0843***	-4.35						
c₃₂	-0.0302	-1.00						
c₃₃	0.0958***	5.10	0.0165***	4.57	0.0325***	2.58	0.0168***	4.33
a₁₁	0.2614***	21.08	0.0774***	8.18	0.0855***	6.23	0.0782***	7.37
a₁₂	0.0562***	3.90	0.0250***	2.78	0.0451***	4.06	0.0256***	2.59
a₁₃	0.0465***	3.61	-0.0110	-0.86	-0.0901***	-4.05	0.0093	0.48
a₂₁	-0.0060	-0.57	0.0064	1.06	0.0103	1.20	0.0181**	2.09
a₂₂	0.1679***	13.87	0.0477***	7.33	0.0430***	6.60	0.0480***	7.00
a₂₃	-0.0035	-0.35	-0.0151	-1.04	-0.0236	-1.50	-0.0166	-1.01
a₃₁	-0.0582**	-2.04	0.0072	1.17	0.0236***	2.05	0.0120	1.33
a₃₂	-0.0201	-0.78	0.0070	1.06	0.0018	0.24	0.0066	0.85
a₃₃	0.2274***	15.30	0.0725***	8.04	0.1243*	8.69	0.0720***	7.37
b₁₁	0.9633***	-289.37	0.9013***	79.91	0.3578***	3.88	0.8863***	42.25
b₁₂	-0.0139***	-3.76	-0.9896	-0.34	-0.5542***	-3.80	0.0239	0.93
b₁₃	-0.0110	-3.69	2478.0470	0.35	17.0111***	3.24	-0.0846***	-2.63
b₂₁	0.0026***	1.08	-0.2329	-0.15	-0.6858***	-4.35	-0.0172	-1.64
b₂₂	0.9847	418.66	0.9467***	128.70	0.8950***	47.05	0.9478***	116.19
b₂₃	0.0022	0.88	11.3067	0.16	19.3968	1.85	-0.0016	-0.04
b₃₁	0.0000	0.01	263.5052	0.19	3.7285***	3.21	-0.0127	-0.92
b₃₂	-0.0097	-1.23	4.7869	0.19	4.2240	1.78	0.0132	-0.92
b₃₃	0.9629***	231.14	0.9119***	83.50	0.3208***	4.00	0.9132***	81.41
ρ₂₁					0.2678***	17.18		
ρ₃₁					0.0654***	3.70		
ρ₃₂					0.0200	1.80		
θ₁							0.0162***	11.30
θ₂							0.9828***	592.52
Log L	-15289.04		-15425.85		-15256.54		-15220.86	
AIC	10.251		10.340		10.229		10.205	
SIC	10.323		10.407		10.301		10.275	

Variable order is CE (1), OIL (2) and TECH (3). In brackets, next to the parameter values estimates are the corresponding t-statistics. ** indicates significance at 5%.

Table 16. Diagnostic tests for standardized residuals (The S&P Global Clean Energy & The Dow Jones Global Technology)

	<i>BEKK</i>			<i>DIAG</i>			<i>CCC</i>			<i>DCC</i>		
	CE	OIL	TECH	CE	OIL	TECH	CE	OIL	TECH	CE	OIL	TECH
Q(20) r	19.82	16.40	22.49	18.04	16.13	19.89	19.44	14.21	18.85	18.17	16.07	20.63
p-value	0.4695	0.6916	0.3144	0.5845	0.7082	0.4647	0.4931	0.8197	0.5318	0.5760	0.7123	0.4190
Q(20) r²	22.05	31.47	36.67	13.14	23.37	25.09	25.37	18.93	40.21	14.21	23.33	25.11
p-value	0.3376	0.0493	0.0128	0.8713	0.2709	0.1979	0.1875	0.5264	0.0047	0.8196	0.2728	0.1974

Table 17. Volatility Spillover Table (The S&P Global Clean Energy & The Dow Jones Global Technology)

	Clean Energy	Oil	Technology	Directional FROM others
Clean Energy	54.3	6.1	39.6	46
Oil	15.2	66.5	18.4	34
Technology	25.3	6.8	67.9	32
Directional TO others	40	13	58	111
Directional including own	95	79	126	Total Spillover Index (111/300): 37%

The results are based on vector autoregression of order 1 and on a generalized variance decomposition of 10-day-ahead volatility forecast errors.

Table 18. Hedge ratio (long/short) summary statistics(The S&P Global Clean Energy & The Dow Jones Global Technology Indexes)

	Mean	St. Dev	Min	Max
CE/OIL	0.27	0.21	-0.02	0.98
CE/TECH	0.04	0.24	-0.51	0.82
OIL/CE	0.32	0.18	-0.52	0.77
OIL/TECH	-0.03	0.19	-1.20	0.34
TECH/CE	0.06	0.17	-0.19	0.85
TECH/OIL	0.00	0.04	-0.16	0.18

Table 19. Portfolio weights summary statistics (The S&P Global Clean Energy & The Dow Jones Global Technology)

	Mean	St. Dev	Min	Max
CE/OIL	0.59	0.20	0.01	0.96
CE/TECH	0.31	0.13	0.05	0.93
OIL/TECH	0.24	0.10	0.03	0.68

Regarding the results obtained for the ETF's proposal, GARCH methodology provides some outcomes in the same line as the original proposal (the Ardour Global Alternative Energy Index and the Dow Jones Global Titans 30 Index). Looking at the mean equation, there is no any evidence of spillovers. In fact, except for some constants (m_{i0}) and (m_{ii}) own terms, there is not any statistically significant cross-parameter at the same time individually in any of the four models. Focusing on the variance model, as it happened with our initial proposal, both b_{ii} and a_{ii} are statistically significant at 1% in each of the four models. In addition, taking into consideration cross-parameters in the BEKK model, it can be seen that a_{13} , a_{31} , b_{13} and also, b_{31} are statistically significant at 1%. The restricted correlation models also have some of these mentioned parameters statistically significant, so again the results are consistent among the different applied models. In such a way, for the ETFs proposal, which replicate the underlying indexes, once again we get to the idea that there are spillover effects between TECH and AE and between AE and TECH. As it happened with the US market, also for the Global Market, shocks to Technology stock prices have a greater impact on the stock prices of Alternative Energy companies than a shock to Oil prices does. Finally, parameters a_{21} and a_{23} are statistically significant at 1% in all of the four models and in the three restricted correlation models, respectively. This outcome indicates that Oil depends both on Alternative Energy and Technology, but there is no evidence of bidirectional volatility spillover.

In addition, AIC and SIC criteria rank DCC as the best model which fits the ETFs data (notice that DCC only has a_{31} and b_{31} parameters statistically significant). The diagnostic tests for the residuals provide us with excellent results so we can

conclude that the applied models fit the data and there is no evidence of serial correlation (see Table 11).

Secondly, according to the outcomes from Diebold and Yilmaz methodology in Table 12 we can highlight the following facts. Again, the strongest effect of volatility spillover is between AE and TECH (from AE to TECH: 30.9 and from TECH to AE: 41.5).

Finally, Table 13 contains the summary statistics for the different hedge ratios. The average value of the hedge ratio between AE and OIL is 0.42 while the average value of the hedge ratio between AE and TECH is 1.13. Again, these results are similar than those obtained with the Ardour Global Alternative Energy and the Dow Jones Technology Titans 30. In addition, the average value of the hedge ratio between OIL and TECH is 0.47, which is higher than the hedge between AE and OIL. This result will imply that a \$1 long position in AE can be hedged for 42 cents with a short position in the Oil market. Similarly, a \$1 long position in OIL can be hedged for 47 cents with a short position in the TECH ETF, that is, in the iShares Global Tech ETF (IXN). So, for this ETF proposal we can again conclude, that it could be not efficient to hedge AE with a short position in TECH, since they present the higher hedge ratio: 1.23. In addition, Table 14 shows the summary statistics for portfolio weights computed from the DCC model. Hence, the average weight for the AE/OIL is 0.43, indicating that for a \$1 portfolio, 43 cents should be invested in AE and 57 cents invested in OIL. The average weight for the OIL/TECH portfolio indicates that 25 cents should be invested in OIL and 75 cents invested in TECH. Finally, the average weight for the AE/TECH portfolio indicates that, since short-selling is not allowed we should invest 1€ in TECH and nothing in AE, so we should not hedge AE by investing in TECH.

According to the second additional proposal of the S&P Global Clean Energy Index and the Dow Jones Global Technology Index in which the US market representation is lower, we observe how results change to some extent. First, looking at Table 15 with the GARCH parameter estimates, the mean models show both m_{12} and m_{21} terms to be statistically significant at 1% in each one of the four models. So this initial results imply that, in contrast of what the previous two proposal have revealed, there could be some evidence that a one period lag of OIL positively affects current period CE and vice versa. Then, once the US market has not such a considerable weight

in the selected indexes the relationship between CE and OIL appears to be stronger, at least in terms of returns.

Variance models provide us with some interesting results. In fact, we can see how the GARCH models suggest that there is evidence of spillovers volatility between CE and OIL and between CE and TECH, so contrary to the previous proposals, it would not be so clear whether CE is more influenced by OIL or by TECH. Again, this method ranks the DCC as the model, which best fits the data and there are no problems of serial correlation.

According to the results in the Table 17, which corresponds to the Diebold and Yilmaz methodology, we note that volatility spillover between OIL and CE is equal to 15.2% and the volatility spillover between TECH and CE show a value of 25.3%. Hence, while in this proposal for the global market the US market has a lower weight, the global Technology sector still has a major influence on Clean Energy than Brent. However, it is also important to consider that contrary to the two previously analyzed proposals (Ardour -Titans and ETFs), in this case, the volatility spillover from Clean Energy to Technology, (39.6%) is higher than that one from Technology to Clean Energy, (25.3%).

Moreover, Table 18 reports the summary statistics for the computed hedge ratios. In this case, the average value of the hedge ratio between CE and OIL is 0.27 while the average value of the hedge ratio between CE and TECH is lower, 0.04. So, we can easily see how things change when the US market representation is not so remarkable. In addition, the average value of the hedge ratio between OIL and TECH is -0.03, contrary to what we have previously observed when we deal with the Ardour and the Dow Jones Titans and also, with ETF data. These results will imply that a \$1 long position in CE can be hedged for 27 cents with a short position in the oil market. Besides, a \$1 long position in OIL can be hedged by selling (short-selling) 3 cents with a long position in the TECH index. However, in this case it could be convenient to hedge CE with a short position in TECH, since a \$1 long position in CE can be hedged for 4 cents with a short position in TECH. The CE/TECH hedge ratio is equal to 0.04. Regarding the maximum and minimum values, minimum values are all below zero and maximum values don't exceed the unity in anyone of the cases. In addition, Table 19 shows the summary statistics for portfolio weights computed from the DCC model. Thus, the average weight for the CE/OIL is 0.59, indicating that for a \$1 portfolio, 59

cents should be invested in CE and 41 cents invested in OIL. The average weight for the OIL/TECH portfolio indicates that 24 cents should be invested in OIL and 76 cents invested in TECH. Finally, the average weight for the CE/TECH portfolio indicates that for a \$1 portfolio, 31 cents should be invested in CE and 69 cents invested in TECH.

Consequently, we conclude that in the case of ETFs, the results are very similar to those obtained previously with the Ardour Global Alternative Energy Index and the Dow Jones Global Technology Titans 30 Index. In the case of the S&P Global Clean Energy Index and the Dow Jones Global Technology Index (in which the US market representation is more limited) the stock prices of Technology companies continue to have a more important role in explaining the fluctuations of the stock prices of Alternative Energy companies than Brent does, but to a lesser extent.

7. CONCLUDING REMARKS

In 2014, world clean energy amounted to \$310 billion. This implies a rise of 16% from a \$268.1 billion in 2013, and more than five times the figure of \$60.2 billion attained a decade earlier, in 2004. Undoubtedly, from the last decade, the Alternative Energy sector (especially renewable sources) has become one of the fastest growing sectors of the energy industry. In fact, energy security issues coupled with an increased concern about the natural environment are the main responsible for such an incredible growth. Nevertheless, very little is known about the volatility dynamics of the global Alternative Energy market and the possible correlation between the stock prices of Alternative Energy companies and other important markets, such as those involving global Oil and Technology sectors. This paper uses multivariate GARCH models and the methodology introduced by Diebold and Yilmaz (2012) to investigate the volatility spillovers between Oil prices and the stock prices of Alternative Energy and Technology companies at a global scale.

Our empirical results show that both unconditional correlations as well as dynamic conditional correlations between global Alternative Energy stock prices and Technology stock prices are more significant than those between Alternative Energy stock prices and Oil prices. The outcomes derived from GARCH models (considering the BEKK model as the benchmark) and those obtained from the methodology of Diebold and Yilmaz (2012) show that the strongest evidence for volatility spillovers is found between Alternative Energy and Technology global markets. Specifically, the second methodology illustrates the intensity and the magnitude of such volatility spillovers among the three global markets, both in a static way (it numerically quantifies such spillovers) and in a dynamic way (via charts). Oil effects on Alternative Energy are important but not as important as Technology stock price effects.

In addition, the conditional volatility from the DCC model can be used to estimate dynamic hedge ratios. On average, a long position in Alternative Energy companies can be hedged with a short position in the Brent crude oil futures market. However, due to the existence of a high and positive correlation between global Alternative Energy and Technology, it is not convenient for investors to hedge an investment in Alternative Energy companies with a short position in Technology

companies. That's why, on average, the hedge ratio between Alternative Energy and Technology is 1.01 whereas the hedge ratio between Alternative Energy and Oil is 0.24. Moreover, when calculating the optimal portfolio holdings, investors should invest a little more than half on Alternative Energy and the rest in Oil. On the contrary, just a 5% of the total should be invested in Alternative Energy and the remainder in Technology. Hence, there is strong empirical evidence of volatility spillovers between Alternative Energy and Technology global markets when we analyze the dynamics of indexes in which the weight of the US market is very high.

However, our robustness checks show that when we examine other indexes in which the US market has a lower representation, which is the case of the S&P Global Clean Energy Index and the Dow Jones Global Technology Index, the results change to some extent in terms of the financial results for investors.

On balance, if we consider that those companies with a higher market capitalization represent current global markets, analyzing the Ardour Global Alternative Energy and the Dow Jones Technology Titans 30 Indexes provides us the results that truly reflect world dynamics in Alternative Energy and Technology sectors. All in all, we can conclude that global Alternative Energy is more influenced and dependent on global Technology than on Oil prices movements.

Considering all these results, international policies and financial markets should be adapted to support the active transformation of the global energy system. Hence, due to the high relationship that exists between Alternative Energy and Technology sectors, evaluating a range of possible technological options for more integrated energy systems will provide an increased number of solutions for countries and regions to achieve such transformation of the global energy system. Nevertheless, policy and market risks increasingly cloud the development picture, raising concerns over how fast Alternative and Renewable Energy can scale up to meet long-term development objectives. In fact, in some emerging economies the lack of targeted policies and access to finance, as well as the persistence in some countries of fossil-fuel subsidies, create serious obstacles to investments in the Alternative Energy sector.

As a result, despite the huge experienced growth in the Alternative and Renewable Energy sector, consistent and credible policies and innovative financing vehicles are needed so they can provide the bridge to pass from a fossil-fuel based

energy system to a new one, based on Alternative Energy sources. Moreover, these policies should ensure that global investment in Alternative Energy offers a sufficiently attractive returns and financial opportunities for investors.

It will take time, realism and determination to harness the skills of the financial world to the ambition for obtaining such transformation in the current energy system and also, for solving energy security issues and reaching climate change targets. However, it is crucial that we begin to work on it as soon as possible. The continued dependence on fossil fuels and recent trends of unexpected energy market fluctuations reinforce the role of governments and private sector to stimulate targeted action to ensure that resources are optimally aligned to accelerate progress. Establishing policy and market frameworks that support innovation and build investor confidence over the long term is a first-order task to deliver.

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