Energy price transmissions during extreme movements[*]

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Abstract

This paper investigates price transmissions across European energy forward markets at distinct maturities during both normal times and extreme fluctuation periods. To this end, we rely on the traditional Granger causality test (in mean) and its multivariate extension in tail distribution developed by Candelon, Joëts, and Tokpavi (2012). Considering forward energy prices at 1, 10, 20, and 30 months, it turns out that no significant causality exists between markets at regular times whereas comovements are at play during extreme periods especially in bear markets. More precisely, energy prices comovements appear to be stronger at short horizons than at long horizons, testifying an eventual Samuelson mechanism in the maturity prices curve. Diversification strategies tend to be more efficient as maturity increases.

JEL Classification: C32, Q40
Keywords: Forward energy prices; Value-at-Risk (VaR); CAViaR approach; risk spillover; Granger causality.

1 Introduction

Energy price dynamics are known to be frequently volatile with extensive amplitude affecting the whole economy (Sadorsky (1999), Hamilton (2003), Kilian (2008), among others). In the literature, these fluctuations are attributed to both real and financial factors, such as international energy demand/supply conditions and market manipulation (Hamilton (2009), Kaufmann and Ullman (2009), Kilian (2009), Cifarelli and Paladino (2010), Ellen and Zwinkels (2010), Lombardi and Van Robays (2011), among others), leading to extreme market risks for energy participants and governments. Moreover, energy markets have recently experienced significant developments likely to influence price dynamics. European gas and electicity markets, initially monopolistic, have become competitive due to the freshly deregulation process, allowing emergence of new contracts making prices more influenced by participants than regulators (Mjelde and Bessler (2009)). In this light, market volatility may increase and the quantification of the maximum prices appears to be primordial in risk management for one's ability to make proper investment, operational, and contractual decisions. Due to the globalization process, economies are related each other notably through trade and investment, so any news about economic fundamentals in one country most likely have implications in other countries (Lin et al. (1994), Ding et al. (2011), among others). From a general viewpoint, this perspective may obviously be extended to energy market behaviors which are known to be interrelated through production, substitution and competitive processes. Indeed, several studies have validated the fact that oil, gas, coal and electricity prices may be interconnected on the long run (Bachmeier and Griffin (2006), Mjelde and Bessler (2009), Mohammadi (2009), Ma and Oxley (2010), and Joëts and Mignon (2011), among others). However, previous analyses mainly focus on "regular" time fluctuations without considering periods of extreme price movements (upward and downard) whereas energy prices are often characterized by intense dynamics. The general feeling along this way is that correlations between assets tend to be stronger during excessive fluctuations periods. This phenomenon, which has been largely studied in the financial literature[1] suggests that comovements are larger when we focus on large absolute-value returns, and seem more important in bear markets. Under this market-comovement scenario, price movements are driven by fads and a herd behavior may be transmittable across markets (in the sense of Black (1986) and Delong et al. (1990)). High volatility is therefore coupled with highly interrelated markets making diversification almost im-

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[1] See King and Wadhwani (1990), Lin, Engle and Ito (1994), Longin and Solnik (1995), Karolyi and Stulz (1996), Longin and Solnik (2001), Ramchand and Susmel (1998), Ang and Bekaert (2002), Hong et al. (2007), Amira et al. (2009), and Ding et al. (2011) to name few.

possible under uncertain movements. These comovements in absolute price changes are often associated with belief dispersion (Shalen (1993)) resulting in a lack of confidence in market fundamentals. When new information occurs, distinct prior beliefs give incitation to trade leading to price changes. When traders revise their prior beliefs according to new information, it takes time for the market to "resolve" these heterogeneous behaviors which contribute to volatility clustering (Shalen (1993) and Lin, Engle and Ito (1994) among others). Thus, the diversification strategy aiming at limiting the impact of excessive movements would be almost impossible because of the markets integration, whereas it has more sense in "regular" times. As periods of extreme high energy prices have been proved to be economically detrimental (Sadorsky (1999), Oberndorfer (2009), among others), this paper proposes to extend this issue by analysing energy price comovements during periods of erratic fluctuations. This phenomenon would have important macroeconomic and microeconomic implications since absence of diversification can lead to heavy potential losses for market participants and governements. For instance, from a macroeconomic viewpoint, a perfect perception of price movements and market risk are of primary importance for policy targeting of energy-importing or exporting countries. At a microeconomic level, the price behavior, market risk and their potential transmission mechanisms are relevant to evaluating real investment decisions using the well-known asset pricing model.

In order to apprehend extreme movements, the Value-at-Risk (VaR) approach is an important tool and is widely used in financial markets.[2] VaR is often used to measure market risk with a single numeric value by means of the probability distribution of a random variable. It is defined as the expected maximum loss over a target horizon for a given confidence interval (see Jorion (2007)). Due to the strong volatility of commodity markets, this methodology has been recently extended to oil markets—see, Cadebo and Moya (2003), Giot and Laurent (2003), Feng et al. (2004), Sadeghi and Shavvalpour (2006), and Fan et al. (2008)—and to the oil and gas markets—see, Aloui and Mabrouk (2006)— which evaluate the risk losses in WTI, Brent crude oil and gas markets using different techniques (Historical simulation standard approach, RiskMetrics (RM), variance-covariance method based on various GARCH models, among others). However, these methodologies are quite restrictive because they are based on several strong assumptions. For instance, the nonparametric Historical simulation approach is based on a time-constant returns unconditional distribution and fractile. The parametric RM approach is based on the linear risk and the normality of price changes, which is not consistent with the market reality. Finally, GARCH methodologies suffer from the positivity and/or symmetry constraints of-

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[2]One of the main advantage of VaR cited in literature is its user friendly way to concisely presents risk supported by the regulatory authorities.

ten imposed on the coefficient parameters. We improve this literature by considering extreme movements (upward and downward) of European oil, gas, coal and electricity markets using the semiparametric Conditional Autoregressive VaR (CAViaR) approach developed by Engle and Manganelli (2004), which is considered to be less restrictive than other methodologies.[3]

Despite the apparent market globalization, transmission effects among energy markets during extensive periods have been scarcely studied. Lin and Tamvakis (2001) first studied spillover effects among NYMEX and IPE crude oil contracts in both non-overlapping and simultaneous trading hours, and found significant transmission mechanism. However, they do not use the crucial information about the quantile of the distribution, which is of primary importance to apprehend tremendous variations.[4] More recently, Fan et al. (2008) evaluate the market risk of daily Brent and WTI crude oil returns from May 20th, 1987 to August 1st, 2006 using a GED-GARCH model. They examine the downside and upside extreme risk spillover between both markets using the Granger causality test developed by Hong et al. (2009). Results show that the VaR model based on GED method perform relatively well, and that the WTI and Brent returns have significant two-way causality effect in both downside and upside risks at 95% or 99% confidence levels. Further analysis reveals that at the confidence level of 99%, the WTI market risk information can help to forecast extreme Brent market risk when negative news occur, but the reverse effect does not exist. However, their results are based on a restrictive parametric GARCH approach which is again not consistent with market reality, and authors investigate risk spillover at specific confidence level (95% and 99%) while the information in tails distribution is of primary importance.[5] To overcome this problem, Candelon, Joëts and Tokpavi (2012) (hereafter CJT) develop a multivariate extension of the Granger causality test in distribution tails and use this specification to investigate international market globalization during periods of extreme price movements of 32 crude oil weekly prices on the period from April 21, 2000 to October 20, 2011.

In this paper, our aim is to investigate energy price return transmissions during both "normal" and extreme fluctuations periods by using the traditional Granger causality test (in mean) and its multivariate CJT extension − the later focusing on causality in distribution tails rather than quantile at specific level. Relying on European forward energy prices rather than spot data, we purge short-run demand and supply from noise that affects market fluctuations and account for both fundamental and speculative pres-

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[3]See Section 3.

[4]According to Gouriéroux and Jasiak (2001), volatility cannot be considered as a statisfactory measure of risk when extreme market movements occur.

[5]According to Engle and Manganelli (2004), dynamics of VaRs can vary considerably across risk levels.

sures (Joëts and Mignon (2011)).[6] Because comovements between markets can vary considerably over time and in order to see if diversification can be more profitable as maturity increases, we propose to investigate forward price transmission mechanims at 1, 10, 20, and 30 months.

We find that energy price return relationships increase during periods of extreme movements, especially in bear markets circumstances. Indeed, while almost no causality exists during "normal" times, price comovements are higher during market downturns as compared to upturns. This phenomenon leads to asymmetric interactions in energy price returns, showing that energy markets behave as stock markets making diversification almost impossible during high volatility periods. However, this phenomenon tends to disappear as maturity increases, indicating that diversification could be more profitable at longer horizons (such as 20 and 30 months).

The rest of the paper is organized as follows. Section 2 describes the econometric methodology. The empirical part is provided in Section 3, and Section 4 concludes the article.

2   Model specification and extreme risk causality test

2.1   CAViaR model

Energy price returns are known to be extremely volatile with clustering phenomenon. These characteristics were well modelled by Engle (1982) and Bollerslev (1986) using ARCH and GARCH models. These models have become common tools to measure market risk by VaR approach due to their relative simplicity and various extensions. However, they are also well known for their limitations such as unrealistic parametric assumptions (normality or i.i.d returns). To overcome these issues, we rely on the semiparametric CAViaR approach developed by Engle and Manganelli (2004) to estimate energy VaR models which does not require any of the extreme assumptions invoked by existing methodologies. In short, this approach has the particularity to estimate directly VaRs using an autoregressive specification for the quantiles rather than inverting a conditonal distribution of returns as usual in a purely parametric framework. This autoregressive evolution of the quantile over time and unknown parameters are then determined by the regression quantile framework introduced by Koenker and Basset (1978). Beside, the autoregressive nature of the CAViaR captures directly in the tails of the distribution some stylized facts in empirical finance, such as

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[6] Indeed, the forward energy markets can result in both physical delivery and speculative purposes.

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autocorrelation in daily returns arising from market microstructure biases and partial price adjustment (Boudoukh et al. (1994), Eom, Hahn and Joo (2004) Ahn et al. (2002)), volatility clustering (Engle (1982) and Bollerslev (1986)), and the time-varying skewness and kurtosis (Hansen (1994), Harvey and Siddique (1999, 2000), Jondeau and Rockinger (2003)).

Following Engle and Manganelli (2004), we consider a vector of portfolio returns $\{y_t\}_{t=1}^{T}$. Let θ, x_t and β_θ be respectively, the probability associated to VaR, a vector of observable variables at time t, and a vector of unknown parameters. Let also $f_t(\beta) \equiv f(x_{t-1}, \beta_\theta)$, the θ-quantile of the distribution of the portfolio returns at time t formed at time $t-1$. In this context, a general CAViaR specification might be as follows:

$$f_t(\beta) = \gamma_0 + \sum_{i=1}^{q} \gamma_i f_{t-i}(\beta) + \sum_{i=1}^{p} \alpha_i l(x_{t-i}, \varphi) \tag{1}$$

where $\beta' = (\alpha', \gamma', \varphi')$ and l the function of a finite number of lagged values of observable variables. To allow a smooth transition quantile, Engle and Manganelli introduce an autoregressive term $\gamma_i f_{t-i}(\beta)$, $i = 1, ..., q$. Moreover, to permit a relationship between the θ-quantile $f_t(\beta)$ and the observable variables they introduce the term $l(x_{t-i}, \varphi)$. According to the general CAViaR formulation, Engle and Manganelli (2004) develop the four following alternative specifications for the function l.

$$Adaptative : f_t(\beta_1) = f_{t-1}(\beta_1) + \beta_1 \left\{ [1 + \exp(G[y_{t-1} - f_{t-1}(\beta_1)])]^{-1} - \theta \right\}$$

$$Symmetric\ Absolute\ Value : f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 |y_{t-1}|$$

$$Asymmetric\ Slope : f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 (y_{t-1})^+ + \beta_4 (y_{t-1})^-$$

$$Indirect\ GARCH\,(1,1) : f_t(\beta) = \left(\beta_1 + \beta_2 f_{t-1}^2(\beta) + \beta_3 y_{t-1}^3 \right)^{1/2}$$

In the first specification, G is some positive finite number which as $G \to \infty$, the last term converges to $\beta_1 [I(y_{t-1} \leq f_{t-1}(\beta_1)) - \theta]$, where $I(.)$ is the indicator function. Following Engle and Manganelli, the *Adaptative* specification allows that whenever you exceed your VaR you should direclty increase it, but when you don't exceed it, you should decrease it very slightly. The second and fourth respond symmetrically to past portfolio returns and are mean reverting since the coefficient of the lagged VaR is not constrained to equal one. The third model is also mean reverting but less restrictive

in the sense that it permits asymmetric response to positive and negative past portfolio returns.[7] Therefore, the asymmetric component adresses the asymmetric response of volatility to news (Black (1976), Christie (1982)). Due to the skewness and kurtosis properties of financial series, the asymmetric CAViaR specification has become the most popular for practitioners.

2.2 CJT risk causality test

In parallel to risk measurement, a new concept of risk causality has recently emerged in line with Granger seminal work. This new approach focuses on tail causality rather than causality in mean and variance, and allows to study extreme risk spillover across markets. Hong et al. (2009) were the first to propose a class of kernel-based tests to check whether a large downside risk in one market will Granger cause a large downside risk in another market. In their Granger causality approach, they consider risk transmission of two time series at a given quantile level α which is relatively restrictive because they do not consider causality between tails behavior. According to Engle and Manganelli (2004), dynamics of VaRs can vary considerably across α risk level. Hence, application of the Hong et al. (2009) test can lead to contradictory results with respect to the risk levels. To overcome these constraints and improve the power properties of the Granger cause approach, we use the multivariate CJT test which extends this setup by testing simultaneous Granger causality in downside risk for multiple risk levels across left tails distribution. More formerly, our testing procedure is an extension in multivariate context of the Granger causality test in mean and contains all tail distribution information. The purpose of the test is to make inference on interactions between groups of variables. Let $A = \{\alpha_1, ..., \alpha_m\}$ be a discrete set of m risk levels which is relevant for downside risk study. Let $W_{i,t}(\theta_{i,A}) = [Z_{i,t}(\theta_{i,\alpha_1}), ..., Z_{i,t}(\theta_{i,\alpha_m})]$ the vector of tail-events variables $Z_{i,t}(\theta_{i,\alpha_1})$ of dimension $(m, 1)$ associated to the risk levels at time t. $\theta_{i,A} = \left(\theta'_{i,\alpha_1}, ..., \theta'_{i,\alpha_m}\right)'$ is the vector of dimension $(4m, 1)$ with parameters of the m CAViaR. Therefore, the multivariate Granger causality test can be stated as follows

$$H_0 : E\left[W_{1,t}(\theta_{1,A}) \mid \Gamma_{t-1}\right] = E\left[W_{1,t}(\theta_{1,A}) \mid \Gamma_{1,t-1}\right] \tag{2}$$

where $\Gamma_{1,t}$ and Γ_t are respectively defined by $\Gamma_{1,t} = \{W_{1,s}(\theta_{1,A}), s \leq t\}$ and $\Gamma_t = \left\{\left(W'_{1,s}(\theta_{1,A}), W'_{2,s}(\theta_{2,A})\right)', s \leq t\right\}$. If the null hypothesis holds,

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[7] $(y)^+ = \max(y, 0)$, $(y)^- = \min(y, 0)$.

downside movements do not Granger cause spillover effect whatever the risk levels α_k considered (with $k = 1, ..., m$). This test can be interpreted as the Granger causality in mean approach for two multivariate process $W_{i,t}(\theta_{i,A})$, $i = 1, 2$. According to Gelper and Croux (2007) and Barret et al. (2010), the CJT test statistic is based on the following multivariate linear regression model

$$W_{1,t}(\theta_{1,A}) = \psi_0 + \psi_1 W_{2,t-1}(\theta_{2,A}) + ... + \psi_p W_{2,t-1}(\theta_{2,A}) + \varepsilon_{1t} \quad (3)$$

where ψ_0 and ψ_s are respectively vectors of constant terms and matrices of parameters, ε_{1t} is the residual vector with covariance matrix Σ_1. Following (3), the null hypothesis can be expressed as follows

$$H_0 : \psi_1 = \psi_2 = ... = \psi_p \quad (4)$$

As a result, the multivariate likelihood ratio test statistic is defined by (5) which followed under the null hypothesis a chi-squared distribution with pm^2 degrees of freedom

$$LR = [T - (mp + 1)] \left[\log \left(\left| \varepsilon_2' \varepsilon_2 \right| \right) - \log \left(\left| \varepsilon_1' \varepsilon_1 \right| \right) \right] \sim \chi^2_{pm^2} \quad (5)$$

Following Candelon et al. (2012), the above approach is not computationally feasible because the multivariate process depends on unknown vector of CAViaR models. However, these vectors can be replaced by consistent estimator $\hat{\theta}_{i,A}$. But in turn, the values of the vector are incertain because they are estimated rather than oberved. This parameter uncertainty could affect the distribution of the test statistic.[8] To overcome this constraint, Candelon et al. (2012) suggest to perform Monte Carlo tests by generating M independent realizations of the test statistic. As shown by Dufour (2006), the Monte Carlo critical region corresponds to $\hat{p}_M(S_0) \leq \eta$ with $1 - \eta$ the confidence level.

$$\hat{p}_M(S_0) = \frac{M \hat{G}_M(S_0) + 1}{M + 1}, \quad (6)$$

where

$$\hat{G}_M(S_0) = \frac{1}{M} \sum_{i=1}^{M} \mathbb{I}(S_i \geq S_0), \quad (7)$$

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[8] For more details, see Candelon et al. (2012).

when $\Pr(S_i = S_j) \neq 0$, or otherwise

$$\hat{G}_M(S_0) = 1 - \frac{1}{M}\sum_{i=1}^{M}\mathbb{I}(S_i \leq S_0) + \frac{1}{M}\sum_{i=1}^{M}\mathbb{I}(S_i = S_0) \times \mathbb{I}(U_i \geq U_0) \quad (8)$$

We use the later specification to investigate transmission mechanisms among energy forward prices of oil, gas, coal and electricity at different maturities during periods of extreme movements.

3   Empirical analysis

3.1   Risk measurement

We consider daily data over the January 3, 2005 to December 31, 2010 period. In order to allow for both fundamental and speculative pressures, we rely on European forward price returns at 1, 10, 20, 30 months for oil, gas, coal and electricity markets.[9] Energy prices are quoted in US dollars per tonne of oil equivalent (\$/toe) and are extracted from the Platt's Information Energy Agency. Figure 1 in Appendix depicts the one month forward returns (defined as prices in first log difference) in the whole sample and reveals the volatility clustering of energy markets.[10],[11] Basic descriptive statistics for prices at 1 month are computed and reported in Table 1. They reveal that each return series, compared to the standard normal distribution, are asymmetric (oil, gas and electricity returns are right skewed while coal returns are left skewed) and leptokurtic, revealing fat tail distributions. Due to the specific nature of its market (i.e. non-storablility, inelasticity of the supply,...) electricity returns are frequently affected by regime switching causing tail behavior higher than fossil energies (1.7 and 25 for skewness and kurtosis respectively).

The energy returns seem to behave as strongly volatile financial assets. The financial properties of forward energy markets lead us to use an asymmetric CAViaR specification to model energy VaRs. From Table 2 to Table 5 in Appendix, estimations and backtesting for each return series (at 1 month) are reported at 1%, 5% and 10% quantile levels for both downside and upside risks. Results confirm the asymmetric behavior of each market

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[9]Due to space constraints, we only report results corresponding to 1 month. The results for the other maturities are similar and are available upon request to the author.

[10]The volatility clustering is effective when strong fluctuations (resp. low) are followed by strong (resp. low) perturbations.

[11]Energy forward prices at 10, 20, and 30 month (not reported here) are characterized by the same clustering property.

for both downside and upside risks ($\theta^{(2)}$ and $\theta^{(3)}$ are significant for all series). This asymmetric component appears between bullish and bearish markets and between left and right tails, which reveals that energy price behaviors are different depending on the mood of the market. Generally, for fossil energies, negative returns are predominant in downside risk while positive returns are higher in upside one. Moreover, left tail behavior (downside risk) seems to be higher than right tail dynamic (upside risk). For electricity returns, relying to CAViaR estimation, asymmetric dynamic seems to be less pronounced. It may come from a misspecified risk model. Indeed, the dynamic quantile (DQ) test is applied to check the adequacy of the VaRs estimation, and results show that our models are well specified for energy fossil only. The misspecification of electricity VaR model may be due to the high occurrence of extreme values and potential regime switching. In our analysis, the misspecified problem is not a constraint because risk apprehension is more widely affected by parameter incertainty. Risk estimation is therefore strongly influenced by model assumptions and parameterizations. In our Granger causality context, CJT approach deals with this issue by using Monte Carlo procedure to compute p-values of test. In this way, p-values are simulated and the misspecified parameters of electricity VaR model are corrected.

Table 1: **Summary statistics for the daily forward energy returns at 1 month**

	Brent	Gas	Coal	Electricity
Mean	0.00053	0.00017	0.00038	-0.00062
Variance	0.00053	0.00035	0.00033	0.00088
Skewness	0.13679	0.00327	-0.57407	1.76840
Kurtosis	8.97939	6.47279	9.93896	25.31240
Jarque-Bera test	2333.29 (0.00)	785.431 (0.00)	3221.56 (0.00)	33236.7 (0.00)

Notes: p-values for corresponding null hypotheses are reported in parentheses.
The statistics are computed over the period 2005-01-04 : 2010-12-30.

3.2 Energy price transmission

Using Granger causality approach, we propose to investigate transmission mechanisms between energy price returns during both regular times and extreme volatility periods.

Table 6 in Appendix reports results of Granger causality in mean, to investigate energy price interactions at 1 month during normal times. It re-

veals that, except for oil and coal prices, no short-run causalities exist across energy markets confirming the results in favor of long-run interactions rather than short-term comovements. The same result (not reported here) is also observable for prices at 10, 20, and 30 months. Considering extreme occurrences, Table 7 gathers Granger causality test in tails distribution for prices at 1 month through CJT approach. It shows that comovements are higher between markets during periods of price decrease, while during situations of price increase no significant causalities exist. These relations appear to be relevant mainly across fossil energies. Energy prices at 1 month behave as stock returns which are characterized by asymmetric causalities between downturn and upturn situations making diversification almost impossible during extreme volatility periods.

According to Ding et al. (2011) for financial markets, this asymmetric phenomenon could be attributed to several fundamental and speculative factors. For instance, a popular incidence documented by many studies (Kim et al., 2008; Campbell and Diebold, 2009, among others) is that when economy experiences negative shock, the volatility of fundamental variables is usually higher and accompanied by an increase of fundamental risk. Moreover, Campbell and Hentschel (1992) find that during extreme price movements, market downturn is more likely associated with high market risk. This finding is consistent with our results on energy market behaviors.

Furthermore, Demirer and Lien (2004) find that during periods of extreme prices decrease, individual firm returns tend to comove more closely causing stronger transmission mechanism between companies. It is therefore reasonable to think that such behaviors also exist across energy industries.

The energy market causality dynamics could also be explained by various behavioral considerations. Indeed, there is evidence that investors react more sensitively to bad news than good news. According to Barberis et al. (1998), following a string of positive shocks, the investors expect that the trend will continue in the same way (i.e. they expect another positive shock). If good news is announced, the positive shock is largely anticipated and the market response appears to be relatively small. However, negative shocks impact returns significanlty since bad news appears more as a surprise. In the same context, the popular prospect theory of Kahneman and Tversky (1979) shows that investors react differently to market circumstances due to the notion of loss aversion. They are more hesitant to sell in overvaluation than to buy in undervaluation (they are more sensitive to undervaluation) causing asymmetric dynamics between bearish and bullish markets. Another possible explanation could be relative to the emotion component of energy markets. Recent researches have found that feelings can have significant impact on equity returns under uncertain and risky environment even if emotions are unrelated to the decision context.[12] According to Forgas

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[12]See Saunders (1993), Hirshleifer and Shumway (2003), Cao and Wei (2002), Kamstra

(1995), feelings will become predominant as risk and uncertainty increase. Considering that market risk increases during downturn periods, investors should be more influenced by their emotions during extreme prices decrease. In this context, Joëts (2012) confirms that energy market dynamics tend to be more influenced by emotions when extreme bearish market movements occur. This phenomenon is likely to cause asymmetric causality behaviors making diversification almost impossible.

3.3 Maturity effect

While energy forward prices at 1 month appear to be characterized by an asymmetric comovement with a downturn predominence, energy markets dynamic seems to be different as maturities increase. Considering comovements during extreme fluctuations, Table 8 to Table 10 gather CJT Granger causality tests for energy forward prices at 10, 20, 30 months respectively.[13] They show that causality between markets varies strongly over time. Indeed, compared to the 1 month prices maturity, energy market interactions seem to be less pronounced as maturity increases. For instance, asymmetric downturn causality remains significant for energy prices at 10 months, while this dynamic fades strongly at 20 and 30 months making diversification more profitable at longer maturities. This phenomenon could be attributable to the well known Samuelson effect which reveals an eventual prices maturity segmentation across energy markets. This effect would tend to influence the volatility of the series across maturity leading to a decrease of comovements between energy markets.

4 Conclusion

This paper investigates energy transmission mechanisms across forward price returns of oil, gas, coal, and electricity during both normal and extreme volatility periods. Using Granger causality approach in mean as well as in tails distribution, we show that energy price comovements increase during extreme fluctuations, while they are almost nonexistent in regular times. More precisely, energy market causalities appear to be stronger during bear markets, indicating a possible relation between volatility and comovements at shorter maturities. The phenomenon could be attributed to several fundamental and speculative factors, showing that energy markets behave as

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et al. (2000), Kamstra et al. (2003), and Dowling and Lucey (2005, 2008), among others.

[13] Granger causality tests in mean (normal times) are also computed showing no significant energy price relationship (results available upon request to the author).

financial assets. Regarding portfolio diversification, unstable asset relationships might lead energy risk managers to exaggerate the benefits of diversification during extreme downturn variations making suboptimal portfolio allocations. However, probably due to a Samuelson effect, energy markets comovements vary from shorter to longer maturity and seem to be fading as maturity increases. This maturity effect shows that, contrary to short maturity, diversification could be more profitable at longer ones.

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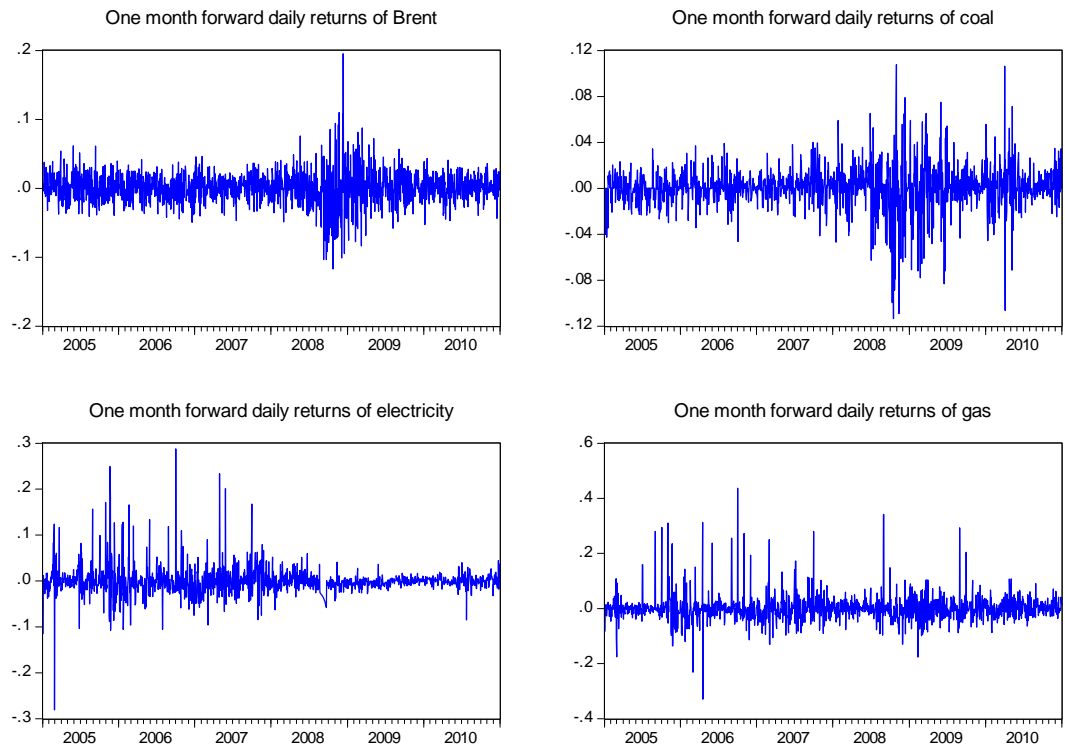
Appendix

Figure 1: One month forward energy returns (prices in first log difference)

Table 2: CAViaR estimation results for daily oil returns at 1 month

	Downside Risk			Upside Risk		
	$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 10\%$	$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$
$\theta^{(0)}$	0.0012 [0.0002] (0.0154)	0.0013 [0.0002] [0.0000]	0.0009 [0.0002] (0.0001)	0.0004 [0.0001] (0.0000)	0.0005 [0.0002] (0.0007)	0.0008 [0.0005] (0.0715)
$\theta^{(1)}$	0.9653 [0.0104] (0.0000)	0.9411 [0.0199] (0.0000)	0.9439 [0.0120] (0.0000)	0.9771 [0.0081] (0.0000)	0.9793 [0.0082] (0.0000)	0.9730 [0.0114] (0.0000)
$\theta^{(2)}$	−0.4880 [0.0359] (0.0000)	0.4635 [0.0478] (0.0000)	0.4443 [0.0476] (0.0000)	1.2285 [0.0186] (0.0000)	1.2759 [0.0150] (0.0000)	2.1296 [0.0387] (0.0000)
$\theta^{(3)}$	−2.4313 [0.00314] (0.0000)	−2.2109 [0.0524] (0.0000)	−1.7239 [0.0196] (0/0000)	0.4087 [0.0177] (0.0000)	0.3987 [0.0196] (0.0000)	0.0140 [0.0435] (0.3735)
% Hit	0.0102	0.0505	0.0997	0.1004	0.0505	0.0090
DQ test Stat	4.8256	1.3346	2.2793	5.5953	4.5916	0.3617
DQ test P-value	0.3057	0.8555	0.6845	0.2315	0.3318	0.9855

Notes: The values in brackets (resp. parentheses) are the standard errors (resp. p-values) of the estimated parameters. Engle and Manganelli's DQ test is applied to check the adequacy of the specified VaR model, where the first four lagged hits are used as instruments.

Table 3: CAViaR estimation results for daily gas returns at 1 month

	Downside Risk			Upside Risk		
	$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 10\%$	$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$
$\theta^{(0)}$	0.0739 [0.0297] (0.0064)	−0.0461 [0.0461] [0.2813]	0.0349 [0.0044] (0.0000)	0.0399 [0.0034] (0.0000)	0.0667 [0.0060] (0.0000)	−0.0013 [0.0011] (0.1105)
$\theta^{(1)}$	0.0974 [0.3091] (0.3763)	0.0429 [1.5356] (0.4889)	0.0146 [0.1087] (0.4468)	−0.0579 [0.0174] (0.0004)	−0.0725 [0.0210] (0.0003)	1.0081 [0.0036] (0.0000)
$\theta^{(2)}$	2.5281 [0.0443] (0.0000)	2.8731 [0.0439] (0.0000)	1.7770 [0.0482] (0.0000)	−0.1407 [0.0282] (0.0000)	−0.2504 [0.0549] (0.0000)	0.4449 [0.0453] (0.0000)
$\theta^{(3)}$	−7.8342 [0.1187] (0.0000)	−7.2216 [0.1727] (0.0505)	−6.4634 [0.1164] (0/0000)	−2.1672 [0.1241] (0.0000)	−3.4997 [0.1301] (0.0000)	0.5623 [0.0581] (0.0000)
% Hit	0.0096	0.0505	0.1010	0.1004	0.0499	0.0077
DQ test Stat	0.7554	2.2095	3.4373	15.8352	16.4263	7.2900
DQ test P-value	0.9443	0.6973	0.4875	0.0032	0.0025	0.1213

Notes: The values in brackets (resp. parentheses) are the standard errors (resp. p-values) of the estimated parameters. Engle and Manganelli's DQ test is applied to check the adequacy of the specified VaR model, where the first four lagged hits are used as instruments.

Table 4: CAViaR estimation results for daily coal returns at 1 month

	Downside Risk			Upside Risk		
	$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 10\%$	$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$
$\theta^{(0)}$	0.0015 [0.0007] (0.0166)	0.0018 [0.0005] [0.0001]	0.0012 [0.0002] (0.0000)	0.0008 [0.0002] (0.0002)	0.0015 [0.0003] (0.0000)	0.0024 [0.0008] (0.0018)
$\theta^{(1)}$	0.9205 [0.0422] (0.0000)	0.8737 [0.0339] (0.0000)	0.8685 [0.0255] (0.0000)	0.9339 [0.0212] (0.0000)	0.9043 [0.0187] (0.0000)	0.9154 [0.0275] (0.0000)
$\theta^{(2)}$	6.5207 [0.0729] (0.0000)	4.8475 [0.0733] (0.0000)	3.0796 [0.0433] (0.0000)	1.2313 [0.0213] (0.0000)	1.8592 [0.0593] (0.0000)	1.6271 [0.0367] (0.0000)
$\theta^{(3)}$	−5.1929 [0.0897] (0.0000)	−5.7090 [0.1048] (0.0000)	−4.5016 [0.0405] (0/0000)	−1.6186 [0.0317] (0.0000)	−4.8571 [0.0491] (0.0000)	−5.6179 [0.0801] (0.0000)
% Hit	0.0096	0.0518	0.1010	0.0991	0.0492	0.0102
DQ test Stat	6.2437	1.0565	5.0378	8.5870	2.1926	4.8216
DQ test P-value	0.1817	0.9011	0.2834	0.0723	0.7004	0.3061

Notes: The values in brackets (resp. parentheses) are the standard errors (resp. p-values) of the estimated parameters. Engle and Manganelli's DQ test is applied to check the adequacy of the specified VaR model, where the first four lagged hits are used as instruments.

Table 5: CAViaR estimation results for daily electricity returns at 1 month

	Downside Risk			Upside Risk		
	$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 10\%$	$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$
$\theta^{(0)}$	0.0216 [0.0162] (0.0911)	0.0010 [0.0003] [0.0003]	0.0023 [0.0003] (0.0000)	0.0001 [0.0000] (0.0000)	0.0002 [0.0001] (0.0001)	−0.0003 [0.0001] (0.0150)
$\theta^{(1)}$	0.5554 [0.3317] (0.0470)	0.9450 [0.0150] (0.0000)	0.8440 [0.0204] (0.0000)	0.9888 [0.0036] (0.0000)	0.9811 [0.0055] (0.0000)	1.0070 [0.0012] (0.0000)
$\theta^{(2)}$	10.1970 [0.3303] (0.0000)	0.5385 [0.0142] (0.0000)	0.6816 [0.0110] (0.0000)	−0.1351 [0.0050] (0.0000)	0.0713 [0.0229] (0.0009)	0.4042 [0.0172] (0.0000)
$\theta^{(3)}$	−6.2203 [0.3773] (0.0000)	−1.8982 [0.0099] (0.0000)	−3.7098 [0.0151] (0/0000)	−0.3443 [0.0068] (0.0000)	−0.8840 [0.0159] (0.0000)	0.9902 [0.0197] (0.0000)
% Hit	0.0102	0.0505	0.1004	0.1017	0.0512	0.0090
DQ test Stat	6.5967	46.4104	80.6409	45.1708	19.3953	7.1560
DQ test P-value	0.1588	0.0000	0.0000	0.0000	0.0007	0.1279

Notes: The values in brackets (resp. parentheses) are the standard errors (resp. p-values) of the estimated parameters. Engle and Manganelli's DQ test is applied to check the adequacy of the specified VaR model, where the first four lagged hits are used as instruments.

Table 6: Results of Granger causality test in mean at 1 month ("normal" times)

$X \Rightarrow Y$	Oil	Gas	Coal	Electricity
Oil	X	1.10 (0.31)	4.05 (0.00***)	0.77 (0.80)
Gas	1.32 (0.11)	X	0.67 (0.90)	0.94 (0.35)
Coal	1.07 (0.35)	1.29 (0.12)	X	0.54 (0.98)
Electricity	0.79 (0.77)	1.22 (0.19)	0.87 (0.66)	X

Notes: Between parentheses p-values. *** denotes rejection of the null hypothesis at 1% significance level. Granger causality tests are computed using p=30 lags. Causality run from the left series to the top series.

Table 7: Results of Granger causality test in distribution tails at 1 month (extreme movements)

	$X \Rightarrow Y$	Oil	Gas	Coal	Electricity
			DR		
DR	Oil	X	301.6 (0.09*)	347.6 (0.00***)	325.7 (0.05*)
	Gas	360.49 (0.00***)	X	372.5 (0.00**)	340.02 (0.05*)
	Coal	2.03 (0.99)	6.05 (0.68)	X	328.27 (0.03**)
	Electricity	11.10 (0.25)	4.29 (0.70)	9.08 (0.38)	X
			UR		
UR	Oil	X	7.83 (0.38)	4.25 (0.86)	4.85 (0.81)
	Gas	4.28 (0.86)	X	6.83 (0.15)	15.25 (0.10)
	Coal	4.26 (0.83)	4.96 (0.79)	X	2.44 (0.98)
	Electricity	3.92 (0.89)	12.92 (0.17)	13.67 (0.14)	X

Notes: Between parentheses p-values. *** (resp. **,*) denotes rejection of the null hypothesis at 1% significance level (resp. 5%, 10%). Granger causality tests are computed using p=30 lags. DR and UR denote Downside and Upside Risks respectively. Causality run from the left series to the top series.

Table 8: Results of Granger causality test in distribution tails at 10 month (extreme movements)

	$X \Rightarrow Y$	DR			
		Oil	Gas	Coal	Electricity
DR	Oil	X	317.23 (0.02**)	376.4 (0.00***)	387.7 (0.00***)
	Gas	230.40 (0.96)	X	246.9 (0.83)	245.47 (0.85)
	Coal	225.81 (0.97)	305.27 (0.06*)	X	245.30 (0.85)
	Electricity	462.14 (0.33)	482.04 (0.10)	439.55 (0.62)	X
		UR			
UR	Oil	X	256.08 (0.71)	464.70 (0.30)	286.80 (0.23)
	Gas	271.20 (0.46)	X	266.16 (0.55)	299.62 (0.10)
	Coal	288.93 (0.20)	259.11 (0.67)	X	260.18 (0.65)
	Electricity	390.62 (0.12)	497.56 (0.17)	225.10 (0.97)	X

Notes: Between parentheses p-values. *** (resp. **,*) denotes rejection of the null hypothesis at 1% significance level (resp. 5%, 10%). Granger causality tests are computed using p=30 lags. DR and UR denote Downside and Upside Risks respectively. Causality run from the left series to the top series.

Table 9: Results of Granger causality test in distribution tails at 20 month (extreme movements)

	$X \Rightarrow Y$	DR			
		Oil	Gas	Coal	Electricity
DR	Oil	X	324.79 (0.01**)	385.15 (0.00***)	461.91 (0.18)
	Gas	278.93 (0.34)	X	276.11 (0.38)	570.51 (0.17)
	Coal	238.69 (0.91)	306.85 (0.06*)	X	247.59 (0.83)
	Electricity	463.15 (0.32)	575.02 (0.14)	581.14 (0.10)	X
		UR			
UR	Oil	X	280.16 (0.32)	466.49 (0.28)	324.26 (0.01**)
	Gas	243.67 (0.87)	X	496.49 (0.06*)	323.88 (0.01**)
	Coal	249.15 (0.81)	295.93 (0.13)	X	552.77 (0.34)
	Electricity	451.93 (0.46)	481.14 (0.14)	252.99 (0.76)	X

Notes: Between parentheses p-values. *** (resp. **,*) denotes rejection of the null hypothesis at 1% significance level (resp. 5%, 10%). Granger causality tests are computed using p=30 lags. DR and UR denote Downside and Upside Risks respectively. Causality run from the left series to the top series.

Table 10: Results of Granger causality test in distribution tails at 30 month (extreme movements)

	$X \Rightarrow Y$	DR			
		Oil	Gas	Coal	Electricity
DR	Oil	X	357.99 (0.00***)	468.71 (0.26)	291.42 (0.17)
	Gas	226.62 (0.97)	X	568.08 (0.19)	398.27 (0.96)
	Coal	236.01 (0.93)	275.22 (0.40)	X	243.78 (0.87)
	Electricity	280.55 (0.31)	311.31 (0.04**)	537.86 (0.51)	X
		UR			
UR	Oil	X	572.70 (0.15)	327.41 (0.00***)	668.19 (0.14)
	Gas	275.01 (0.40)	X	455.79 (0.41)	268.84 (0.50)
	Coal	267.81 (0.52)	381.29 (0.13)	X	272.98 (0.43)
	Electricity	446.29 (0.54)	562.14 (0.00***)	476.28 (0.28)	X

Notes: Between parentheses p-values. *** (resp. **,*) denotes rejection of the null hypothesis at 1% significance level (resp. 5%, 10%). Granger causality tests are computed using p=30 lags. DR and UR denote Downside and Upside Risks respectively. Causality run from the left series to the top series.