The Systemic Risk of Energy Markets

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Abstract

We investigate the concept of systemic risk in the energy market and propose a methodology to measure it. By analogy with financial markets, the energy market is regarded as a sector that supports the entire economy. Energy Systemic Risk is defined by the risk of an energy crisis raising the prices of all energy commodities with negative consequences for the real economy. We propose a measure of Energy Systemic Risk (EnSysRISK) that represents the total cost of an energy product to the rest of the economy during an energy crisis. This measure is a function of the Marginal Expected Shortfall (MES) capturing the tail dependence between the asset and the energy market factor. To estimate the MES, common movements in energy asset prices are analyzed through measures of causality, common factor exposure and sensitivity to extreme market events. We find evidence of linear and non-linear causality among the daily returns of energy assets and an industrial index. After removing causal relationships, we estimate the dynamic exposure of energy assets to the common market factor and analyze the impact of recent energy market events (Russia-Ukraine gas dispute, BP's oil leak, Fukushima accident).

1 Introduction

Systemic risk has received renewed interest in the finance literature since the 2007-2009 financial crisis. Systemic risk is generally defined as the risk of the financial sector as a whole being threatened and its spillover to the economy at large. The events of 2007-2009 and the recent European sovereign debt crisis have demonstrated that measuring the risk of an asset seen in isolation is no longer relevant during crisis time. Therefore, new risk measures have been proposed to capture externalities imposed by one institution on others and on the system at large, and externalities imposed by the system on institutions.

Contrary to the financial sector, there is no general consensus on the importance of systemic risk in energy markets, or on its nature. On one hand, regulators believe that energy trading does not pose similar degree of systemic risk compared to equity markets. On the other hand, rising

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energy prices may sometimes surpass leverage as perceived systemic risk concern for investors. Energy markets are connected (directly or indirectly) to all sectors through energy production or consumption and financial contracts. Demand for energy is usually inelastic showing evidence of the strong dependence of the economy on energy prices. The negative impact of increasing energy prices on the aggregate economic output was identified in Hamilton (1983) and followed by many others (e.g. Rotemberg and Woodford (1996), Carruth et al. (1998), Lee (2002)). The idea to investigate the systemic risk in energy markets is driven by the analogy between energy and financial liquidity. Both are essential for all sectors and the scarcity of one of them is susceptible to trigger serious damages to the real economy.

In this paper, we attempt to understand and measure the systemic risk associated to an energy crisis. To our knowledge, it is one of the first paper with the paper of Lautier and Raynaud (2011) that poses the question of systemic risk in the energy sector. We define the energy systemic risk as the risk of an energy crisis raising the prices of all energy commodities with negative consequences for the real economy. In our definition, the systemic crisis is not caused by the failure of companies in the energy sector but comes from the price (co-)movements of energy products. Increased complex interdependence of energy prices and increased dependence of the economy on energy, coupled with low available reserves may constitute the perfect conditions for energy systemic risk to appear. If an extreme price shock happens in these conditions, we expect the consequences for the energy market and the broader economy to be severe.

We provide a measure of energy systemic risk that focus on the co-movements of the financial prices of energy products. The Energy Systemic Risk measure (EnSysRISK) represents the total cost of an energy product to the rest of the economy during an energy crisis. The goal of this measure is to shed light on the potential costs energy products would impose to the non-energy sector if an energy crisis had to occur. This measure is a function of the Marginal Expected Shortfall (MES) defined by Acharya et al. (2010). To measure energy systemic risk, we adapt the conditional MES of Brownlees and Engle (2011) to describe the dynamic sensitivity of energy assets to energy crises.

The paper presents some econometric innovations to take account for the co-movements in the means, the variances and the tails of energy assets. In order to understand the complex dependence of these assets, we separate causality from common factor exposure. Causal relationships reflect the physical relationships of energy markets through substitution of primary energy commodities and the merit-order of electricity, and financial relationships through the term structure of energy futures contracts. Our model for the mean of returns accounts for linear causality and cointegration through error correction terms. The variance model is a multiplicative GARCH model where a GARCH component is multiplied by an interaction component that allows for non-linear causality in the variances.

While causality allows modeling direct relationships between assets, we also suspect the presence of common drivers of risk. After removing causal relationships in the means and variances, we measure the linear exposure and the tail exposure of standardized residuals to common risk factors. Causal relationships are removed to concentrate on the pure commonality or contagion phenomenon (Forbes and Rigobon (2002), Billio and Caporin (2010)) where variance spillovers are a consequence of the contagion effect and simply spread the shocks among the products. Next to the methodology of Brownlees and Engle (2011), we present a methodology to account for latent factors in the conditional MES. The latent factors are estimated using a principal component analysis based on time-varying correlation matrices estimated with the Dynamic Conditional Correlation (DCC) model of Engle (2002). Therefore, the dynamic principal components incorporate conditional information and the time-varying eigenvectors show the evolution of the exposure of standardized residuals to the most important risk factors.

Causality and exposure to common factors are combined in a single measure writing the conditional MES as a function of means, variances and tail expectations. The conditional MES, the final consumption quantities and the inventory levels are then used to derive the EnSysRISK measure and the impact of several energy market events is analyzed. Recent market events in Europe include the natural gas crisis of January 2009 following a commercial dispute between Russia and Ukraine, the reaction to BP's oil spill in the Gulf of Mexico in April 2010 and the political actions against nuclear power following the accident at Fukushima power plant in March 2011.

Our methodology for systemic risk measurement is applied to futures on electricity, natural gas, coal and carbon emission rights traded on the European Energy Exchange (EEX). Our application comprises a larger set of energy products (crude oil, coal and carbon emission rights spot indices) selected for their high correlations with EEX futures. Since EEX futures are related to the German market area, the DAX industrial index is also included to study the connection between the energy market and the industry.

The paper is structured as follows: in Section two, we discuss and define the concept of energy systemic risk. We introduce the energy systemic risk measure (EnSysRISK) in Section three. In Section four, the econometric methodology to estimate the conditional MES of energy assets is presented. We estimate the conditional MES and the EnSysRISK measure of EEX futures and other energy assets in Section five.

2 Systemic Risk and the Energy Market

There is no consensus on the existence or the importance of systemic risk in the energy market. At the same time, different definitions and understandings of systemic risk and concepts relating to systemic risk exist in the literature. In this section, we try to clarify the conditions for systemic risk to appear as well as its importance for energy markets and the rest of the economy. In the first subsection we do not provide an exhaustive review on the literature of systemic risk but our own synthesis of what we think as key concepts and approaches that are applicable to model systemic risk outside the financial sector. In the second subsection, we introduce the systemic risk of energy markets by analyzing some past examples of energy crises or 'events' and discuss how systemic risk would appear in energy markets.

2.1 Systemic Risk

At the heart of systemic risk, there is the concept of dependence: dependence between individual institutions and dependence between the financial sector and the rest of the economy. In the literature we find different concepts and measures relating to systemic risk. There are mainly two approaches; one part of the literature sees systemic risk as arising from one or several shock(s) spreading to a network of financial relationships while the other part sees systemic risk as arising from an aggregate economy-wide shock.

In Battiston et al. (2009), systemic risk is not necessarily associated to an aggregate shock but can originate from a single node and spread to the network due to financial *contagion* and positive feedback mechanism. Contagion is interpreted in Billio and Caporin (2010) as the change in transmission mechanisms that take place during a crisis. In their paper, contagion is associated with an increase in unconditional correlations of markets. Contagion is accompanied in the econometric literature with other concepts pointing out the directionality of transmission mechanisms like *causality, externality* and *spillover effects*. Billio et al. (2010) consider risk arising from a complex network of dynamic relationships. In the network, spillovers among market participants are quantified by the number of significant linear and non-linear Granger-causal relationships.

Market integration is referred in Lautier and Raynaud (2011) as a necessary condition for systemic risk to appear. Market integration reflects the degree of commonality or interconnectedness among institutions or markets, and concentrates on global or system-wide measures instead of pairwise associations. In Billio et al. (2010), the evolution of market integration is analyzed using a time rolling window for a principal component analysis. The fraction of the total variance of firms returns explained by a fixed number of principal components is used to capture commonality among firms. This ratio is called the absorption ratio in Kritzman et al. (2011) and is interpreted as a measure of implied systemic risk; markets are more fragile when the ratio is high as negative shocks propagate more easily when market integration is high.

Dependence does not necessarily imply systemic risk; linear dependence actually only captures the systematic risk component. A measure of systemic risk also needs to be related to shocks, crises or extreme events. The systemic risk literature traditionally compares the ability of different measures to predict the ranking of systematically risky financial institutions during the 2007-2009 financial crisis. Among these measures we find the size, the leverage, the market-to-book ratio, the equity return volatility, the market beta, etc. and new measures relating to the *tail dependence* between the financial institution and the market like the CoVaR of Adrian and Brunnermeier (2010) or the Marginal Expected Shortfall (MES) of Acharya et al. (2010).

The CoVaR is the Value-at-Risk (VaR) of the market conditional on an institution being in distress. Hautsch et al. (2011) define the systemic risk beta as the time-varying sensitivity of the market VaR to the VaR of a firm. By reversing the condition, we find the MES defined as the expected losses of a firm during the 5% past worst days of the market. Acharya et al. (2010) show that the MES and the leverage of financial institutions predict their financial losses during the 2007-2009 crisis.

In Acharya et al. (2010) and Brownlees and Engle (2011), the systemic event is defined by an aggregate market shock and systemic risk is measured by modeling comovements between the institution and the market factor. Brownlees and Engle (2011) achieve higher forecasting performance defining a conditional MES as a function of volatility, correlations and tail expectations. They model the conditional MES of a bivariate series of firm and market returns using asymmetric GARCH models for volatilities, asymmetric Dynamic Conditional Correlation (DCC) model (Engle (2002)) for correlations and a kernel estimator for tail expectations (Scaillet (2004, 2005)). The MES and the leverage are then used to compute the systemic risk measure (SRISK) that represents the amount of capital an institution would have to raise during another financial crisis.

2.2 Energy Systemic Risk

Systemic risk in energy markets may be difficult to apprehend. It is sometimes described as the risk of running out of primary energy commodities, the risk of bad regulation, demand risk, production and transportation capacity risk or the risk associated with physical supply security in electricity markets. Operational, technological, macro-economic, political or environmental events create large energy price fluctuations that are susceptible to generate systemic risk in the energy market with short-term or long-term consequences.

Among other energy and oil crises, the most well known example is the oil embargo of 1973-1974. The oil embargo was imposed by Arab members of the OPEC against countries supporting Israel in the context of the Arab-Israeli conflict of 1973. Oil prices rose dramatically due to production cutbacks by some Arab oil producers while dependence on oil imports in Western countries was increasing in a period of high economic growth and high inflation. Oil prices increased by 51% between November 1973 and February 1974 (Hamilton (2011)) and a period of excessive inflation and economic downturn followed. To a certain extent, the high level of oil prices may have been responsible for pushing inflation to higher levels in the US due to the low elasticity of oil demand. The crisis resulted in a fuel cost increase that directly affected most sectors of the economy (Zaleski (1992)). Perron (1989) shows that the Great crash of 1929 and the oil crisis of 1973 lead to a permanent downward shift of the US GNP trend. Barsky and Kilian (2004) argue that oil price shocks are not necessary or sufficient to explain periods of stagflation. Hamilton (2011) however suggests that such oil crises should be viewed as causal to the subsequent economic recessions.

A more recent example is the nuclear disaster that followed the accident at Fukushima Daiichi power plant after it was hit by the tsunami on the Pacific coast of Japan in March 2011. Joskow and Parsons (2012) identify two probable consequences of Fukushima accident for the nuclear power industry; the increased cost of nuclear power generation due to increased safety measures and the reduction of public and political support to nuclear power. Therefore, a reduction in the trends of nuclear power generation expansion is expected. It is still unclear whether the Fukushima power plant outage will have significant adverse global effects on the energy market or on the economy. However, nuclear power currently accounts for the largest share of carbon-free base load generation in many countries and the share of nuclear electricity generation was a key assumption behind many forecasts of future greenhouse gas emissions (Joskow and Parsons (2012)).

Germany was the first country to take political actions against nuclear power after Fukushima. On March 15, 2011, the German government shut down 8 of its 17 nuclear plants and a law was passed in summer 2011 to phase out the remaining units by 2022. The reaction on the German power exchange was immediate; electricity futures prices rose suddenly on March 15 and stayed at a higher level during several months.

This decision and its implementation are challenging the power sector in several ways. There is a long-term challenge of replacing the nuclear generation capacity while maintaining greenhouse gas emissions to the target levels. The sector is under pressure due to the long implementation times on the investment side when we know it takes more than five years to build a new power line or plant. The shutdown of the eight nuclear units also caused immediate stress on the transmission network where power lines had to cope with sudden demand changes.[1] Spot price spikes happened in February 2012 where a major blackout came close due to high winter demand and the fragility of the transmission network. However, an impact of Fukushima on other energy products and on the rest of the economy has not been demonstrated yet and is perceived to be small at this time compared to other energy market events.

We mentioned dependence as the heart of systemic risk. In energy markets, dependence may be found along several dimensions; dependence between different regional markets, underlying products, maturities or parts of the value chain. Further integration of energy markets is also observed. In electricity markets, horizontal integration is seen as the natural step after the liberalization of the European electricity market.

All other sectors of the economy are also dependent on energy prices. This is especially true for the industry due to the very low elasticity of energy demand. In a report on the impact of systemic risk regulation for the energy sector, Tieben et al. (2011) identify a direct impact of energy markets to the real economy and an indirect impact via the financial sector. The direct impact operates through the price mechanism as extreme high prices and high volatility produce higher inflation, reduced growth and increased uncertainty. According to Hamilton (2011), it should not be controversial that oil prices may exert some pressure on the economy, as energy is an essential production factor on the supply side. Furthermore, Hamilton (2003) finds that oil prices increases

[1] *Germany feels fallout amid nuclear shutdown*, Financial Times, March 26, 2012.

affect more negatively the economy than oil price decreases would stimulate it. Gronwald et al. (2011) also point out carbon emission rights as a production factor and find stronger dependence between emission rights futures and equity spot returns during the global financial crisis.

Next to the direct impact on the economy, the indirect impact of Tieben et al. (2011) refers to the contagion channels of energy derivatives to the real economy via energy derivative trade positions of financial institutions. Benink (1995) indeed indicates that the growth of derivatives has increased systemic risk by expanding linkages among markets and financial institutions. Tieben et al. (2011) find a small indirect effect as financial institutions hold relatively small positions in energy derivative markets. However, increasing integration of energy markets with other markets is foreseen as the liquidity of energy derivatives grows and attract investors outside the energy sector. Lautier and Raynaud (2011) study the links between commodity, energy and equity derivative markets and show that connections between sectors are insured by energy products.

Dependence in energy markets is complex. The jumps in power spot (day-ahead) prices are mainly of operational nature and less susceptible to spread to other markets. Most events have very short-term impacts because of the physical nature of assets: prices have strong mean reversion because the supply side is reacting quickly. Jumps are not really extreme events; they are expected to happen at a certain frequency due to the shape of supply and demand curves. For these reasons, it may be argued that such markets cannot impose systemic risk to the economy.

For very volatile spot markets like electricity and gas, futures represent a larger market as they represent insurance contracts against spot price fluctuations. Futures contracts are bought and sold for the future planned consumption and generation so that spot trading is only used to optimize the procurement and sale of power in the short run. Despite the small correlation between futures and spot prices, futures prices are impacted by shocks on physical spot markets. Futures prices also react to news coming from other markets (e.g. 2007-2009 financial crisis) and news that may have long-term consequences for the energy market (e.g. German government announcement about their exit from nuclear energy). Due to their higher correlations with other markets, we consider electricity and natural gas futures prices as better candidates than spot prices to study systemic risk.

Even if the energy market integration and the dependence of the real economy on energy prices were accepted, this is not sufficient for systemic risk to appear. We need to understand what type of event will lead to systemic risk. The definition of the systemic event also depends on the position of the agent in the energy value chain. For oil and gas producers, a crisis might be triggered by high demand, production shortage and low inventory levels. For power generators and system operators, drivers of crises include unexpected peaks in demand, plant outages, rising fuel prices, insufficient reserve generation capacity and an inefficient transmission network. These drivers of risk are only known by the supply side. On the demand side, the risks faced by energy end consumers include price increases and supply disruptions.

We take the viewpoint of the demand side as we define the systemic risk for the non-energy sector. Therefore, we define the energy systemic risk as the risk of an energy crisis raising the prices of all energy commodities with negative consequences for the real economy. Increased integration coupled with low reserves may pave the way for an energy systemic crisis to occur. If an extreme market shock caused by a political crisis or a natural disaster arises in such conditions, we expect consequences to be severe for the energy market and the entire economy.

3 The Energy Systemic Risk Measure

Following the definition of Acharya et al. (2010) and Brownlees and Engle (2011) of the Marginal Expected Shortfall, the conditional MES of an energy asset i is given by

$$MES_{it} = \mathrm{E}_{t-1}\left(r_{it} | energy\, crisis\right). \tag{1}$$

This quantity represents the expected daily return of an energy asset at time t conditional on the past worst days of the energy market and past information up to time $t-1$. The conditional MES of energy assets allows to derive corresponding systemic prices from past price levels

$$sysprice_{it} = p_{it-1} * \exp(MES_{it}).$$

Based on systemic energy prices, the Energy Systemic Risk measure is defined by

$$EnSysRISK_{it} = \max(0, sysprice_{it} * w_{it}), \tag{2}$$

where w_{it} is the quantity exposure of the economy to asset i at time t. For an energy contract i with maturity and delivery period ν, the exposure at time t is

$$w_{it}(\nu) = \varsigma_i \mathrm{E}_{t-1}\left(fincons_\tau - inv_\tau\right) \text{ for } \tau \in \left[t+\nu; t+2\nu-1\right],$$

where $fincons_\tau$ is the daily final consumption of energy during delivery period ν starting at $t+\nu$, inv_τ are the energy reserves available to the non-energy sector during the same delivery period, and ς_i is the proportion of energy delivered during period ν via energy futures contracts i. Expected inventory levels or reserves are a function of current levels and a depletion rate during a crisis. The quantity exposure defines the expected amount of energy physically delivered outside the energy sector with futures contracts i of maturity and delivery period ν. High dependence of the non-energy sector on energy via final consumption and low reserves increases the quantity exposure to systemic prices.

The energy systemic risk measure defined in (2) represents the total cost of energy asset i to the rest of the economy during an energy crisis. The definition of the systemic condition (the energy crisis) is however subject to discussion. The systemic event is defined in this paper by an abnormal rise in energy prices (i.e. extremely high returns) as we define the energy systemic risk measure for the non-energy sector. It has been shown that positive returns on energy assets create more stress on energy markets than negative returns (Carpantier (2010), Knittel and Roberts (2005)), and have more (negative) impact on the economy (Hamilton (2003)). However higher energy prices may also be the consequence of strong demand during periods of economic growth and we may want to disentangle demand and supply shocks in the energy market. One way to do that is to only consider energy price increases when the rest of the economy is slowing down. We therefore write the energy MES conditionally on the right tail of the energy market return distribution and negative shocks in the non-energy sector

$$MES_{it}(C) = \mathrm{E}_{t-1}\left(r_{it} | r_{EnM,t} > C,\, r_{M,t} < 0\right), \tag{3}$$

where $r_{EnM,t}$ is the energy market return, $r_{M,t}$ is the return of the non-energy sector and C represents the VaR of the energy market at $(1-\alpha)\%$. As in Brownlees and Engle (2011), the MES is a conditional expectation of observing an unconditional systemic event as systemic events are considered independently from current market conditions. The probability of observing the unconditional systemic event is time-varying because the market volatility is time-varying; the probability of a systemic event increases with the market volatility. The systemic event is defined by the past worst days of the energy market. It is however not guaranteed that a crisis is contained in the past worst days of the sample. Acharya et al. (2010) use extreme value theory to establish a connection between the moderately bad days (5% past worst days of the market) and the real crisis (that only happens once or twice a decade).

In the next section we present our methodology for modeling the co-movements in the means, the variances and the tails of energy assets in order to estimate the conditional MES.

4 Econometric methodology

We can write the conditional MES of equation (3) as a function of mean, volatility and tail expectation

$$MES_{it}(C) = \mathrm{E}_{t-1}\left(\mu_{it} + \sigma_{it} u_{it} | r_{EnMt} > C,\, r_{Mt} < 0\right) = \mu_{it} + \sigma_{it}\mathrm{E}_{t-1}\left(u_{it} | r_{EnMt} > C,\, r_{Mt} < 0\right) \tag{4}$$

where μ_{it} and σ_{it}^2 are the conditional mean and variance of asset return i and $u_{it} = (r_{it} - \mu_{it})/\sigma_{it}$ are the standardized residuals.

In the following subsections we successively describe how to account for causality and cointegration in the means, causality in variances, and common factors in tail expectations. Our methodology relates to the literature on common movements and the modeling of the joint distribution of energy prices. Cointegration was found in the spot prices of different European regional markets (Escribano et al. (2011) and Haldrup and Nielsen (2006)), in natural gas and electricity futures prices (Emery and Liu (2001)), and in electricity futures of different maturities (Bauwens et al. (2012)). Bunn and Fezzi (2008) model electricity, gas and carbon returns using a vector-error correction model with one cointegration vector. Bauwens et al. (2012) propose a semi-parametric multiplicative DCC model for the multivariate volatility of electricity futures contracts of different maturities. Chevallier (2012) find cross-volatility spillovers and time-varying correlations in oil, gas and carbon returns applying different multivariate GARCH models. Benth and Kettler (2010) propose a dynamic copula to model the joint distribution of electricity and gas prices. Copulas are also used by Boerger et al. (2009) and Gronwald et al. (2011) to model the dependence of different energy commodities.

4.1 Causality in mean and in variance

Following the methodology of Billio et al. (2010), we apply Granger-causality tests to measure the degree of interconnectedness of the energy market. The causal relationships reflect physical relationships in the energy market based on the supply curve (merit-order) of electricity and substitutions between primary energy commodities for electricity generation and other consumption purposes. Causal relationships also reflect financial relationships through the term structure of futures prices and possible spillover effects between energy and industrial markets. We test for causal relationships in returns means and variances using an augmented vector error correction model for the means and a multiplicative causality GARCH model for the variances.

4.1.1 Augmented Vector Error Correction Model

The prices are collected in the $(n \times T)$ matrix p_t, from which the matrix of daily returns $\mathrm{r}_t = 100 \times (\ln(\mathrm{p}_t) - \ln(\mathrm{p}_{t-1}))$ is derived.[2] Given the structure of energy returns, a Vector Error Correction Model (VECM) capturing autocorrelation, cointegration, causality, and seasonality is specified

$$r_{it} = \pi_i \eta' \ln(\mathrm{p}_{t-1}) + \sum_{k=1}^{K} \delta'_{ik} \mathrm{r}_{t-k} + \sum_{m=1}^{M} \theta'_{im} \mathrm{x}_{t-m} + \varphi'_i \mathrm{q}_t + \epsilon_{it} \tag{5}$$

where η are the cointegrating vectors, π_i are error-correction parameters, δ_{ik} is a $(n \times 1)$ vector of autocorrelation and Granger-causal parameters of order k, x_{t-m} are exogenous variables lagged by m days and q_t are deterministic (seasonal) factors. Cointegration vectors represent long-term equilibrium relationships between energy prices and the error-correction parameters represent the speed of adjustment of each return variable to the cointegration vector. The number of cointegration vectors v is selected based on the trace rank test of Johansen (1991). The matrices η and π are identified by imposing $\eta = \begin{pmatrix} I_v & B' \end{pmatrix}'$. Our model for the mean of energy returns is similar to the

[2] Adjusted for contract switches in the price series of futures contracts.

vector-error correction model of Bunn and Fezzi (2008), except that all energy products are here considered to be endogenous variables (as part of the 'system').

4.1.2 Multiplicative Causality GARCH models

From the augmented VECM estimation, we obtain the $(n \times T)$ matrix of mean-zero residuals ϵ_t. Next to the causal relationships present in the mean, we suspect the existence of causality at the variance level. To remove spillover effects present in the conditional variances of ϵ_t, we define the multiplicative causality GARCH model allowing for non-linear causality

$$\epsilon_{it} = \sigma_{it} u_{it} = \sqrt{\phi_{it} g_{it}} u_{it} \tag{6}$$

where

$$g_{it} = (1 - \alpha_{ii} - \beta_i - \frac{\gamma_{ii}}{2}) + \alpha_{ii} \left(\frac{\epsilon_{it-1}^2}{\phi_{it-1}} \right) + \beta_i g_{it-1} + \gamma_{ii} \left(\frac{\epsilon_{it-1}^2}{\phi_{it-1}} \right) I_{\{\epsilon_{it-1} < 0\}}, \tag{7}$$

$$\phi_{it} = f \left(u_{1t-1}, ..., u_{i-1,t-1}, u_{i+1,t-1}, ..., u_{nt-1} \right) l_i(t), \tag{8}$$

$I_{\{\epsilon_{it-1} < 0\}}$ is a dummy variable equal to one when the past shock of asset i is negative, and $l_i(t)$ is a deterministic function of time. The multiplicative model decomposes the asset variance into two components. The first component is the usual GARCH equation (GARCH component) capturing the asset variance 'own' dynamics. It is augmented to account for asymmetric effects due to the sign of shocks with the additional term of the GJR model (Glosten et al. (1993)). The second component captures asset variance dynamics from interaction with other asset returns (interaction component).

The main motivation for the multiplicative form comes from empirical observations. Our estimation results show that the incorporation of interaction terms in an additive way makes the asset own ARCH and GARCH parameters non significant and negative. By separating own and interaction dynamics, the parameter estimates of both GARCH and interaction components are easier to interpret. The model is a multivariate model for the variances and requires a joint estimation of all variance processes since the interaction component is a function of other standardized residuals.

Note that, if $\epsilon_{it-1}^2 / \phi_{it-1}$ are replaced by $\epsilon_{it-1}^2 / l_i(t-1)$ in (7), then a model similar to the exponential causality GARCH model of Caporin (2007) would be obtained, with additional deterministic factors $l(t)$. The advantage of standardizing returns by ϕ_{it} rather than $l_i(t)$ is that the process g_{it} becomes a standard GARCH/GJR process, for which theoretical results are broadly available. This model can also be viewed as a simplified version of the spline-GARCH model of Engle and Rangel (2008) but the components in the multiplicative causality model are both low frequency components. When the second component simplifies to a constant, the equation simplifies to the GARCH or GJR model.

In our application, the interaction component is specified as

$$\phi_{it} = c_i \exp\left(\sum_{j=1,j\neq i}^{n} (\vartheta_{ij} u_{jt-1} + \alpha_{ij}|u_{jt-1}|) + \kappa_i' \mathrm{d}_t\right), \quad (9)$$

where d_t are deterministic terms including seasonal dummies. This function has a similar form as the EGARCH model of Nelson (1991) and allows for asymmetric causality effects when $\vartheta_{ij} \neq 0$.

4.2 Factor Models and Tail Expectations

The standardized residuals may be decomposed as a linear function of common factors $\mathrm{y}_t = (y_{1t}, y_{2t}, ..., y_{st})$ and idiosyncratic terms ζ_{it}

$$u_{it} = f(\mathrm{y}_t, \zeta_{it}).$$

In Brownlees and Engle (2011), standardized residuals are decomposed as a function of an observable market return and idiosyncratic terms in a single-factor model similar to the capital asset pricing model (CAPM). An alternative to capture the common structure hidden in energy returns is to consider the common factors as latent. In Rangel and Engle (2009), some assumptions of the CAPM are relaxed and conditionally correlated idiosyncratic terms imply the presence of latent unobserved factors. In the context of energy markets, the CAPM may also present some limitations. For example, one assumption of the CAPM implies that all agents possess the same information at all times. While this assumption is likely to hold in major financial markets, it does not hold for energy markets. A market index may not be available or reliable for less liquid markets like energy markets. Latent factors may be present in such markets where certain sources of risk (environmental, political, technological, etc.) are hidden and hard to quantify. The latent factors can be estimated with orthogonal factor models by maximum likelihood or by principal component analysis (PCA) (Tsay (2005), p. 428).

The basic PCA approach estimates the factors from a spectral decomposition of the correlation matrix of u_{it}. However, the probability of a systemic event will be constant when the principal components are extracted from the sample correlation matrix, since components have constant variances equal to their eigenvalues. It is possible to obtain conditional variances of the principal components as in the O-GARCH model of Alexander (2002). In the context of systemic risk, it would also be interesting to allow for time-varying eigenvectors for measuring the evolution of the exposure of initial returns to the principal components that are interpreted as common risk factors. The dynamic exposures are obtained from dynamic conditional PCAs based on the daily correlation matrices obtained from the DCC model. This approach can be viewed as a multivariate extension of Brownlees and Engle (2011) as it is based on the whole correlation matrix of asset returns instead of the bivariate correlations between the asset and the market.

The DCC process is defined for the $n \times n$ symmetric positive-definite matrix Q_t by

$$Q_t = (1 - a - b)\bar{Q} + a u_{t-1} u_{t-1}' + b Q_{t-1} \tag{10}$$

where $a+b < 1$, $a, b \geq 0$ and $\bar{Q}$ is a parameter matrix. Then the DCC correlation matrix is obtained by transforming this to

$$R_t = (\text{diag}Q_t)^{-1/2} Q_t (\text{diag}Q_t)^{-1/2}$$

and the covariance matrix of mean zero residuals ($\epsilon_{it} = r_{it} - \mu_{it}$) is given by $H_t = D_t R_t D_t$ where $D_t = \text{diag}(\sigma_{1t}, \sigma_{2t}, ..., \sigma_{nt})$ is a $n \times n$ diagonal matrix collecting the univariate conditional volatilities of residuals on the diagonal. If the distribution of $z_t = H_t^{1/2} \epsilon_t$ in (10) is assumed Gaussian, the DCC model is estimated by a two-stage quasi-maximum likelihood (QML) estimation procedure, where in the first stage the parameters of the conditional variance processes are estimated. In the second stage, the parameters of the conditional correlation process are estimated conditionally on the estimates obtained in the first stage.

Our dynamic conditional PCA approach is based on the spectral decomposition of the DCC correlation matrix. Therefore, the covariance H_t is decomposed in

$$H_t = D_t R_t D_t = D_t \left(A_t \Lambda_t A_t' + R_{\zeta_t} \right) D_t \tag{11}$$

where A_t is a matrix of s eigenvectors associated with the s largest eigenvalues that are contained in the diagonal matrix $\Lambda_t = \text{diag}(\lambda_{1t}, \lambda_{2t}, ..., \lambda_{st})$ with $\lambda_{1t} \geq \lambda_{2t} \geq ... \geq \lambda_{st}$, $s \leq n$ and R_{ζ_t} is the correlation matrix of idiosyncratic terms ζ_t.

In the dynamic conditional PCA, standardized residuals are decomposed as a function of the first s principal components associated with the s largest eigenvalues and idiosyncratic terms

$$u_{it} = \sum_{j=1}^{s} a_{ijt} y_{jt} + \zeta_{it} \tag{12}$$

where a_{ijt} is the element of the eigenvector associated with asset i and principal component y_{jt} extracted from the estimated correlation matrix at time t, and $\zeta_{it} = u_{it} - \sum_{j=1}^{s} a_{ijt} y_{jt}$.

The energy crisis condition of the tail expectations is defined by two factors: the energy market return and the return on the non-energy sector. The return on the non-energy sector is approximated by an industrial index. Since factors are mutually uncorrelated by definition in the PCA, the other factors have to be orthogonal to the non-energy returns. This is implemented using a restricted dynamic PCA similar to the restricted PCA used in Ng et al. (1992). The first dynamic component is restricted to be the non-energy index, where all elements of the eigenvector associated to energy returns are restricted to be zero. The other dynamic components are obtained applying the regular dynamic PCA and are mutually orthogonal and orthogonal to the non-energy component.

The energy market factor is not observed and is approximated by the second dynamic principal component y_{EnMt} that maximizes the variance of all returns and is orthogonal to the restricted non-energy market component y_{Mt}. The energy market factor is positively correlated to all energy assets and is interpreted as the energy trend component (as in Alexander (2002)); a variable that explains the majority of common movements in the energy market after removing causal relationships. The components in (12) have time-varying variances λ_{jt} and the second dynamic eigenvalue, interpreted as the energy market variance, is used to derive a conditional probability of energy systemic risk $\mathrm{P}_{t-1}(r_{EnMt} > C,\, r_{Mt} < 0) \simeq \mathrm{P}_{t-1}(y_{EnMt} > C,\, y_{Mt} < 0) = \mathrm{P}(y_{EnMt}/\sqrt{\lambda_{EnMt}} > C/\sqrt{\lambda_{EnMt}},\, y_{Mt} < 0)$. Tail expectations are then approximated by

$$\mathrm{E}_{t-1}\left(u_{it}|r_{EnMt} > C,\, r_{Mt} < 0\right) \simeq \sum_{j=1}^{s}\left[a_{ijt}\mathrm{E}_{t-1}\left(y_{jt}|y_{EnMt} > C,\, y_{Mt} < 0\right)\right] + \mathrm{E}_{t-1}\left(\zeta_{it}|y_{EnMt} > C,\, y_{Mt} < 0\right) \tag{13}$$

In this definition of tail expectations, the idiosyncratic terms and the factors are uncorrelated but are not independent. Extreme shocks are expected to happen simultaneously in all asset prices when there is a crisis. To capture the sensitivity to extreme events in the energy market, the next step is to estimate the tail expectations in (13). Nonparametric estimation of tail expectations is an alternative to copula functions where the joint distribution of idiosyncratic and factor disturbances is left unspecified. Brownlees and Engle (2011) propose a kernel estimator of tail expectations based on the literature on the nonparametric estimation of the expected shortfall (Scaillet (2004)) and the conditional expected shortfall (Scaillet (2005), Kato (2012)). A nonparametric estimator of tail expectations is

$$\hat{\mathrm{E}}\left(\zeta_{it}|y_{EnMt} > C,\, y_{Mt} < 0\right) = \frac{\sum_{\tau=1}^{T}\zeta_{i\tau}\Phi\left[\left(\frac{y_{EnM\tau}}{\sqrt{\lambda_{EnM\tau}}} - \frac{C}{\sqrt{\lambda_{EnMt}}}\right)h^{-1}\right]I(y_{M\tau} < 0)}{\sum_{\tau=1}^{T}\Phi\left[\left(\frac{y_{EnM\tau}}{\sqrt{\lambda_{EnM\tau}}} - \frac{C}{\sqrt{\lambda_{EnMt}}}\right)h^{-1}\right]I(y_{M\tau} < 0)} \tag{14}$$

where $\Phi(\cdot)$ is the Gaussian cummulative distribution function, h is a positive bandwidth, and $I(y_{M\tau} < 0)$ is an indicator function equal to one when the the non-energy factor is negative. The same estimation procedure applies to $\mathrm{E}\left(y_{jt}|y_{EnMt} > C,\, y_{Mt} < 0\right)$.

This estimation of tail expectations assigns higher weights to observations that are closer to the threshold C and zero weight when the non-energy market return is positive. The threshold C is the $(1-\alpha)$ quantile of the energy market return distribution and C standardized by the market volatility replaces the conditional quantile in Scaillet (2005) and Kato (2012). As a result, observations will be assigned higher weights when the energy market volatility is high.

5 Application to the EEX market

In the following section, we describe the energy and industrial products selected in our application. Causality in energy markets is explored by analyzing the links between products through their conditional means μ_{it} and variances σ^2_{it} in Subsections 5.2 and 5.3. In Subsection 5.4, we measure the evolution of market integration and the evolution of common risk factor exposure. The estimation of the conditional MES of energy assets is the subject of Subsection 5.5 and the EnSysRISK measure is derived in Subsection 5.6.

5.1 Data description

We consider the daily price series of ten energy futures, three energy spot indices and the DAX industrial index. The portfolio of energy products contains Brent crude oil, European coal and European Union Allowances (EUA) spot indices, as well as electricity (Phelix), natural gas (Gaspool), coal (ARA) and EUA futures traded on the European Energy Exchange (EEX).[3]

Electricity futures are financial futures written on the German Physical Electricity index (Phelix). Natural gas futures are physical futures for the German market area operated by Gaspool Balancing Services GmbH. Coal ARA (Amsterdam-Rotterdam-Antwerp) futures are financial futures written on the API#2 (ARA coal) index published in the Argus/McCloskey's Coal Price Index Report. For EUA futures, the delivery of EU emission allowances (EUA) for the second EU Emission Trading Scheme (ETS) period constitutes the underlying. One EU emission allowance confers the right to emit one ton of carbon dioxide or one ton of carbon dioxide equivalent.[4]

The EEX futures we consider have monthly, quarterly and yearly maturities and corresponding delivery periods, except for EUA futures, which have yearly maturity and delivery during the second EU ETS period (five-year period starting on January 1, 2008). The futures price series are composed of successive nearest contracts over the period 07.03.2007 until 06.01.2011 and returns are adjusted for contract switches. We also include in the analysis the Brent crude oil price per barrel and the Merrill Lynch Commodity index (MLCX) for EUA and European coal spot markets. The DAX industrial index is mainly composed of energy consuming companies and is taken as a proxy for the non-energy sector in the following analyses.

The prices and returns of the fourteen series are illustrated in Figures 1 and 2 and the descriptive statistics of returns are given in Table 1. We see that DAX industrial, Brent crude oil and short-term contracts on natural gas are the most volatile series while short-term electricity futures have the largest kurtosis caused by the extreme events of mid-March 2011 after the tsunami in Japan. This set of products is selected based on the high sample correlations observed between returns (the correlations are given in Table 2 in the Appendix).

[3]Source: Datastream. Series codes: EBMCS00, EBQCS00, EBYCS00, EGMCS00, EGQCS00, EGYCS00, ECMCS00, ECQCS00, ECBCS00, MLCXEUS, OILBRNP, MLCXECS, PRIMIND. Prices in US dollars are converted in Euros (using US $ TO EURO (WMR&DS) - EXCHANGE RATE).

[4]EEX Product Brochure : EU Emission Allowances, 2011

Name	Underlying	Maturity/ Delivery	Mean	Std. Dev.	Skewness	Excess kurtosis
MPhelix	Phelix (Physical	1/1 month	-0.098	2.063	0.214	9.087
QPhelix	Electricity index)	1/1 quarter	-0.036	1.454	0.895	11.123
YPhelix		1/1 year	-0.015	1.253	0.094	3.081
MGaspool	Natural Gas delivery	1/1 month	-0.100	2.733	-0.236	2.875
QGaspool	in Gaspool area	1/1 quarter	-0.071	2.307	0.212	2.308
YGaspool		1/1 year	-0.023	1.774	0.289	2.316
MARA	API#2 ARA	1/1 month	0.044	2.138	-0.617	3.461
QARA	coal index	1/1 quarter	0.016	2.104	-0.588	2.563
YARA		1/1 year	0.036	1.815	-0.494	3.046
YEUA	Delivery of EU carbon emission allowances	1 year/ 2nd EU ETS	-0.034	2.222	-0.276	3.005
EUA spot	EUA spot index	-	-0.022	2.266	-0.048	2.860
Brent	Brent crude oil index	-	0.042	2.329	-0.030	4.322
Coal spot	European coal spot index	-	0.042	1.916	-0.494	2.243
DAX industrial	DAX industrial index	-	-0.013	2.322	-0.090	6.782

Table 1: Summary and descriptive statistics of returns. Sample period: 07.03.2007 - 06.01.2011 (989 observations)

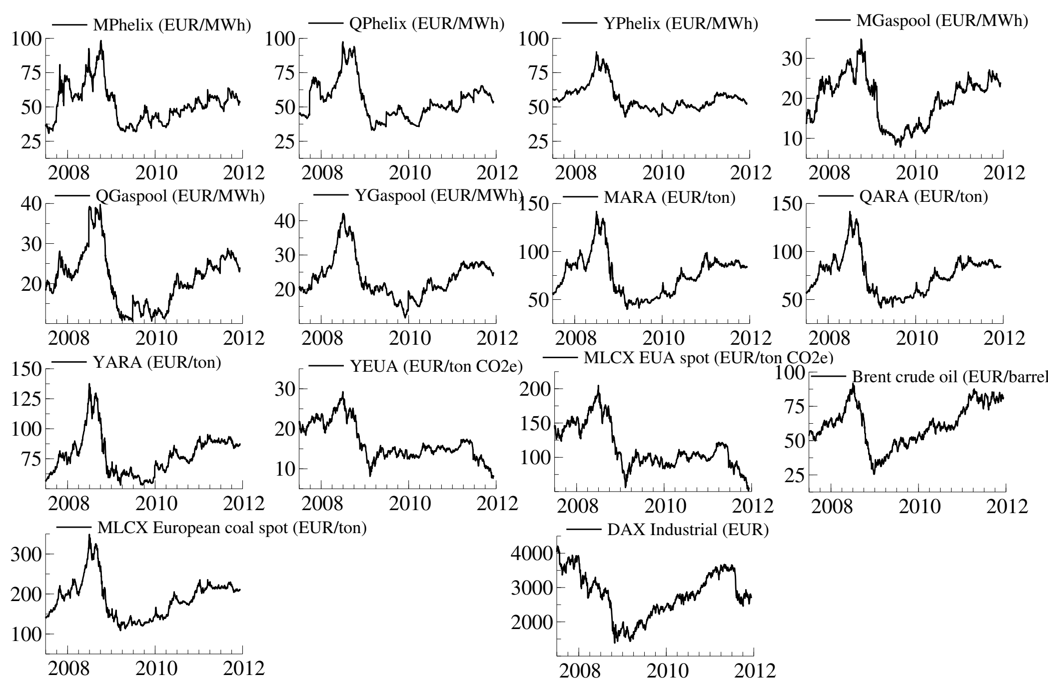

Figure 1: Prices. Sample period: 07.03.2007 - 06.01.2011 (989 observations). M, Q, Y letters before the names of futures contracts stand for monthly, quarterly and yearly maturity.

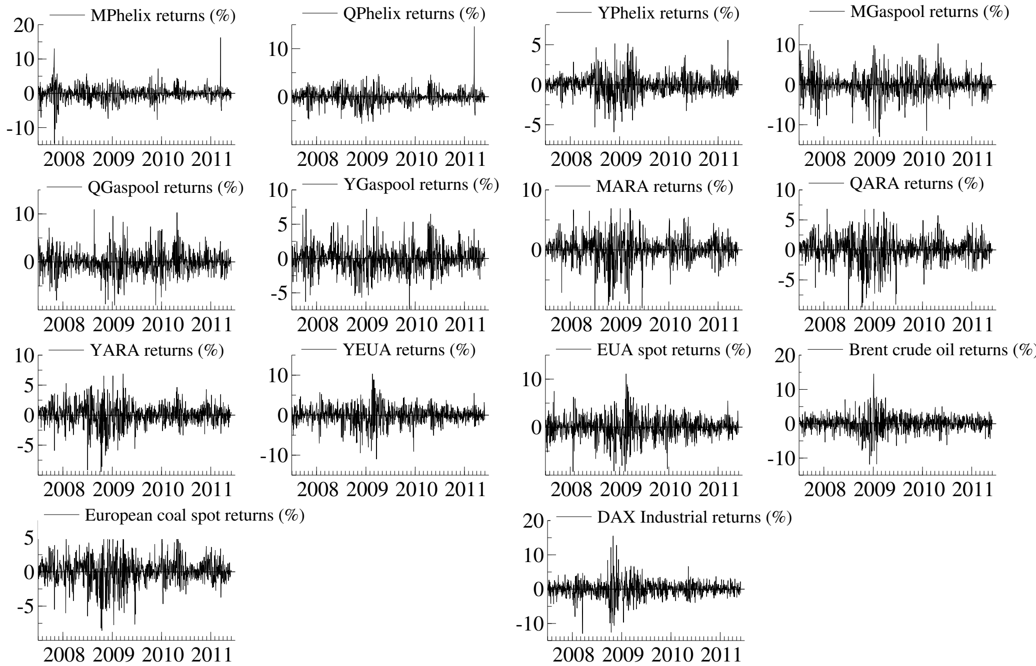

Figure 2: Returns. Sample period: 07.03.2007 - 06.01.2011 (989 observations)

The sample correlation matrix constitutes a first simple way to study the links between products and markets. The highest correlations are observed between groups of products with the same underlying asset (electricity, natural gas, coal, carbon dioxide). DAX industrial and crude oil returns are the least correlated with other returns; the correlation between the month Phelix future and the DAX industrial index is not significant at 1%. On the opposite, the year Phelix future is the most correlated with all asset returns and seems to act as a transmission asset between physical and financial markets, as well as between short-term and long-term futures markets.

5.2 Cointegration and causality in the mean

We test the parameters of the VECM model (eq. (5)) where the endogenous variables are the thirteen energy asset returns and the DAX industrial returns. The trace rank test of Johansen (1991) indicates the presence of nine cointegration vectors among the fourteen price series. Cointegration vectors estimates are reported in Table 3 in the Appendix. The matrices η and π are identified by imposing $\eta = \begin{pmatrix} I_9 & B' \end{pmatrix}'$. Other restrictions on η are tested. The parameters of equation (5) are then estimated by maximum likelihood conditional on the estimated matrix $\hat{\eta}$. The high number of cointegration vectors makes the interpretation of the parameter estimates difficult but the strong significance[5] of estimates indicates that all prices (including the DAX industrial index) contribute to the long-term price equilibrium.

In order to account for short-memory autocorrelation and causality up to the weekly lag (as in Billio and Caporin (2010)), we chose K and M of eq. (5) equal to five. The estimated coefficients and robust[6] standard errors of significant relationships at the 5% level are presented in Tables 4 and 5 in the Appendix.[7]

The tables of estimation results show that the EUA spot index returns are not subject to error-correction. This result is in line with the results of Bunn and Fezzi (2008) and Fezzi and Bunn (2009) showing that carbon prices are weakly exogenous in the long run. Bunn and Fezzi (2008) explain this effect by the fact that carbon allowances are traded at the European level while other products in the sample are exclusively traded in the German market area. For the same reason, it is not surprising that Brent crude oil is Granger-causal for EUA returns.

As expected, Brent crude oil returns are not caused by any variable. Conversely, Brent crude oil is causal for many other energy products (long-term Gaspool futures, coal spot, coal quarter futures and EUA spot and futures returns). More surprising, the only variable explaining DAX industrial returns is the quarter Phelix future; the estimated parameter is negative meaning that increasing electricity futures prices have a negative impact on DAX industrial returns.

Granger-causality reflects the complex term structure of energy futures where the spot causes futures returns but futures returns also cause spot returns (e.g. coal and EUA). Other relationships reflect the merit-order of electricity in Germany. The daily log demand for electricity is an exogenous variable that explains the returns on the European coal spot index. Coal is usually referred as the marginal fuel for electricity generation during off-peak hours in Germany and it is significant to explain returns of long-term electricity futures. The negative sign of the log demand is also as expected; when electricity demand decreases coal spot prices decrease as well. Natural gas is the marginal fuel for peak load hours in Germany and it is significant to explain returns of short-term Phelix futures.

5.3 Causality in variances

The estimated coefficients and standard errors of significant relationships at the 5% level of the Multiplicative Causality GARCH model (eq. (6)) are reported in Tables 6 and 7 in the Appendix.[8]

Concerning the asymmetric parameter of the GJR model in (7), we find a positive estimate of γ for the DAX industrial index and EUA products and a negative estimate for month Phelix futures. For the DAX industrial index, the parameter γ is the usual "leverage" parameter; negative shocks

[5] All estimates have t-values above 5 in absolute value.

[6] Newey-West heteroskedasticity- and autocorrelation-consistent standard errors (HACSE)

[7] The estimation results of this section are obtained using the PcGive module of OxMetrics version 6.10 (see Doornik and Hendry (2009)).

[8] These results and the results of the next sections are generated using Ox version 6.10 (see Doornik (2009)).

have a larger impact on volatility. For both DAX and EUA returns, this asymmetric effect is so strong that the usual ARCH parameter is not significant anymore meaning that only the negative news affect the volatility of these products. The negative estimate of γ for month Phelix futures is consistent with the findings of Knittel and Roberts (2005) and Bauwens et al. (2012). Knittel and Roberts (2005) attribute this effect in electricity returns to the convexity of the supply function, since positive demand shocks have a larger impact on prices than negative demand shocks.

The interaction component that we define in (9) incorporates seasonal effects and causal relationships. The EEX futures market closes during weekend days. Therefore, higher volatility is found for all EEX futures (except coal futures) at the beginning of the week (positive Monday effect). The seasonality is different for the volatility of coal spot and futures returns where we find monthly effects.

Most causal relationships in the variances come from the year EUA future through the multiplicative interaction component. The year EUA future is causal for electricity and short-term natural gas futures. We find that higher Brent crude oil returns increase the volatility of long-term natural gas futures. Causal relationships also take place between products with the same underlying energy but different maturities, as it is the case for electricity and coal.

From the results of the tests, causal relationships can be summarized through a network representation. The networks of causal relationships in the means (left part) and in the variances (right part) are illustrated in Figure 3. Arrows reflect the direction of causality.

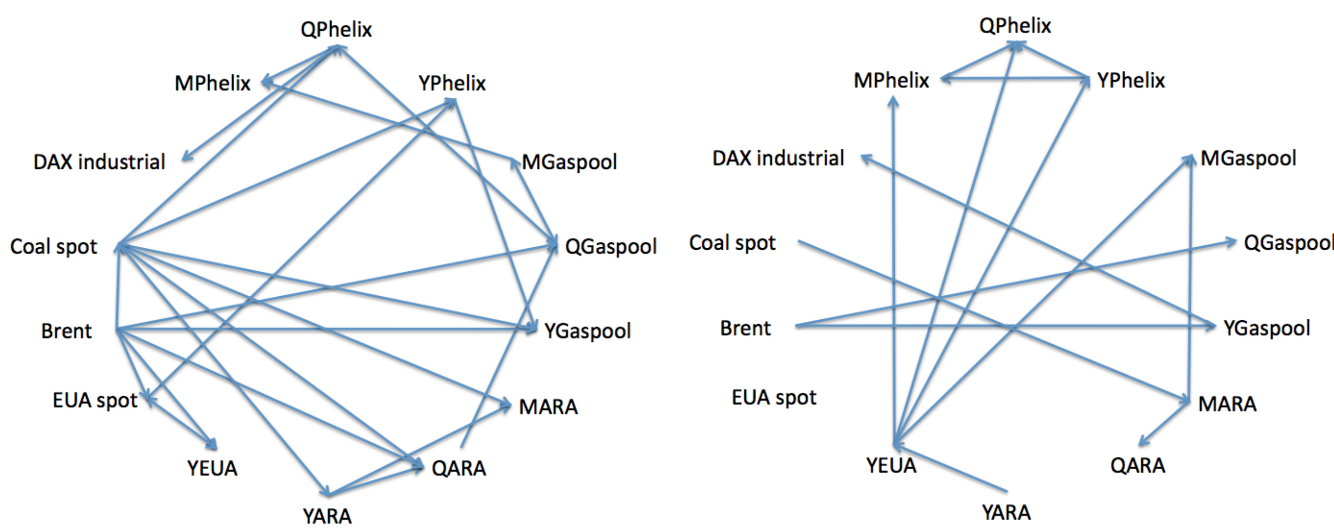

Figure 3: Mean (left part) and variance (right part) causal networks: significant causal relationships at the 5% level. Sample period: 07.04.2007 - 06.01.2011 (988 observations)

5.4 Energy Market Integration and Systematic Risk

After removing causal relationships, we measure market integration or commonality among energy returns due to the presence of common factors. Billio et al. (2010) show that commonality among asset returns can be detected using a principal component analysis. From a restricted PCA on the sample correlation matrix of estimated standardized residuals u_t, we obtain an industrial component and an energy trend component (first and second principal components) that respectively account for 7% and 49% of the total variance of all energy and industrial assets. Three other principal components have larger eigenvalues than the industrial component. The third component is highly correlated to coal assets and separates coal and Brent crude oil products from the other assets. The fourth component opposes emission rights to natural gas, and natural gas futures have the highest correlations with this component. The fifth component is highly correlated to electricity short-term futures. From the PCA on the sample correlation matrix, the cumulative contribution of the first four energy components accounts for 78%.

In order to assess the evolution of market integration, we measure the evolution of the cumulative percentage of variance explained by the most important principal components (also called absorption ratio in Kritzman et al. (2011)). This measure can be interpreted as an aggregate measure of correlations between products. Using a restricted dynamic PCA based on DCC correlations as defined in Subsection (4.2), we show the evolution of market integration in Figure 4. The eigenvalue contribution of the energy trend component is the most volatile, with values between 40% and 54%.

From Figure 4, we identify several events of market integration due to increasing correlations. These events are not necessarily inherent to the European energy market; they can either come from other sectors or other continents. The first event is due to the financial crisis; the eigenvalue contribution of the first PC is higher during the years 2008-2009 with a peak in October 2008 (just after the announcement of the Lehman Brothers bankruptcy in September 2008).

Winter 2009 was characterized by an extended period of cold weather, the spreading out of the effects of the financial turmoil to the real economy and a disruption in natural gas supply from Russia (Kovacevic (2009)). The disruption arose from a commercial dispute between Russia and Ukraine. The Russian gas supplier Gazprom refused to conclude a gas supply agreement for 2009 with Ukraine until the Ukrainian gas company Naftogas fully repaid its debts to the Russian supplier. As a result, from January 6, 2009, all natural gas supplies from Russia flowing via Ukraine were cut off. Countries in Central and South Eastern Europe were the most affected. There was no substantial price increase on German natural gas markets but the volatility of prices increased as reserves were depleting at alarming speeds.[9]

Another event happens in April 2010 where the volatility of all EEX futures increased and especially the volatility of natural gas futures. At the end of April, the maximum value of 10% return is reached for month and quarter Gaspool futures following the explosion of BP's offshore

[9] Quarterly Report on European Gas Markets, QREGaM, Volume 2, Issue 1, January 2009 – Mars 2009.

oil-drilling platform, Deepwater Horizon, in the Gulf of Mexico on April 20, 2010. On April 26, the returns of Gaspool futures surge; this date corresponds to the first trading day after April 23 where the complete information about BP's oil leak had been transmitted to energy markets. In Europe, the shale gas industry was in its infancy but was expected to grow rapidly as shale gas represents an important unconventional fuel source for the future. The environmental disaster in the Gulf of Mexico indicated the possibility of tighter European regulation on shale gas drilling projects leading to project delays and the consequent weakening of the natural gas industry.[10]

The last event of the sample happens in mid-March 2011 after the Japanese tsunami and the nuclear disaster of Fukushima on March 12. On March 14, the German Chancellor A. Merkel announced a three-month moratorium on the extension of the lifetimes of 17 German nuclear power plants. The next day, month and quarter Phelix futures returns reached their maximum and most extreme values of 16% and 15% respectively.

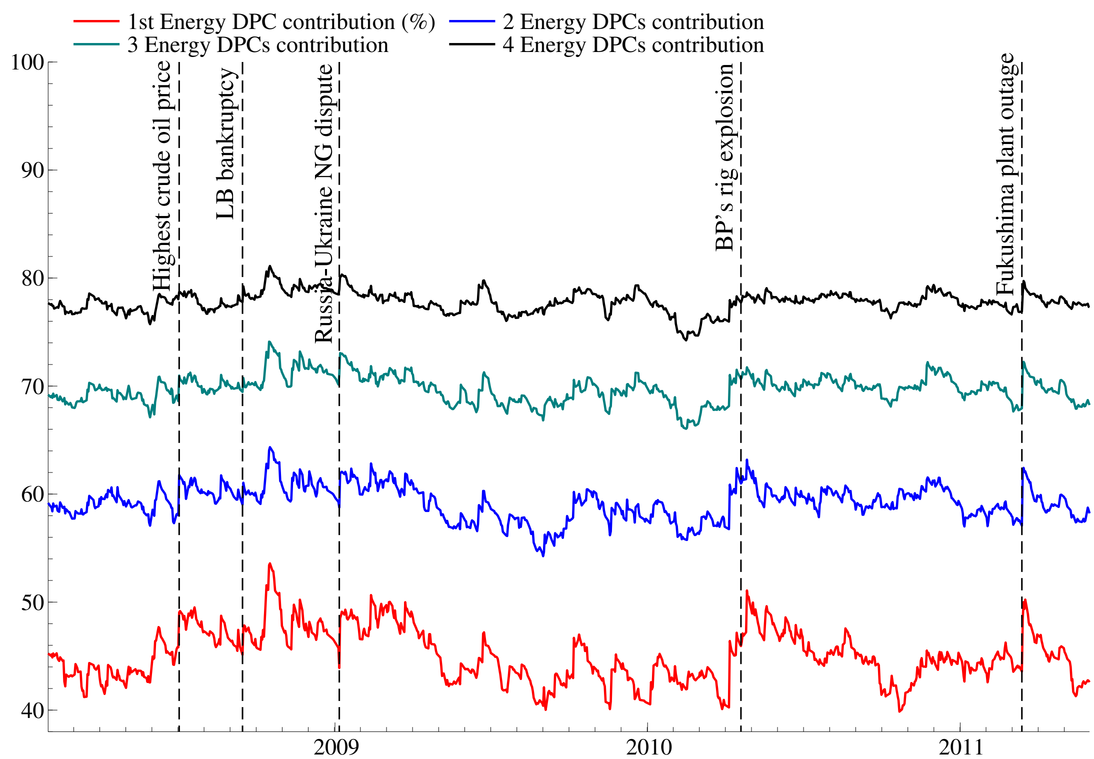

Figure 4: Cumulative percentage of variance explained by the first four dynamic principal components associated to energy returns (contribution). Contribution of the first $s-1$ energy components: $\sum_{j=2}^{s} \lambda_{jt} / \sum_{j=1}^{n} \lambda_{jt}$.

Next to the aggregate measure of market integration, we are interested in measuring the marginal exposure of each product to the energy market risk factor. This marginal measure is interpreted

[10] *BP's Gulf of Mexico oil spill to affect EU shale gas projects*, Energy Risk, May 2010.

as the systematic risk associated to the energy market and can be estimated by a correlation with the energy market. In the dynamic PCA, dynamic correlations of the standardized residuals u_{it} with the principal component y_{jt} are given by $\lambda_{jt}a^2_{ijt}$. If we interpret the second component of the restricted dynamic PCA as the energy market factor, the correlation with the energy trend component ($\lambda_{EnMt}a^2_{i,EnMt}$) defines a measure of energy systematic risk.

Figure 5 shows the cross-sectional average correlations of each energy commodity class (electricity, natural gas, coal, EUA, Brent crude oil) with the common energy market factor. From the evolution of dynamic correlations, we can identify which asset contributed to market events observed in Figure 4. For example, we observe that the systematic risk rises for Gaspool futures during April 2010 (BP's oil spill) and Phelix futures during March 2011 (Fukushima accident). The systematic risk of emission rights also increases in March 2011. The demand for emission rights is indeed expected to rise in Germany as short run replacement capacitiy for nuclear generation is mainly composed of old gas-fired power plants. The German decision to move away from nuclear energy did not however impact the systematic risk of primary energy commodities according to this measure.

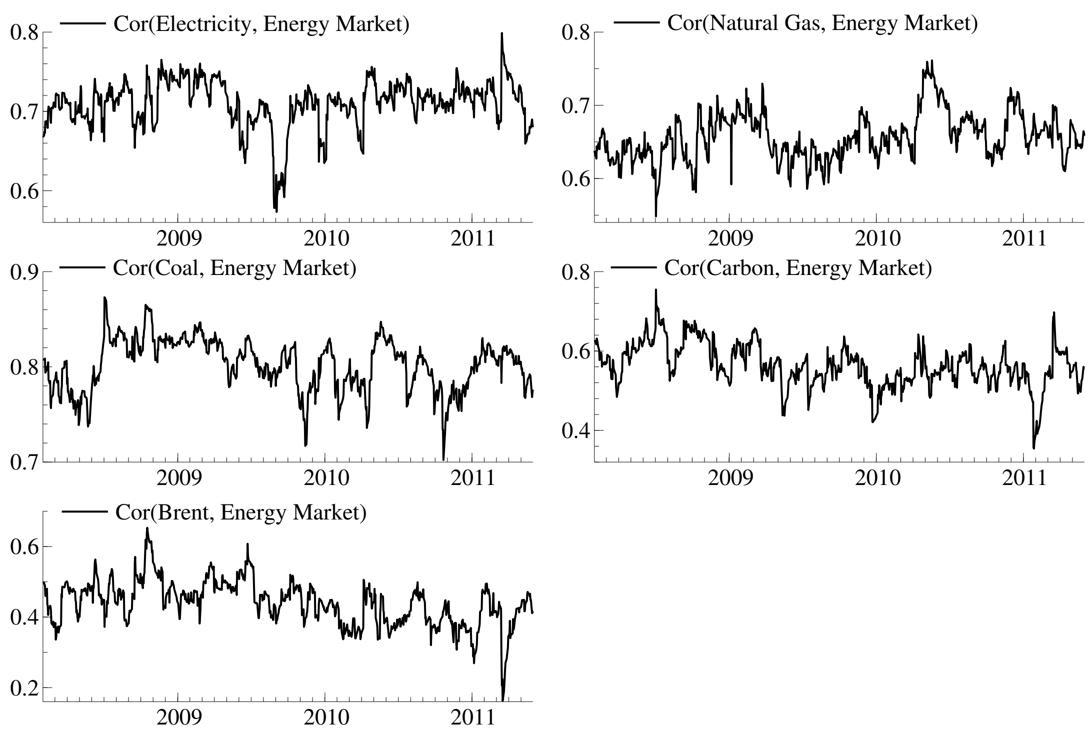

Figure 5: Energy Systematic Risk: correlations of standardized returns u_t with the energy trend component. Correlations are average correlations per energy commodity class (Electricity, Natural Gas, Coal, EUA, Brent crude oil).

Note that the systematic risk attached to crude oil is probably underestimated due to the composition of the initial set of energy products selected for the analysis. The set includes several products of each energy commodity class but only one crude oil index. If we want to measure the systematic risk of crude oil using this methodology, we should more equally balance the initial set of products. However, if the goal is to measure the systematic risk associated to EEX products, the choice of energy products in our application appears to be adequate.

5.5 The conditional MES of energy assets

We turn to the estimation of the conditional MES of EEX futures. This measure is an adapted version of the conditional MES of Brownlees and Engle (2011) accounting for causality, common factor exposure and sensitivity to extreme events in energy markets. The conditional means μ_{it} and the conditional variances σ_{it}^2 incorporate the causal relationships identified with the augmented VECM and the multiplicative causality GARCH models of Section 4. The tail expectations are functions of common factors and idiosyncratic terms as defined in (13). In Figure 6, we show the cross-sectional average of the conditional MES for each energy commodity class (with $s = 5$, so that 86% of the unconditional variance of u_t is explained by common risk factors).

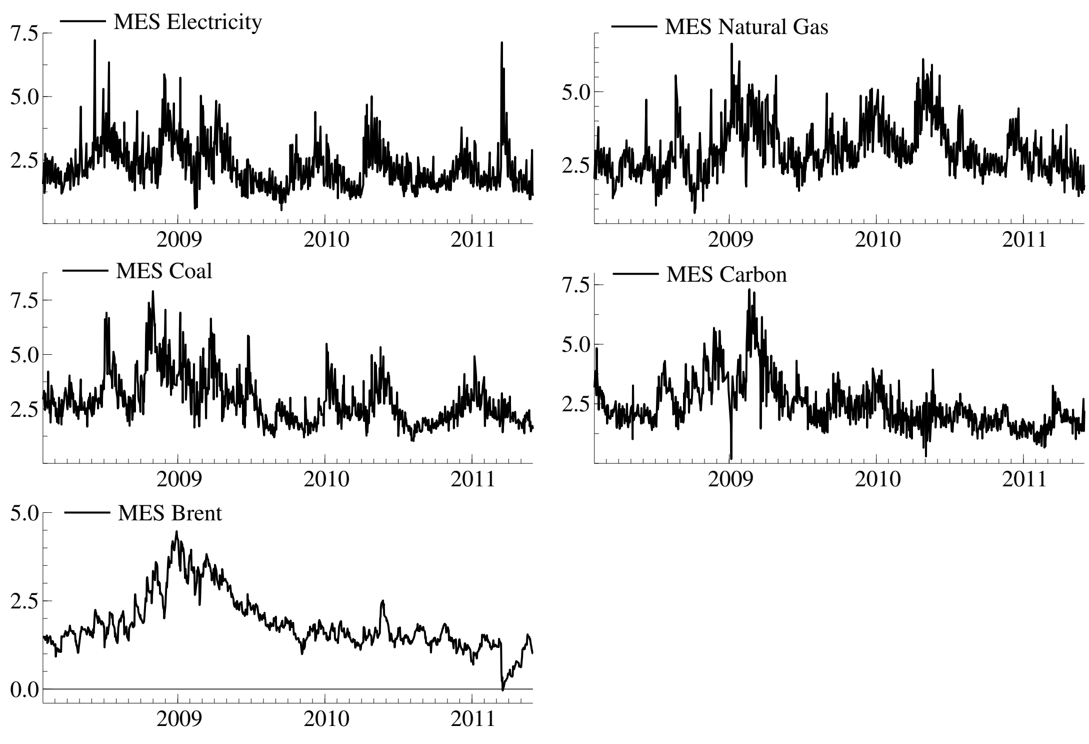

Figure 6: The average conditional MES ($MES_{it}(C)$) in percentage for each energy commodity class (Electricity, Natural Gas, Coal, EUA, Crude oil). C is the unconditional VaR at 95% of the market factor.

The conditional MES for the German energy market appears to be higher for coal and emission rights and lower for crude oil with this measure. The MES of crude oil may be underestimated compared to the MES of EEX futures for the same reasons discussed in the section on systematic risk. However, in absence of a 'real crisis' in the sample (the identified 'market events' are only moderately bad days as described by Acharya et al. (2010)), it is difficult to assess the quality of the estimated conditional MES.

The MES increases for all EEX futures after the financial crisis due to high volatility of energy markets when oil prices started to plummet. Some futures reach a maximal MES at the beginning of January 2009 when returns became highly positive due to the combination of several adverse events (economic downturn, unusual cold winter, and gas supply disruptions in Europe). The release of the information about BP's oil leak had an impact on the MES of all futures but this impact seems to be more important for natural gas futures. The German political reaction following Fukushima events had a major impact on short-term electricity futures but is also visible on carbon emission rights. Not shown here, the conditional MES is also larger for short-term futures because of their high volatility and high sensitivity to extreme market events.

5.6 Estimated Energy Systemic Risk

In a final step, the conditional MES is used to derive the Energy Systemic Risk measure (EnSys-RISK) as we define it in (2). This measure represents the total cost in million euros of each energy commodity class to the German non-energy sector during a potential energy crisis and is illustrated in Figure 7. The EnSysRISK measure is a conditional measure and evolves dynamically based on past information about quantities and prices.

The quantity exposure is approximated by the final consumption, assuming no reserves available to the non-energy sector. Therefore, the energy systemic risk measure will probably be overestimated for storable energy commodities. The expected final consumption is the final consumption of the last month and it is assumed that the only available energy products for the end consumers are the energy assets we considered in our analysis.

Most energy products seem to be characterized by an increasing trend of systemic risk as prices and systemic prices are increasing. The systemic risk of natural gas has a seasonal pattern where systemic risk increases during winter, as natural gas is an important heating fuel in Germany. The systemic risk of natural gas is high in winter 2009 with the disruption in European gas supply, but is even higher in winter 2011. The systemic risk of emission rights follows the seasonal pattern of natural gas. There is a peak in the systemic risk measure of electricity in March 2011 but the measure reverts to its pre-Fukushima level in May 2011. The increase of systemic risk after the Fukushima accident is also present in all other energy commodities, except crude oil.

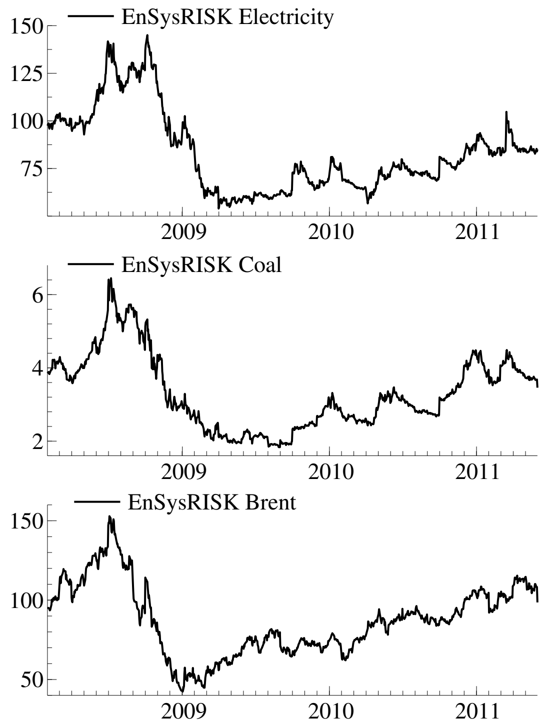

Figure 7: Energy Systemic Risk measure (EnSysRISK) in million euros for each energy class (Electricity, Natural Gas, Coal, EUA, Crude oil).

6 Conclusion

The existence of systemic risk in energy markets may be subject to discussions and different understandings. In this paper, we discuss, define and measure the systemic risk associated to an energy crisis. Our energy systemic risk measure (EnSysRISK) represents the total cost of an energy product to the rest of the economy during an energy crisis. A high degree of dependence of the economy on energy will increase the EnSysRISK measure.

EnSysRISK is a function of the Marginal Expected Shortfall (MES). We adapt the conditional MES of Brownlees and Engle (2011) to account for the co-movements in the means, the variances and the tail expectations of energy assets. The systemic event is defined by an extreme positive energy market shock from the supply side; we are therefore measuring the upper-tail dependence between the energy product and the energy market in the cases where the non-energy returns are negative.

Our definition of the MES allows for linear and non-linear causal relationships in the conditional means and variances. Tail expectations are a function of common risk factors and idiosyncratic terms. We estimate the dynamic linear and tail dependence of energy returns on the market and analyze the impact of several energy market events (Russia-Ukraine gas dispute, BP's oil leak, Fukushima power plant outage). Finally, from the estimated conditional MES and the final consumption quantities, we derive the EnSysRISK measure and find increasing energy systemic risk for all energy products.

This analysis of systemic risk in the energy market is a first attempt to understand how systemic risk may be present in such markets. We provide a methodology to organize and understand the complex dependence of energy assets. Further research opportunities are left open. Forecasting the MES is probably the most important. One-day ahead forecasts are straightforward to obtain from our methodology. Long-run forecasts are also possible to obtain from a simulation procedure as described in Brownlees and Engle (2011). The long-term horizon in the energy sector is however longer than in the financial sector; forecasts over six months may not be enough to help investment decisions in generation capacitity. The long-term of the energy sector is also subject to technology and regulatory changes that are difficult to incorporate into a forecasting exercise. Other dimensions for systemic risk propagation in the energy market are to explore; the most important one being the transmission between regional markets. Then, the impact of energy systemic risk on other markets such as equity markets may also be interesting to study.

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Appendix

Correlation matrix

Phelix Month	1													
Phelix Quarter	0.79	1												
Phelix Year	0.53	0.79	1											
Gaspool Month	0.37	0.40	0.37	1										
Gaspool Quarter	0.39	0.47	0.48	0.81	1									
Gaspool Year	0.36	0.53	0.63	0.63	0.78	1								
Coal ARA Month	0.31	0.48	0.63	0.31	0.37	0.47	1							
Coal ARA Quarter	0.33	0.52	0.66	0.33	0.40	0.51	0.94	1						
Coal ARA Year	0.31	0.51	0.67	0.32	0.40	0.54	0.88	0.93	1					
EUA Year	0.27	0.42	0.57	0.23	0.30	0.37	0.27	0.29	0.30	1				
EUA spot index	0.26	0.39	0.52	0.20	0.28	0.34	0.25	0.27	0.28	0.93	1			
Brent crude oil	0.12	0.24	0.42	0.14	0.21	0.38	0.33	0.37	0.40	0.30	0.30	1		
Coal spot index	0.30	0.48	0.61	0.30	0.40	0.50	0.83	0.88	0.85	0.31	0.32	0.44	1	
DAX industrial	0.07	0.14	0.28	0.09	0.13	0.19	0.23	0.24	0.23	0.28	0.28	0.36	0.28	1

Table 2: Correlation matrix of returns. Sample period: 07.03.2007 - 06.01.2011 (989 observations)

Cointegration results

	η_1	η_2	η_3	η_4	η_5	η_6	η_7	η_8	η_9
Phelix Month	1								
Phelix Quarter		1							
Phelix Year			6.640	5.097	2.979	2.503	-0.342	1.734	5.358
Gaspool Month			1						
Gaspool Quarter				1					
Gaspool Year	4.588	3.493							-1.799
Coal ARA Month					1				
Coal ARA Quarter						1			
Coal ARA Year	-12.668	-4.583	-6.121	-6.681	-6.818	-5.380	0.546	-5.049	
EUA Year		-2.091	-2.682	-2.057	-0.292	-0.426	-0.976		-2.106
EUA spot index							1		
Brent crude oil	6.824		2.997	3.945	4.911	3.620	-0.513	3.551	
Coal spot index								1	
DAX industrial									1

Table 3: Estimated cointegration vectors (η). Sample period: 07.03.2007 - 06.01.2011 (989 observations)

Augmented VECM results

		Coefficient	HACSE	t-value
Phelix Month	Cst	12.694	4.669	2.72
	Wednesday (φ)	0.235	0.087	2.71
	Phelix Quarter$_{t-1}$ (δ_1)	0.125	0.042	2.97
	Gaspool Month$_{t-1}$ (δ_1)	0.084	0.020	4.19
	$\eta_2' \mathrm{y}_{t-1}$ (π)	-0.363	0.142	-2.55
	$\eta_9' \mathrm{y}_{t-1}$ (π)	-0.937	0.309	-3.04
Phelix Quarter	Cst	7.485	2.956	2.53
	Phelix Quarter$_{t-1}$ (δ_1)	0.096	0.029	3.29
	Gaspool Quarter$_{t-1}$ (δ_1)	0.032	0.011	2.79
	Coal spot index$_{t-1}$ (δ_1)	0.053	0.015	3.46
	$\eta_2' \mathrm{y}_{t-1}$ (π)	-0.441	0.096	-4.58
	$\eta_9' \mathrm{y}_{t-1}$ (π)	-0.688	0.192	-3.59
Phelix Year	Cst	10.802	2.622	4.12
	Coal spot index$_{t-1}$ (δ_1)	0.061	0.015	4.16
	EUA spot index$_{t-1}$ (δ_1)	0.048	0.009	5.27
	$\eta_2' \mathrm{y}_{t-1}$ (π)	-0.304	0.078	-3.88
	$\eta_9' \mathrm{y}_{t-1}$ (π)	-0.789	0.167	-4.72
Gaspool Month	Cst	14.673	3.993	3.67
	Gaspool Quarter$_{t-1}$ (δ_1)	0.166	0.029	5.83
	MA(Coal ARA Year returns, 5)	-0.278	0.061	-4.53
	$\eta_1' \mathrm{y}_{t-1}$ (π)	0.403	0.138	2.92
	$\eta_3' \mathrm{y}_{t-1}$ (π)	-1.438	0.379	-3.79
Gaspool Quarter	Cst	-3.325	3.393	-0.98
	Gaspool Month$_{t-1}$ (δ_1)	0.088	0.015	6.05
	Coal ARA Quarter$_{t-3}$ (δ_3)	-0.063	0.016	-3.92
	Brent crude oil$_{t-5}$ (δ_5)	-0.053	0.017	-3.19
	$\eta_1' \mathrm{y}_{t-1}$ (π)	0.674	0.148	4.56
	$\eta_3' \mathrm{y}_{t-1}$ (π)	-0.879	0.215	-4.09
	$\eta_4' \mathrm{y}_{t-1}$ (π)	-0.984	0.296	-3.33
	$\eta_9' \mathrm{y}_{t-1}$ (π)	1.162	0.268	4.34
Gaspool Year	Cst	0.994	0.348	2.86
	Phelix Year$_{t-1}$ (δ_1)	0.080	0.033	2.42
	Coal spot index$_{t-1}$ (δ_1)	0.048	0.022	2.22
	Brent crude oil$_{t-1}$ (δ_1)	0.043	0.014	3.01
	$\eta_4' \mathrm{y}_{t-1}$ (π)	-0.887	0.163	-5.43
	$\eta_8' \mathrm{y}_{t-1}$ (π)	0.683	0.128	5.33
Coal ARA Month	Cst	10.084	2.196	4.59
	Coal ARA Year$_{t-1}$ (δ_1)	-0.165	0.052	-3.17
	Coal spot index$_{t-1}$ (δ_1)	0.378	0.058	6.52
	$\eta_3' \mathrm{y}_{t-1}$ (π)	-0.332	0.095	-3.51
	$\eta_7' \mathrm{y}_{t-1}$ (π)	-2.871	0.766	-3.75
	$\eta_9' \mathrm{y}_{t-1}$ (π)	-0.269	0.092	-2.94

Table 4: Augmented VECM model estimates of eq. (5) (1/2). MA(x_t, τ) is a moving average of variable x_t over the past τ days. Sample period: 07.04.2007 - 06.01.2011 (988 observations)

		Coefficient	HACSE	t-value
Coal ARA Quarter	Cst	1.250	0.469	2.67
	Coal ARA Year$_{t-1}$ (δ_1)	-0.189	0.043	-4.41
	Coal spot index$_{t-1}$ (δ_1)	0.393	0.050	7.87
	Brent crude oil$_{t-1}$ (δ_1)	-0.026	0.008	-3.42
	$\eta_5' y_{t-1}$ (π)	5.729	0.884	6.45
	$\eta_6' y_{t-1}$ (π)	-7.674	1.203	-6.38
Coal ARA Year	Cst	-0.458	0.340	-1.35
	Coal ARA Year$_{t-1}$ (δ_1)	-0.132	0.050	-2.63
	Coal spot index$_{t-1}$ (δ_1)	0.269	0.052	5.21
	$\eta_4' y_{t-1}$ (π)	-0.429	0.104	-4.11
	$\eta_8' y_{t-1}$ (π)	0.539	0.117	4.60
EUA Year	Cst	-8.357	2.541	-3.29
	Brent crude oil$_{t-1}$ (δ_1)	-0.136	0.031	-4.34
	EUA spot index$_{t-1}$ (δ_1)	0.622	0.041	15.1
	EUA Year$_{t-1}$ (δ_1)	-0.449	0.054	-8.32
	$\eta_7' y_{t-1}$ (π)	5.193	1.605	3.24
	$\eta_8' y_{t-1}$ (π)	0.752	0.225	3.34
EUA spot index	Cst	-0.002	0.068	-0.032
	EUA Year$_{t-1}$ (δ_1)	0.144	0.0410	3.57
	Brent crude oil$_{t-1}$ (δ_1)	-0.132	0.031	-4.23
	EUA Year$_{t-2}$ (δ_2)	0.388	0.045	8.59
	EUA Year$_{t-3}$ (δ_3)	0.207	0.038	5.44
	EUA spot index$_{t-2}$ (δ_2)	-0.397	0.049	-8.18
	EUA spot index$_{t-3}$ (δ_3)	-0.208	0.037	-5.68
Brent crude oil	Cst	6.124	1.610	3.80
	$\eta_3' y_{t-1}$ (π)	-0.786	0.206	-3.82
Coal spot index	Cst	20.909	6.072	3.44
	Coal spot index$_{t-1}$ (δ_1)	-0.124	0.043	-2.89
	Coal spot index$_{t-2}$ (δ_2)	-0.193	0.034	-5.65
	Brent crude oil$_{t-1}$ (δ_1)	-0.054	0.013	-4.08
	Coal ARA Quarter$_{t-1}$ (δ_1)	0.321	0.036	9.01
	Coal ARA Quarter$_{t-2}$ (δ_2)	0.181	0.032	5.68
	Electricity daily demand$_{t-1}$ (θ_1)	-1.224	0.402	-3.04
	$\eta_5' y_{t-1}$ (π)	10.764	1.899	5.67
	$\eta_6' y_{t-1}$ (π)	-9.155	1.724	-5.31
	$\eta_8' y_{t-1}$ (π)	-5.329	1.365	-3.90
DAX industrial index	Cst	48.802	8.972	5.44
	Phelix Quarter$_{t-1}$ (δ_1)	-0.140	0.051	-2.75
	$\eta_1' y_{t-1}$ (π)	-2.581	0.559	-4.62
	$\eta_2' y_{t-1}$ (π)	1.632	0.486	3.36
	$\eta_5' y_{t-1}$ (π)	12.2098	3.048	4.01
	$\eta_8' y_{t-1}$ (π)	-11.238	3.590	-3.13
	$\eta_9' y_{t-1}$ (π)	-4.065	0.703	-5.78

Table 5: Augmented VECM model estimates of eq. (5) (2/2) . Sample period: 07.04.2007 - 06.01.2011 (988 observations)

Multiplicative Causality GARCH results

		Coefficient	Std. error	t-value
Phelix Month	Cst (c)	2.935	1.435	2.046
	ARCH (α)	0.175	0.033	5.256
	GARCH (β)	0.845	0.028	30.341
	GJR (γ)	-0.073	0.034	-2.159
	Monday (κ)	0.815	0.102	8.004
	EUA Year (α)	0.283	0.059	4.774
	Phelix Year (ϑ)	0.156	0.044	3.564
Phelix Quarter	Cst (c)	1.208	0.375	3.224
	ARCH (α)	0.122	0.023	5.428
	GARCH (β)	0.856	0.024	36.061
	Monday (κ)	0.711	0.103	6.922
	EUA Year (α)	0.270	0.066	4.062
	Phelix Month (α)	0.152	0.070	2.178
	Phelix Year (ϑ)	0.156	0.045	3.490
Phelix Year	Cst (c)	1.175	0.336	3.501
	ARCH (α)	0.121	0.023	5.324
	GARCH (β)	0.859	0.025	34.238
	Monday (κ)	0.418	0.101	4.148
	EUA Year (ϑ)	0.209	0.041	5.150
Gaspool Month	Cst (c)	10.054	4.965	2.025
	ARCH (α)	0.104	0.015	6.992
	GARCH (β)	0.891	0.016	57.003
	Monday (κ)	0.658	0.104	6.333
	April (κ)	0.589	0.225	2.617
	Coal ARA Month (ϑ)	0.169	0.045	3.715
	EUA Year (α)	0.169	0.072	2.339
Gaspool Quarter	Cst (c)	5.177	0.980	5.283
	ARCH (α)	0.139	0.031	4.507
	GARCH (β)	0.803	0.039	20.412
	Monday (κ)	0.441	0.105	4.205
	May (κ)	-0.594	0.230	-2.577
	Brent crude oil (ϑ)	0.123	0.044	2.814
Gaspool Year	Cst (c)	2.686	0.380	7.066
	ARCH (α)	0.063	0.015	4.077
	GARCH (β)	0.907	0.021	42.397
	Monday (κ)	0.385	0.108	3.553
	Brent crude oil (ϑ)	0.152	0.042	3.588

Table 6: Multiplicative Causality GARCH model estimates of eq. (6) (1/2). Sample period: 07.04.2007 - 06.01.2011 (988 observations)

		Coefficient	Std. error	t-value
Coal ARA Month	Cst (c)	3.834	0.954	4.019
	ARCH (α)	0.111	0.022	5.152
	GARCH (β)	0.865	0.026	33.205
	Thursday (κ)	-0.386	0.105	-3.655
	January (κ)	0.888	0.233	3.813
	August (κ)	-0.882	0.234	-3.775
	Coal spot index (ϑ)	0.140	0.044	3.215
Coal ARA Quarter	Cst (c)	3.379	0.750	4.508
	ARCH (α)	0.097	0.022	4.453
	GARCH (β)	0.880	0.027	32.585
	January (κ)	0.794	0.232	3.426
	August (κ)	-0.754	0.225	-3.359
	Coal ARA Month (ϑ)	0.146	0.043	3.426
Coal ARA Year	Cst (c)	2.148	0.486	4.424
	ARCH (α)	0.088	0.020	4.415
	GARCH (β)	0.893	0.025	36.374
	Phelix Month (α)	0.159	0.065	2.439
EUA Year	Cst (c)	3.845	0.775	4.960
	ARCH (α)	0.031	0.017	1.832
	GARCH (β)	0.898	0.023	38.240
	GJR (γ)	0.093	0.027	3.378
	Monday (κ)	0.214	0.102	2.107
	Coal ARA Year (ϑ)	0.151	0.042	3.582
EUA spot index	Cst (c)	4.509	0.857	5.260
	ARCH (α)	0.037	0.018	2.045
	GARCH (β)	0.901	0.026	35.162
	GJR (γ)	0.072	0.026	2.814
Brent crude oil	Cst (c)	3.988	0.762	5.236
	ARCH (α)	0.042	0.009	4.782
	GARCH (β)	0.947	0.011	85.526
Coal spot index	Cst (c)	3.045	0.776	3.926
	ARCH (α)	0.114	0.021	5.374
	GARCH (β)	0.862	0.025	34.357
	January (κ)	0.767	0.240	3.195
DAX industrial index	Cst (c)	4.912	1.558	3.152
	ARCH (α)	0.022	0.016	1.369
	GARCH (β)	0.909	0.017	52.986
	GJR (γ)	0.109	0.035	3.139
	Gaspool Year (ϑ)	0.134	0.047	2.869

Table 7: Multiplicative Causality GARCH model estimates of eq. (6) (2/2). Sample period: 07.04.2007 - 06.01.2011 (988 observations)