The Systemic Risk of Energy Markets

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Abstract: This paper investigates the meaning of systemic risk in energy markets and proposes a methodology to measure it. 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. Measures of the total cost (EnSysRISK) and the net impact ($\triangle MES$) of an energy crisis on the rest of the economy are proposed. The measures are derived from the Marginal Expected Shortfall (MES) capturing the tail dependence between the asset and the energy market factor. The adapted MES accounts for causality and dynamic exposure to common latent factors. The methodology is applied to the European Energy Exchange and the DAX industrial index, where a minor decline in industrial productivity is observed from recent energy shocks.

Keywords: energy crisis, factor models, marginal expected shortfall, market integration.

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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 a crisis. 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 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 by many others. 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 (2012) 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

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crisis is not caused by the failure of companies in the energy sector but comes from the price (co-)movements of energy products. Increased integration within energy markets and increased dependence of the economy on energy 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 measures of energy systemic risk that focus on the comovements 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. EnSysRISK is complemented by a measure of the net impact ($\triangle MES$) of an energy crisis on the rest of the economy. EnSysRISK and $\triangle MES$ are 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 of the comovements in the means, the variances and the tails of energy assets. Causal relationships in the conditional means and variances reflect physical relationships through substitution between primary energies and the merit-order of electricity, financial relationships between energy contracts and possible spillover effects between markets. The model for the mean of returns accounts for 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 causality in the variances.

While causality allows modeling the interdependence in the energy market, we also suspect the presence of common drivers of risk. Causal relationships are removed from returns to concentrate on the pure contagion phenomenon, i.e. an increase in correlations during

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a crisis (Billio and Caporin (2010); Forbes and Rigobon (2002)), whereas causal relationships simply spread the shocks among the products in all states of the world. We present a methodology to account for latent factors in the conditional MES. The latent factors are estimated from principal component analyses on the time-varying correlation matrices estimated with the Dynamic Conditional Correlation (DCC) model of Engle (2002). Therefore, the common factors incorporate conditional information and the tail expectations have a dynamic exposure to the most important risk factors. Causality and exposure to common factors are then combined in a single measure writing the conditional MES as a function of means, variances and tail expectations.

The methodology is applied on energy futures of the European Energy Exchange (EEX) where the impact of recent energy market events is analyzed. 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. From the conditional MES and final consumption data, we derive the EnSysRISK of EEX futures and find that energy crises would impose increasing costs to the economy. However, $\triangle MES$ shows little impact of energy shocks on the DAX industrial index, suggesting a relatively small decline in industrial productivity due to extreme increases in energy prices.

The paper is structured as follows: in Section two, we define energy systemic risk and present the related literature. We introduce the measures of energy systemic risk (EnSysRISK and $\triangle MES$) 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 derive the EnSysRISK and the $\triangle MES$ of EEX futures in Section five.

2 Systemic risk, comovements and energy crises

There is no consensus on the existence or the importance of systemic risk in the energy market. At the same time, the systemic risk of energy markets may be a difficult concept

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to apprehend. In this section, we clarify the conditions for systemic risk to appear in energy markets and its consequences for the rest of the economy. It starts by exposing the related literature on systemic risk (1), energy price comovements (2), past energy crises and their impact on the economy (3), and concludes with the definition of energy systemic risk.

At the heart of systemic risk (1), there is the concept of dependence: dependence between individual financial institutions and dependence between the financial sector and the rest of the economy. There are mainly two approaches in the systemic risk literature; one part of the literature sees systemic risk as arising from one or several shock(s) spreading to a network of financial relationships (Billio et al. (2012); Diebold and Yilmaz (2011); Hautsch et al. (2011)) while the other part sees systemic risk as arising from an aggregate economy-wide shock (Acharya et al. (2010); Brownlees and Engle (2011)).

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. Among the proposed measures of systemic risk we find measures of 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 MES represents the expected losses of a firm during an aggregate market shock. By reversing the condition, we find the CoVaR defined as the value-at-risk of the market conditional on an institution being in distress. Acharya et al. (2012) however point out a shortcoming of the CoVaR as the measure does not depend on the volatility of the financial institution but only depends on its correlation with the market. Therefore, two institutions with the same market correlation will be assigned the same CoVaR even if they have very different volatilities.

We mentioned dependence as the heart of systemic risk. In energy markets, dependence may be found along several dimensions; dependence between different regional markets, energy commodities, maturities or parts of the value chain. Energy market integration and

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comovements in energy prices play a central role in energy systemic risk as they neutralize the substitution effects that are supposed to bring energy prices to a new viable equilibrium for the rest of the economy. Our methodology therefore relates to the literature on comovements and the modeling of the joint distribution of energy prices (2): comovements in the mean with cointegration and causality models (Bunn and Fezzi (2008); Escribano et al. (2011); Haldrup and Nielsen (2006)), comovements in the volatility with multivariate volatility models (Bauwens et al. (2012); Chevallier (2012)) and comovements in the tails with copulae (Benth and Kettler (2010); Boerger et al. (2009); Gronwald et al. (2011)).

Dependence in energy markets is complex. The jumps in power spot (day-ahead) prices have very short-term impacts because of the physical nature of assets and are less susceptible to spread to other markets. For these very volatile spot markets like electricity and gas, futures represent a larger market as they represent insurance contracts against spot price fluctuations. Futures prices are impacted by shocks on physical spot markets, but 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 in March 2011). 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.

All other sectors of the economy are also dependent on energy prices. A large part of the literature on energy crises and their impact on the economy (3) followed the oil embargo of 1973-1974 (Barsky and Kilian (2004); Brown and Yücel (2002); Carruth et al. (1998); Hamilton (1983, 2011); Kilian (2008); Lee (2002); Rotemberg and Woodford (1996); Zaleski (1992), among others). A direct impact of energy crises on the economy operates through the price mechanism as energy is an essential production factor. The energy demand has very low elasticity such that extreme high prices and high volatility produce higher inflation, reduced growth and increased uncertainty (Tieben et al. (2011)). Hamilton (1983, 2011)

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shows that the historical correlation between energy crises and economic downturns appears to be too strong to be a coincidence.

Next to the direct impact on the economy, the indirect impact refers to the contagion channels of energy derivatives to the real economy via energy derivative trade positions of financial institutions (Tieben et al. (2011); Hamilton (2009)). Benink (1995) also indicates that the growth of derivatives has increased systemic risk by expanding linkages among markets and financial institutions. Increasing integration of energy markets with other markets is also foreseen as the liquidity of energy derivatives grows and attracts investors outside the energy sector. Lautier and Raynaud (2012) study the links between commodity, energy and equity derivative markets and show that connections between sectors are insured by energy products. Tieben et al. (2011) however find a small indirect effect as financial institutions hold relatively small positions in energy derivative markets.

If the energy market integration and the dependence of the economy on energy prices are accepted, we also need to understand what type of event leads to systemic risk. External shocks to the energy market like natural disasters or geopolitical events create large energy price fluctuations susceptible to generate systemic risk in the energy market. The unsustainable interaction between demand growth and production declines (Hamilton (2011)), regulatory and technological uncertainty may also constitute important sources of systemic risk. As dependence on oil is believed to decrease and shift to substitutes in most developed economies, the energy crisis we consider is not restricted to an oil crisis. All energy commodities are considered equally important and causal relationships may go in all directions.

The definition of energy systemic risk also depends on the position of the agent in the energy value chain. We take the viewpoint of the demand side as we define the systemic risk for the non-energy sector. Therefore, 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. Increased integration within the energy market and increased dependence of the

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economy on energy may pave the way for an energy systemic crisis to occur. If an extreme energy market shock arises in such conditions, we expect consequences to be severe for the energy market and the entire economy.

3 Measuring Energy Systemic Risk

In the context of energy markets, the conditional Marginal Expected Shortfall (Acharya et al. (2010); Brownlees and Engle (2011)) of an energy asset 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 energy asset i at time t conditional on an energy crisis and past information up to time $t-1$, with $i = 1, 2, ..., n$ and $t = 1, 2, ..., T$. From the conditional MES and past price levels, we derive the Energy Systemic Risk measure defined by

$$EnSysRISK_{it} = \left[p_{it-1} * \exp(MES_{it})\right] * w_{it}, \tag{2}$$

where w_{it} is the quantity exposure of the economy to asset i at time t. For an energy contract i with maturity τ_{i0} and delivery period ν, the exposure at time t is

$$w_{it} = \frac{\varsigma_i}{\nu_i} \sum_{\tau=\tau_{i0}}^{\tau_{i0}+\nu_i} \max\left[0, \mathrm{E}_{t-1}\left(fincons_\tau - inv_\tau\right)\right] \quad \text{with } t < \tau_{i0} \leq \tau,$$

where $fincons_\tau$ is the daily final consumption of energy during delivery period ν_i of contract i starting at τ_{i0}, inv_τ are the energy stocks available to the non-energy sector during the same delivery period, and ς_i is the proportion of energy delivered during period ν_i via energy futures contracts i. Expected inventory levels or stocks 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_i. High dependence of the non-energy sector on energy via final consumption

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and low inventories increases the quantity exposure to systemic risk.

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 energy crisis is defined in this paper by an abnormal rise in energy prices (i.e. extreme positive returns) as we define energy systemic risk 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 associated with strong demand growth in the later stages of a business cycle expansion (Hamilton (2011)). To ensure that energy market shocks are not associated to business cycles, we only consider energy price increases when the rest of the economy is slowing down. The MES conditional on an energy crisis is therefore defined by

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

where $r_{EnM,t}$ is the energy market return, $r_{M,t}$ is the return of the non-energy sector, C represents the $(1-\alpha)$ quantile of $r_{EnM,t}$, and D is the median of $r_{M,t}$. Section 4 presents our methodology for modeling the comovements in the means, the variances and the tails of energy returns in order to estimate $MES_{it}(C,D)$.

The EnSysRISK measure defined in (2) represents the total cost of an energy crisis to the non-energy sector. There is however an opportunity cost of not producing using energy during an energy crisis. Next to EnSysRISK, we define a measure of the net impact of an energy crisis on the non-energy sector by

$$\Delta MES_{Mt}(C,D) = MES_{Mt}(C,D) - MES_{Mt}(q_{EnMt,0.5},D), \tag{4}$$

where $MES_{Mt}(C,D)$ is the conditional MES of the non-energy return ($r_{M,t}$) conditional on an energy crisis and $q_{EnMt,0.5}$ is the median of the energy market return (r_{EnMt}). This measure is inspired by the $\triangle CoVaR$ of Adrian and Brunnermeier (2010) and represents the difference between the expected return of the non-energy index during an energy crisis and the expected non-energy return during 'normal' times. The energy crisis is expected to have a negative net impact on the economy, i.e. ΔMES is expected to be negative.

4 Econometric methodology

The conditional MES of equation (3) can be decomposed as a function of mean, volatility and tail expectation

$$\begin{aligned} MES_{it}(C,D) &= \mathrm{E}_{t-1}\left(\mu_{it} + \sigma_{it}u_{it} | r_{EnMt} > C,\, r_{Mt} < D\right) \\ &= \mu_{it} + \sigma_{it}\mathrm{E}_{t-1}\left(u_{it} | r_{EnMt} > C,\, r_{Mt} < D\right), \end{aligned} \tag{5}$$

where μ_{it} and σ_{it} are the conditional mean and volatility of asset i and $u_{it} = (r_{it} - \mu_{it})/\sigma_{it}$ is a standardized shock of zero conditional mean and unit conditional variance. In this section, we successively describe how to account for causality and cointegration in the means, causality in variances, and common factors in tail expectations. Common factors are extracted from u_t as Forbes and Rigobon (2002) show that heteroskedasticity present in returns may lead to an upward bias in the estimation of the contagion risk during a crisis. Causality is removed from returns in order to concentrate on the pure contagion phenomenon (also called market integration in this paper), i.e. an increase in correlations during a crisis whereas causal relationships refer to the interdependence phenomenon, i.e. market linkages that are present in all states of the world (Billio and Caporin (2010); Forbes and Rigobon (2002)).

4.1 Causality in mean and variance

Following the methodology of Billio et al. (2012), we apply Granger-causality tests to measure the degree of interdependence of the energy market. The causal relationships reflect physical relationships in the energy market based on the supply curve (merit-order) of electricity

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and substitution between primary energy commodities for electricity generation and other consumption purposes. Causal relationships also reflect substitution between different energy futures contracts and spillover effects between 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 of $(n-1)$ energy assets and a non-energy sector index are collected in the $(n \times T)$ matrix P, from which the vector of daily returns $\mathrm{r}_t = 100 \times (\ln(\mathrm{p}_t) - \ln(\mathrm{p}_{t-1}))$ is derived. Given the structure of energy returns, a Vector Error Correction Model (VECM) capturing autocorrelation, cointegration, causality, and seasonality is specified

$$r_{it} = \pi_i \eta' \ln(\mathrm{p}_{t-1}) + \sum_{k=1}^{K} \delta'_{ik} \mathrm{r}_{t-k} + \sum_{m=1}^{M} \theta'_{im} \mathrm{x}_{t-m} + \varphi'_i \mathrm{q}_t + \epsilon_{it}, \tag{6}$$

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) terms. 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), and the matrices η and π are identified by imposing $\eta = \begin{pmatrix} I_v & B' \end{pmatrix}'$. This model is similar to the vector-error correction model of Bunn and Fezzi (2008), except that all energy products are here considered as endogenous variables (as part of the 'system').

4.1.2 Multiplicative Causality GARCH Model

From the augmented VECM estimation, we obtain the vector 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

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the multiplicative causality GARCH model allowing for non-linear causality

$$\epsilon_{it} = \sigma_{it} u_{it} = \sqrt{\phi_{it} g_{it}} u_{it}, \tag{7}$$

where

$$g_{it} = (1 - \alpha_{ii} - \beta_i - \frac{\gamma_{ii}}{2}) + \alpha_{ii} \left(\frac{\epsilon_{it-1}^2}{\phi_{it-1}} \right) + \beta_i g_{it-1} + \gamma_{ii} \left(\frac{\epsilon_{it-1}^2}{\phi_{it-1}} \right) I_{\{\epsilon_{it-1}<0\}}, \tag{8}$$

$$\phi_{it} = f\left(u_{1t-1}, ..., u_{i-1,t-1}, u_{i+1,t-1}, ..., u_{nt-1}\right) l_i(t), \tag{9}$$

$I_{\{\epsilon_{it-1}<0\}}$ 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 multiplicative form, by separating own and interaction dynamics, makes the parameter estimates of both GARCH and interaction components 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 shocks.[1]

In our application, the interaction component is specified as

$$\phi_{it} = c_i \exp\left(\sum_{j=1, j\neq i}^{n} \left(\vartheta_{ij} u_{jt-1} + \alpha_{ij} |u_{jt-1}|\right) + \kappa_i' \mathrm{d}_t \right), \tag{10}$$

where d_t are deterministic terms including seasonal dummies. This function has a similar

[1] Note that, if $\epsilon_{it-1}^2/\phi_{it-1}$ are replaced by $\epsilon_{it-1}^2/l_i(t-1)$ in (8), 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.

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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 shocks u_t may be decomposed as a linear function of common factors and idiosyncratic terms. In Brownlees and Engle (2011), standardized shocks are decomposed as a function of an observable market return and idiosyncratic terms using a single-factor model similar to the capital asset pricing model (CAPM). In the context of energy markets, the CAPM may 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. Additionally, a market index may not be available or reliable for less liquid markets like energy markets.

An alternative is to consider the common factors as latent. 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). In the PCA, the factors are estimated from a spectral decomposition of the sample correlation matrix of u_t. However, the probability of an energy crisis will be constant when the principal components are extracted from the sample correlation matrix, since factors have constant variances equal to their eigenvalues.

Conditional variances of the principal components can be obtained with the O-GARCH model of Alexander (2002). In the context of systemic risk, we may also want to measure the evolution of the exposure of returns to the principal components that are interpreted as common risk factors. Dynamic eigenvectors are obtained from spectral decompositions of the daily correlation matrices estimated with the Dynamic Conditional Correlation (DCC) model of Engle (2002). This approach can be viewed as a multivariate extension of Brownlees

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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

$$Q_t = (1 - a - b)\bar{Q} + a u_{t-1} u'_{t-1} + b Q_{t-1}, \tag{11}$$

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

$$R_t = (I_n \odot Q_t)^{-1/2} Q_t (I_n \odot Q_t)^{-1/2}$$

where I_n is a $n \times n$ identity matrix. 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 $z_t = H_t^{1/2} \epsilon_t$ 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 process of eq. (7) are estimated. In the second stage, the parameters of the conditional correlation process are estimated conditionally on the estimates obtained in the first stage.

Dynamic eigenvectors and dynamic eigenvalues at time t are obtained from the spectral decomposition of the DCC correlation matrix R_t. Therefore, the covariance H_t is decomposed in

$$H_t = D_t R_t D_t = D_t \left(A_t \Lambda_t A'_t + R_{\zeta_t} \right) D_t, \tag{12}$$

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.

The standardized shocks are then written as a function of the first s principal components

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and idiosyncratic terms

$$u_{it} = \sum_{j=1}^{s} a_{ijt} y_{jt} + \zeta_{it}, \tag{13}$$

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 expectation in (5) is defined by two factors: the energy market return (r_{EnMt}) and the return on the non-energy sector (r_{Mt}). The non-energy return will be approximated by the return on the observable non-energy index. The orthogonality of the other factors to the non-energy factor is ensured by imposing restrictions on the eigenvector elements as in the restricted PCA used in Ng et al. (1992). The first principal component y_{1t} (y_{Mt}) is restricted to be the standardized non-energy return (u_{Mt}), where all elements of its eigenvector associated to energy returns are restricted to be null

$$\max_{a_{1t}} a'_{1t} R_t a_{1t}$$

$$\text{s.t. } a'_{1t} a_{1t} = 1, \; a_{i1t} = 0 \quad \forall t, \forall i \neq M.$$

The other factors are obtained by

$$\max_{a_{jt}} a'_{jt} R_t a_{jt}$$

$$\text{s.t. } a'_{jt} a_{jt} = 1, \; a'_{jt} a_{lt} = 0 \quad \forall t, \forall l \neq j, j > 1,$$

and are mutually orthogonal and orthogonal to the non-energy factor.

The second principal component y_{2t} is positively correlated to all energy assets and is interpreted as the energy market factor (y_{EnMt}); a variable that explains the majority of comovements in the energy market after removing causal relationships. The factors in (13) have time-varying variances λ_{jt} and the second dynamic eigenvalue λ_{2t} (λ_{EnMt}) is interpreted as the energy market variance.

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Tail expectations are then approximated by

$$\begin{aligned} \mathrm{E}_{t-1}\left(u_{it}|r_{EnMt} > C,\, r_{Mt} < D\right) \;\; &\simeq \;\; \sum_{j=1}^{s}\left[a_{ijt}\mathrm{E}_{t-1}\left(y_{jt}|y_{EnMt} > \tilde{C},\, y_{Mt} < \tilde{D}\right)\right] \\ &\quad + \mathrm{E}_{t-1}\left(\zeta_{it}|y_{EnMt} > \tilde{C},\, y_{Mt} < \tilde{D}\right), \end{aligned} \tag{14}$$

where $\tilde{C}$ is the (1-α) quantile of the energy market factor and $\tilde{D}$ is the median of the non-energy factor.

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 during a crisis. To capture the sensitivity to extreme events in the energy market, the next step is to estimate the tail expectations of eq. (14). Nonparametric estimation of tail expectations is an alternative to copula functions where the joint distribution of factors and idiosyncratic terms 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)). The proposed nonparametric estimator of tail expectations is

$$\hat{\mathrm{E}}\left(y_{jt}|y_{EnMt} > \tilde{C},\, y_{Mt} < \tilde{D}\right) = \frac{\sum_{\tau=1}^{T} y_{j\tau}\Phi\left[\left(\frac{y_{EnM\tau}}{\sqrt{\lambda_{EnM\tau}}} - \frac{\tilde{C}}{\sqrt{\lambda_{EnMt}}}\right)h^{-1}\right] I(y_{M\tau} < \tilde{D})}{\sum_{\tau=1}^{T} \Phi\left[\left(\frac{y_{EnM\tau}}{\sqrt{\lambda_{EnM\tau}}} - \frac{\tilde{C}}{\sqrt{\lambda_{EnMt}}}\right)h^{-1}\right] I(y_{M\tau} < \tilde{D})}, \tag{15}$$

where $\Phi(\cdot)$ is the Gaussian c.d.f., h is a positive bandwidth parameter, and $I(y_{M\tau} < \tilde{D})$ is an indicator function equal to one when the the non-energy factor is below the threshold $\tilde{D}$. The same estimation procedure applies to $\mathrm{E}\left(\zeta_{it}|y_{EnMt} > \tilde{C},\, y_{Mt} < \tilde{D}\right)$.

This estimator assigns higher weights to observations that are close to the threshold $\tilde{C}$ and zero weight when the non-energy factor is above $\tilde{D}$. The threshold $\tilde{C}$ divided 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.

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5 Application to the EEX market

The European Energy Exchange (EEX) is the leading energy exchange in continental Europe. The study of systemic risk in the EEX market is motivated by the size and the central location of the exchange. In the following subsection, we describe the products selected in our application. Causality in energy markets is explored by analyzing the links between products through their conditional means and variances in Subsections 5.2 and 5.3. In Subsection 5.4, we measure the evolution of energy market integration. The estimation of the conditional MES of energy assets is the subject of Subsection 5.5, the $EnSysRISK$ and the ΔMES measures are derived in Subsection 5.6.

5.1 Data description

We consider the daily price series of ten EEX energy futures, three energy spot indices and the DAX industrial index.[2] The portfolio of EEX futures contains futures on electricity (Phelix), natural gas (Gaspool), coal (ARA) and carbon emission rights (EUA). 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.[3]

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 fu-

[2]Source: Datastream. Series codes: EBMCS00, EBQCS00, EBYCS00, EGMCS00, EGQCS00, EGYCS00, ECMCS00, ECQCS00, ECYCS00, ECBCS00, MLCXEUS, OILBRNP, MLCXECS, PRIMIND. Prices in US dollars are converted in Euros (using US $ TO EURO (WMR&DS) - EXCHANGE RATE).

[3]One EU emission allowance confers the right to emit one ton of carbon dioxide or one ton of carbon dioxide equivalent. EEX Product Brochure : EU Emission Allowances, 2011

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tures 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, based on their high correlations with EEX futures (the sample correlation matrix can be found in Table 3 in the Appendix). The DAX industrial index is mainly composed of energy consuming companies and is taken as a proxy for the non-energy sector index.

The descriptive statistics of the returns of the fourteen series are presented in Table 1. The table reveals the DAX industrial, Brent crude oil and short-term contracts on natural gas to be the most volatile series. Short-term electricity futures have the largest kurtosis caused by the extreme returns of mid-March 2011 when Germany announced its exit from nuclear energy following the Japanese tsunami and the accident at Fukushima power plant.

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: Descriptive statistics of returns. Sample period: 07.03.2007 - 06.01.2011 (989 observations).

The sample correlation matrix (Table 3 in the Appendix) constitutes a first simple way

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to study the links between products and markets. The highest correlations are observed between groups of products with the same underlying commodity (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.

5.2 Cointegration and causality in the mean

We test the parameters of the VECM model (eq. (6)) 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.[4] Cointegration vectors estimates are reported in Table 4 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 (6) are then estimated by maximum likelihood conditionally 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. (6) equal to five. The estimated coefficients and robust standard errors[6] of significant relationships at the 5% level are presented in Table 5 in the Appendix.

The table of estimation results shows 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); Fezzi and

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

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

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

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Bunn (2009) showing that carbon prices are weakly exogenous in the long run. Bunn and Fezzi (2008) explain this finding by the geographical scope of products; carbon allowances are traded at the European level while other products in the sample (electricity and natural gas futures) are exclusively traded in the German market area.

Granger-causality 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 the marginal fuel for electricity generation during off-peak hours in Germany and it is significant to explain returns of long-term electricity futures. Similarly, natural gas is the marginal fuel for peak load hours and it is significant to explain returns of short-term Phelix futures.

Brent crude oil returns are not caused by any variable but are causal for many other energy products (long-term Gaspool futures, coal spot, coal quarter futures and EUA spot and futures returns). As for the relationship between energy and industrial returns, only the quarter Phelix future explains industrial returns and the estimate is negative; increasing electricity futures prices have a negative impact on the DAX industrial return.

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. (7)) are reported in Table 6 in the Appendix.[7]

In the GARCH(-GJR) component of eq. (8), we find a positive estimate of the asymmetric parameter γ for the DAX industrial index and EUA products and a negative estimate for month Phelix futures. The negative estimate of γ for the month Phelix future 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 sup-

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

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ply function, since positive demand shocks have a larger impact on prices than negative demand shocks. For DAX and EUA returns, the asymmetric parameter is so strong that the ARCH parameters are not significant and only the negative news affect the volatility of these products.

The interaction component defined in (10) incorporates seasonal effects and causal relationships. The EEX futures market closes during weekend days and consequently, higher volatility is found at the beginning of the week (positive Monday effect). The seasonality in the volatility of coal spot and futures returns is different 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 futures contracts with the same underlying commodity but different maturities and delivery periods, as it is the case for electricity and coal.

The gain in terms of likelihood of the Multiplicative Causality GARCH model compared to the standard GARCH model is small (the log-likelihood is -27335 for the GARCH, -27059 for the Multiplicative Causality GARCH), and the estimated variances are very close in both models. For modeling univariate variances, standard GARCH models are more parsimonious and more convenient to estimate (allowing for separate estimations of the univariate variances). The Multiplicative Causality GARCH however identifies potential interactions in variances and allows separating interdependence from the pure contagion phenomenon as described in Forbes and Rigobon (2002) and Billio and Caporin (2010).

5.4 Energy Market Integration

After removing heteroskedasticity and causality from returns, we concentrate on the integration of energy markets due to the presence of common factors. Contagion or mar-

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ket integration refers to an increase of commonality and is measured by the percentage of variance of estimated standardized residuals u_t explained by the energy market factor $(\lambda_{EnMt}/\sum_{j=1}^{n}\lambda_{jt})$.[8] The eigenvalue ratio (also used in Billio et al. (2012); Kritzman et al. (2011)) can be interpreted as an aggregate measure of correlations between energy returns.

The non-energy market factor y_{Mt}, approximated by the standardized DAX industrial return, has a constant eigenvalue ratio (7%) due to the restriction on its eigenvector. From a restricted PCA on the sample correlation matrix of standardized residuals u_t, four energy factors have unconditional eigenvalue ratios larger than 7%; the energy market factor (47.3%) positively correlated to all energy commodities, the second energy factor (12.6%) opposing coal to emission rights, the third energy factor (10.9%) opposing natural gas to emission rights, and the fourth energy factor (7.8%) highly correlated to electricity futures.

Figure 1 presents the dynamic ratios of the first four energy factors obtained from a restricted PCA on DCC correlations as described in Subsection 4.2. All dynamic ratios tend to fluctuate around their unconditional levels and the ratio of the energy market factor is the most volatile, with values between 40% and 54%. The sign of dynamic eigenvectors is stabilized using a sign function[9] and the resulting dynamic conditional eigenvector elements also fluctuate around their unconditional levels.

From Figure 1, we identify several events of market integration due to increasing correlations. The first event is consequent to the energy price bubble of 2007-2008. The 2007-2008 energy shock is attributed in Hamilton (2009) to an extremely low elasticity and a strong growth of the energy demand confronting a stagnating oil production. Market integration increased further when the energy bubble burst after the highest crude oil price of all times

[8] Next to the aggregate measure of market integration, a dynamic measure of *systematic* risk associated to the energy market is given by the correlation of the standardized residuals u_{it} with the energy market factor $\sqrt{\lambda_{EnMt}}a_{i,EnMt}$.

[9] The eigenvector element a_{ijt} is multiplied for all i by -1 when the sign of $a_{i^\star,jt}$ is different from the sign of $a_{i^\star,jt-1}$ and $i^\star$ is the asset return that has the highest unconditional correlation with component j. The sign identification is actually not a problem for $j = 1, 2$ as the first eigenvector is a restricted constant vector and the sign of the elements of the second eigenvector does not change over time for our set of variables.

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was reached on July 3, 2008. A peak of market integration appears in October 2008 when the trend of all energy prices reverted due to the adverse economic news of fall 2008 and the shift in the energy demand elasticity (Hamilton (2009)).

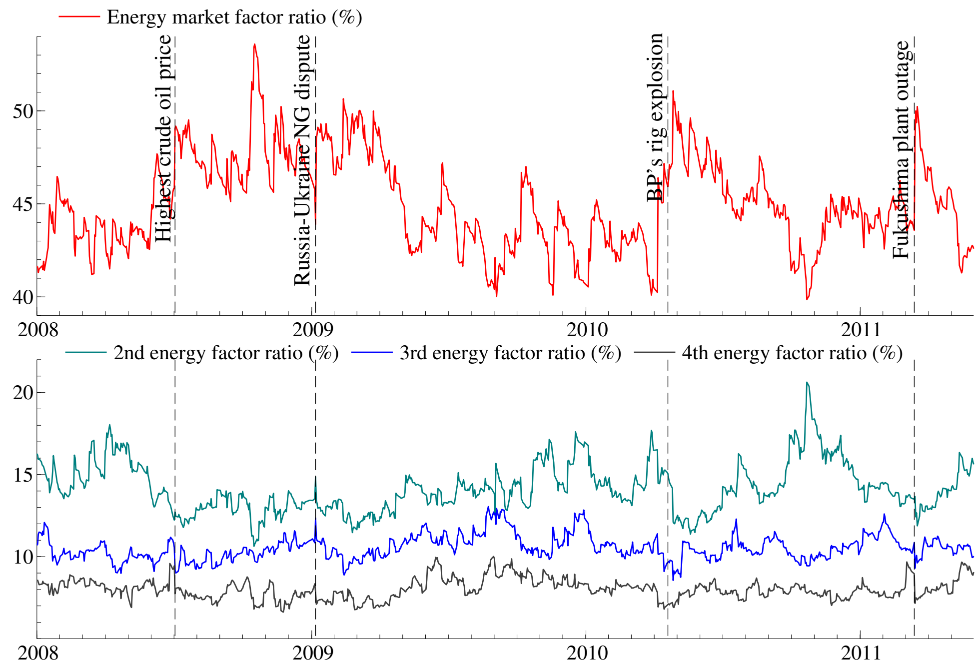

Figure 1: Percentage of variance (eigenvalue ratio) explained by energy factors: $\lambda_{jt}/\sum_{j=1}^{n}\lambda_{jt}$ for $j = 2, 3, 4, 5$.

Winter 2009 was characterized by an extended period of cold weather, the spreading out of the effects of the financial crisis 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. 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.[10]

Market integration also increased in April 2010 and coincides with an increase in prices

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

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and volatilities of all EEX futures. Market integration increased further at the end of April following the explosion of BP's offshore oil-drilling platform, Deepwater Horizon, in the Gulf of Mexico on April 20, 2010. This event mostly affected natural gas futures; BP's oil spill indicated the possibility of tighter European regulation of shale gas drilling projects leading to project delays and the consequent weakening of the natural gas industry.[11] Gaspool returns surged on April 26, corresponding to the first trading day after April 23 where the complete information about BP's oil leak had been transmitted to energy markets (Jin et al. (2012)).

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, 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.

5.5 The conditional MES of EEX futures

We turn to the estimation of the conditional MES of EEX futures. For its estimation, the conditional MES is decomposed in mean, variance and tail expectation components. The estimated conditional means μ_{it} and conditional variances σ_{it}^2 incorporate the causal relationships identified in Subsections 5.2 and 5.3. Tail expectations of eq. (14) include the first five principal components ($s = 5$) so that 86% of the unconditional variance of u_t is explained by common risk factors. The tail expectations are estimated with the nonparametric estimator of eq. (15) where the bandwidth is set to correspond to a six-month time window ($h = 0.132$).

In-sample fit of the conditional MES is measured with the root mean square error (RMSE) on the subsample of observations satisfying the condition $y_{EnMt} > C \ and \ y_{Mt} < D$.[12] There

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

[12] For ease of notation, C (resp. D) replaces $\tilde{C}$ (resp. $\tilde{D}$) of Section 4.

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are 19 observations satisfying the systemic condition where C is the sample VaR at 95% of the energy market factor ($C = 4.169$) and D is the sample median of the non-energy factor ($D = 0.042$). The cross-sectional average RMSE for the 14 variables is 1.656 and only increases to 1.669 when the idiosyncratic component is ignored in (14). The conditional MES is therefore estimated assuming no idiosyncratic terms. Table 2 shows relatively low average RMSE for different values of C and D.

Quantiles	C(.5) D(.75)	C(.5) D(.5)	C(.75) D(.5)	C(.95) D(.75)	C(.95) D(.5)
# obs.	348	219	98	31	19
Average RMSE (%)	1.458	1.396	1.471	1.627	1.669

Table 2: In-sample fit of the conditional MES. Average RMSE (in percentage) = $\frac{1}{n}\sum_{i=1}^{n}\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(MES_{it}(C,D) - [r_{it} * I(y_{EnMt} > C, y_{Mt} < D)]\right)^2}$, where $T = 988$, $n = 14$. Quantiles: C(α) (resp. D(α)) is the (1-α) quantile of the sample distribution of the energy market factor (resp. non-energy factor). # obs. = $\sum_{t=1}^{T} I(y_{EnMt} > C, y_{Mt} < D)$.

The cross-sectional average of the conditional MES of electricity, natural gas and coal futures is shown in Figure 2 (left part). The MES increases for all EEX futures after the financial crisis due to high volatility of energy markets when oil prices started to plummet. Most futures reach record MES levels in winter 2008-2009 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 in April 2010 had an impact on the MES of all futures and this impact seems to be slightly more important for natural gas futures. The German political reaction following Fukushima events had a major impact on short-term electricity futures. 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.

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5.6 Measuring systemic risk of the EEX market

In a final step, the estimated conditional MES is used to derive energy systemic risk measures associated to the EEX market. EnSysRISK represents the total cost in million Euros of each energy commodity to the German non-energy sector during a potential energy crisis. The EnSysRISK measure defined in (2) is a conditional measure and evolves dynamically based on past information about quantities and prices.

The quantity exposure is approximated by the final consumption due to the lack of reliable data on energy stocks. The assumption of the absence of stocks available to the non-energy sector will therefore produce conservative estimates for storable energy commodities. The expected final consumption is the daily average final consumption of the last month and it is assumed that the energy products presented in Table 1 are the only energy products available to the non-energy sector.[13]

The total EnSysRISK of EEX futures on electricity, natural gas and coal are illustrated in Figure 2 (right part). The systemic risk of electricity futures is higher due to their higher prices per MWh compared to other energy futures. Coal has the lowest systemic risk according to this measure as final consumption and prices are lower. All energy products seem to be characterized by an increasing trend of systemic risk as energy 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. There is a peak in the systemic risk 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.

Next to EnSysRISK, we estimate the ΔMES of the non-energy factor defined in (4).

[13] Monthly energy consumption data are downloaded from Eurostat (natural gas, coal, crude oil) and Entso-e (electricity), and converted in the adequate quantity units (corresponding to the price definitions) using the conversion factors of the BP Statistical Review (2011).

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This measure is the difference in non-energy returns between energy crisis times and normal times and represents the net impact of energy crises on the economy. As the non-energy factor is restricted to the DAX industrial returns, a negative ΔMES is associated to a decline in industrial productivity. The ΔMES of the DAX industrial index is illustrated in Figure 3. The ΔMES is negative as expected but is relatively small, suggesting that energy market events identified earlier had little impact on the productivity of the companies in the DAX industrial index.

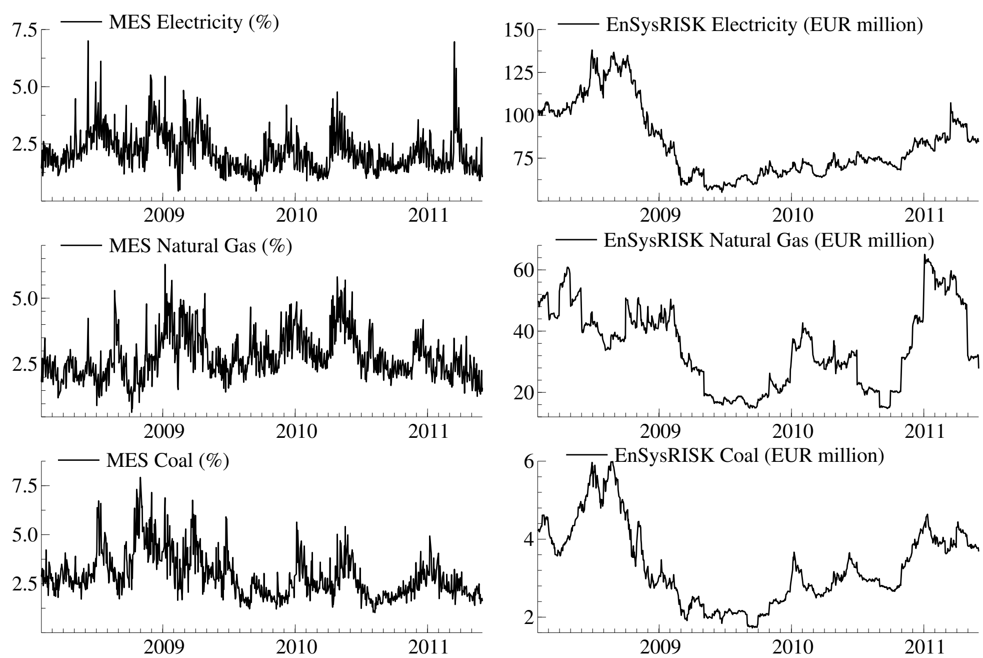

Figure 2: The average conditional MES in percentage (left) and the total EnSysRISK in million Euros (right) of EEX futures on electricity, natural gas and coal.

Extreme energy returns seem to be more harmful when the economy is weak, i.e. during the toughest period of the financial crisis between September 2008 and January 2009. An abrupt change of ΔMES also appears in March 2008 when adverse news on financial markets (Federal Reserve emergency loan, Bear Stearns sale) combined with soaring crude oil prices indicated the worsening of the credit crisis and the possibility of an economic recession.

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ΔMES has a correlation of -0.58 with the monthly crude oil final consumption in Germany, meaning that the negative impact of an energy crisis increases with oil dependence. The correlation with the energy market variance (λ_{EnMt}) is less important (-0.34) but also indicate a larger negative impact when energy markets are more volatile.

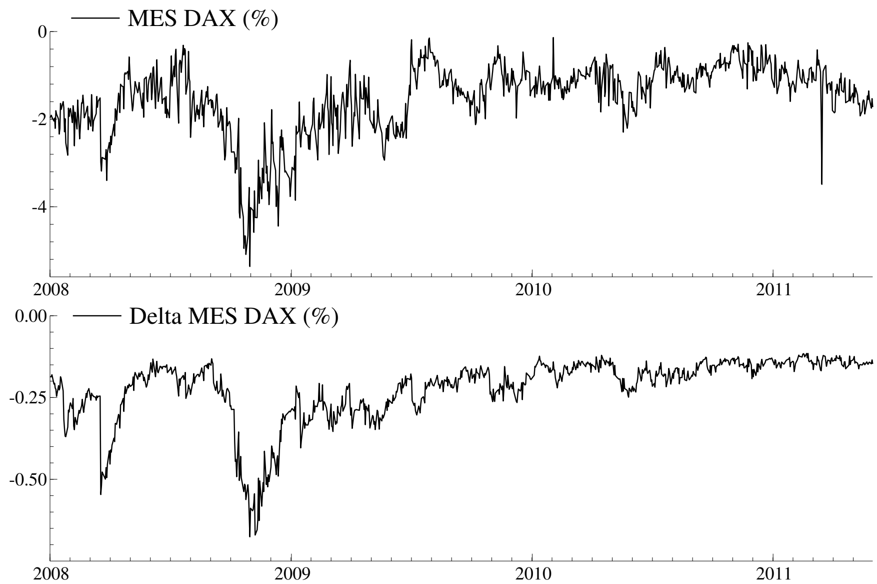

Figure 3: MES and ΔMES of the DAX industrial index.

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. The energy systemic risk measure (EnSysRISK) represents the total cost of an energy product to the non-energy sector during an energy crisis. It is complemented by a measure of the net impact (ΔMES) of an energy crisis on the rest of the economy.

EnSysRISK and ΔMES are derived from the Marginal Expected Shortfall (MES) conditional on an energy crisis. The energy crisis is defined by an extreme positive energy market shock that is unconnected to business cycles; we are therefore measuring the upper-tail dependence between the asset and the energy market factor when the rest of the economy is slowing down.

The MES is decomposed in mean, variance and tail expectation components. Causal relationships in the conditional means and variances capture the interdependence between energy returns from market fundamentals and spillover effects present in all states of the world. Contrastingly, contagion (or market integration) refers to an increase in correlations due to the presence of common factors. Common latent factors in the energy market are extracted from time-varying correlation matrices estimated with the DCC model of Engle (2002). Tail expectations, conditional on an energy crisis, have a dynamic exposure to the common energy factors with this model.

The methodology is applied to the European Energy Exchange (EEX) where several energy market events are shown to contribute to market integration (2007-2008 oil shock, Russia-Ukraine gas dispute, BP's oil leak, Fukushima power plant outage). We derive the EnSysRISK of EEX futures from the conditional MES and final consumption data, and find that energy crises would impose increasing costs to the economy. However, the $\triangle MES$ of the DAX industrial index shows little impact of energy market events on industrial returns, suggesting a rather small decline in industrial productivity due to the energy shocks of the sample.

This analysis of systemic risk in the energy market is a first attempt to understand how systemic risk may be present in such markets. Further research opportunities are left open. Forecasting the MES is probably the most important. One-day ahead forecasts are straightforward to obtain from this methodology. Long-run forecasts are also possible to obtain from a simulation procedure as described in Brownlees and Engle (2011). The long-term of the energy sector is however subject to technology and regulatory changes that are difficult to incorporate into a forecasting exercise. Other dimensions for contagion in energy markets are also to explore; the most important one being the horizontal (regional) integration of energy markets.

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Appendix

Table 3: Sample correlation matrix of returns. Sample period: 07.03.2007 - 06.01.2011 (989 observations)

MPhelix	1													
QPhelix	0.79	1												
YPhelix	0.53	0.79	1											
MGaspool	0.37	0.40	0.37	1										
QGaspool	0.39	0.47	0.48	0.81	1									
YGaspool	0.36	0.53	0.63	0.63	0.78	1								
MARA	0.31	0.48	0.63	0.31	0.37	0.47	1							
QARA	0.33	0.52	0.66	0.33	0.40	0.51	0.94	1						
YARA	0.31	0.51	0.67	0.32	0.40	0.54	0.88	0.93	1					
YEUA	0.27	0.42	0.57	0.23	0.30	0.37	0.27	0.29	0.30	1				
EUA spot	0.26	0.39	0.52	0.20	0.28	0.34	0.25	0.27	0.28	0.93	1			
Brent	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	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 4: Estimated cointegration vectors (η). Sample period: 07.03.2007 - 06.01.2011 (989 observations)

	η_1	η_2	η_3	η_4	η_5	η_6	η_7	η_8	η_9
MPhelix	1								
QPhelix		1							
YPhelix			6.640	5.097	2.979	2.503	-0.342	1.734	5.358
MGaspool			1						
QGaspool				1					
YGaspool	4.588	3.493							-1.799
MARA					1				
QARA						1			
YARA	-12.668	-4.583	-6.121	-6.681	-6.818	-5.380	0.546	-5.049	
YEUA		-2.091	-2.682	-2.057	-0.292	-0.426	-0.976		-2.106
EUA spot							1		
Brent	6.824		2.997	3.945	4.911	3.620	-0.513	3.551	
Coal spot								1	
DAX industrial									1

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Table 5: Parameter estimates of the augmented Vector Error Correction Model model (eq. (6)). Sample period: 07.04.2007 - 06.01.2011 (988 observations)

		Coefficient	HACSE	t-value
MPhelix	Cst	12.694	4.669	2.72
	Wednesday (φ)	0.235	0.087	2.71
	QPhelix$_{t-1}$ (δ_1)	0.125	0.042	2.97
	MGaspool$_{t-1}$ (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
QPhelix	Cst	7.485	2.956	2.53
	QPhelix$_{t-1}$ (δ_1)	0.096	0.029	3.29
	QGaspool$_{t-1}$ (δ_1)	0.032	0.011	2.79
	Coal spot$_{t-1}$ (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
YPhelix	Cst	10.802	2.622	4.12
	Coal spot$_{t-1}$ (δ_1)	0.061	0.015	4.16
	EUA spot$_{t-1}$ (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
MGaspool	Cst	14.673	3.993	3.67
	QGaspool$_{t-1}$ (δ_1)	0.166	0.029	5.83
	MA(YARA 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
QGaspool	Cst	-3.325	3.393	-0.98
	MGaspool$_{t-1}$ (δ_1)	0.088	0.015	6.05
	QARA$_{t-3}$ (δ_3)	-0.063	0.016	-3.92
	Brent$_{t-5}$ (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
YGaspool	Cst	0.994	0.348	2.86
	YPhelix$_{t-1}$ (δ_1)	0.080	0.033	2.42
	Coal spot$_{t-1}$ (δ_1)	0.048	0.022	2.22
	Brent$_{t-1}$ (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
MARA	Cst	10.084	2.196	4.59

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		Coefficient	HACSE	t-value
MARA	YARA_{t-1} (δ_1)	-0.165	0.052	-3.17
	Coal spot_{t-1} (δ_1)	0.378	0.058	6.52
	$\eta_3' \text{y}_{t-1}$ (π)	-0.332	0.095	-3.51
	$\eta_7' \text{y}_{t-1}$ (π)	-2.871	0.766	-3.75
	$\eta_9' \text{y}_{t-1}$ (π)	-0.269	0.092	-2.94
QARA	Cst	1.250	0.469	2.67
	YARA_{t-1} (δ_1)	-0.189	0.043	-4.41
	Coal spot_{t-1} (δ_1)	0.393	0.050	7.87
	Brent_{t-1} (δ_1)	-0.026	0.008	-3.42
	$\eta_5' \text{y}_{t-1}$ (π)	5.729	0.884	6.45
	$\eta_6' \text{y}_{t-1}$ (π)	-7.674	1.203	-6.38
YARA	Cst	-0.458	0.340	-1.35
	YARA_{t-1} (δ_1)	-0.132	0.050	-2.63
	Coal spot_{t-1} (δ_1)	0.269	0.052	5.21
	$\eta_4' \text{y}_{t-1}$ (π)	-0.429	0.104	-4.11
	$\eta_8' \text{y}_{t-1}$ (π)	0.539	0.117	4.60
YEUA	Cst	-8.357	2.541	-3.29
	Brent_{t-1} (δ_1)	-0.136	0.031	-4.34
	EUA spot_{t-1} (δ_1)	0.622	0.041	15.1
	YEUA_{t-1} (δ_1)	-0.449	0.054	-8.32
	$\eta_7' \text{y}_{t-1}$ (π)	5.193	1.605	3.24
	$\eta_8' \text{y}_{t-1}$ (π)	0.752	0.225	3.34
EUA spot	Cst	-0.002	0.068	-0.032
	YEUA_{t-1} (δ_1)	0.144	0.0410	3.57
	Brent_{t-1} (δ_1)	-0.132	0.031	-4.23
	YEUA_{t-2} (δ_2)	0.388	0.045	8.59
	YEUA_{t-3} (δ_3)	0.207	0.038	5.44
	EUA spot_{t-2} (δ_2)	-0.397	0.049	-8.18
	EUA spot_{t-3} (δ_3)	-0.208	0.037	-5.68
Brent	Cst	6.124	1.610	3.80
	$\eta_3' \text{y}_{t-1}$ (π)	-0.786	0.206	-3.82
Coal spot	Cst	20.909	6.072	3.44
	Coal spot_{t-1} (δ_1)	-0.124	0.043	-2.89
	Coal spot_{t-2} (δ_2)	-0.193	0.034	-5.65
	Brent_{t-1} (δ_1)	-0.054	0.013	-4.08
	QARA_{t-1} (δ_1)	0.321	0.036	9.01
	QARA_{t-2} (δ_2)	0.181	0.032	5.68
	$\text{Electricity daily demand}_{t-1}$ (θ_1)	-1.224	0.402	-3.04
	$\eta_5' \text{y}_{t-1}$ (π)	10.764	1.899	5.67
	$\eta_6' \text{y}_{t-1}$ (π)	-9.155	1.724	-5.31
	$\eta_8' \text{y}_{t-1}$ (π)	-5.329	1.365	-3.90

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		Coefficient	HACSE	t-value
DAX industrial	Cst	48.802	8.972	5.44
	QPhelix$_{t-1}$ (δ_1)	-0.140	0.051	-2.75
	$\eta_1' \mathrm{y}_{t-1}$ (π)	-2.581	0.559	-4.62
	$\eta_2' \mathrm{y}_{t-1}$ (π)	1.632	0.486	3.36
	$\eta_5' \mathrm{y}_{t-1}$ (π)	12.2098	3.048	4.01
	$\eta_8' \mathrm{y}_{t-1}$ (π)	-11.238	3.590	-3.13
	$\eta_9' \mathrm{y}_{t-1}$ (π)	-4.065	0.703	-5.78

Table 6: Parameter estimates of the multiplicative Causality GARCH model (eq. (7)). Sample period: 07.04.2007 - 06.01.2011 (988 observations)

		Coefficient	Std. error	t-value
MPhelix	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
	YEUA (α)	0.283	0.059	4.774
	YPhelix (ϑ)	0.156	0.044	3.564
QPhelix	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
	YEUA (α)	0.270	0.066	4.062
	MPhelix (α)	0.152	0.070	2.178
	YPhelix (ϑ)	0.156	0.045	3.490
YPhelix	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
	YEUA (ϑ)	0.209	0.041	5.150
MGaspool	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
	MARA (ϑ)	0.169	0.045	3.715
	YEUA (α)	0.169	0.072	2.339

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		Coefficient	Std. error	t-value
QGaspool	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 (ϑ)	0.123	0.044	2.814
YGaspool	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 (ϑ)	0.152	0.042	3.588
MARA	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 (ϑ)	0.140	0.044	3.215
QARA	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
	MARA (ϑ)	0.146	0.043	3.426
YARA	Cst (c)	2.148	0.486	4.424
	ARCH (α)	0.088	0.020	4.415
	GARCH (β)	0.893	0.025	36.374
	MPhelix (α)	0.159	0.065	2.439
YEUA	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
	YARA (ϑ)	0.151	0.042	3.582
EUA spot	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	Cst (c)	3.988	0.762	5.236
	ARCH (α)	0.042	0.009	4.782
	GARCH (β)	0.947	0.011	85.526

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		Coefficient	Std. error	t-value
Coal spot	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	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
	YGaspool (ϑ)	0.134	0.047	2.869

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