Volatility Spillovers in Energy Markets

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Abstract

We investigate the extent and evolution of the links between energy markets using a broad data set consisting of a total of 17 series of prices for commodities such as electricity, natural gas, coal, oil and carbon. The results shed light on a number of relevant issues such as the volatility spillover effect in energy markets (within and across sectors) and the identification of those markets that are exporters (importers) of volatility to (from) other markets, as well as evidence of the time-varying nature of these effects. The main conclusions are: (i) the most integrated European electricity markets appear to be those of Germany, France and the Netherlands; (ii) the Dutch Title Transfer Facility might be on the way to becoming the benchmark price for natural gas in Europe, and (iii) natural gas may be replacing crude oil as the global benchmark price for energy commodities.

JEL Code: G14, C10, C32, L97

Keywords: Spillover effect, market integration, international benchmark, forecast error variance decomposition.

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1. INTRODUCTION

Electricity is considered to be a strategic asset because of its extensive use by virtually all sectors in modern economies. Apart from renewable generation sources, which are progressively more and more present in the supply mix of electricity markets across the world, the most important fuels used to generate power are natural gas, oil and coal. These three are generally competitors in the production of electricity, while all four commodities are substitutes for each other in consumption, which may lead to their prices being somewhat linked. Additionally, since 2005, power generators and energy intensive industries from signatory countries to the Kyoto Protocol receive European Union Emission Allowances (EUA) that can be traded. They must report annually on their greenhouse gas emissions and surrender the corresponding number of EUA. Installations cannot exceed their maximum number of emission allowances. In December 2015, 145 countries adopted the Paris Agreement, which entered into force shortly thereafter, on November 2016. The Paris Agreement has reconfirmed the role of emissions trading schemes as an instrument for achieving global climate change goals. According to the United States Environmental Protection Agency (EPA), allowances are fully marketable commodities, since once allocated they may be bought, sold, traded or banked for use in future years.[1] Therefore, it makes sense to extend the study to the interactions between

[1] From the EPA website: https://www.epa.gov/airmarkets/clean-air-markets-allowance-markets (last accessed: 2017, June).

energy and carbon markets, by analyzing potential volatility transmission between them.

The main purpose of our paper is to assess the extent and evolution of the links between energy markets. Specifically, we are interested in answering the following questions: (1) What is the total volatility spillover effect in energy markets? (2) What is the evolving nature of volatility spillovers? (3) Which markets are exporters (importers) of volatility to (from) other markets? (4) Are volatility spillovers higher within or across energy sectors? (5) Is there evidence of increasing European energy markets' integration over time?

King and Wadhwani (1990) present volatility spillovers as a consequence of rational agents trying to infer relevant information from price changes across different markets. In the same line, Strohsal and Weber (2015) state that volatility spillovers across assets may indicate the spread of valuable information among fundamentally linked markets. The information content of price movements is not observable, but it might be deducted from observed price changes in one of the assets if they are interpreted as informative enough by traders of the other related assets. In fact, volatility would be zero in absence of relevant news, but price adjustments in an asset provoked by the arrival of new information will increase its volatility. Thus, the volatility spillover effect refers to the impact that events in one market may have on the volatility of other markets, being the information flow connected to volatility whenever observed price changes are used to infer valuable information from price changes in the related market.[2] This research issue is closely related to price discovery, since knowing the direction in which information flows between markets, one can anticipate price movements in relatively less liquid assets that incorporate information less rapidly than others to which they are shown to be linked. It can also be considered the existence of volatility spillovers as an evidence of whether markets within and across regions are integrated, as stated in Bekaert et al. (2005). An integrated electricity market for the whole European Union is a long-term goal of the European authorities. Some voices claim there is significant progress being made in the integration of European energy markets, which is actually hard to assess. The more integrated markets are, the higher the volatility transmission between them. This work is not limited solely to electricity markets but extends the analysis to other energy prices such as natural gas, CO2 emission allowances, crude oil and coal to evaluate the current state of integration between European energy markets, as well as to investigate their relationships with other non-European markets

The linkages across and within energy markets have been widely studied in the literature. Most of the studies focus on analyzing market integration and price relationships and some other papers look at volatility spillovers.[3] Within the first

[2] Return spillover measures have also been calculated and the results are similar to those for volatility.
[3] A review of econometric methods used in the literature on the relationship between oil and stock market returns and volatility can be found in Degiannakis et al. (2018).

group, Granger causality, cointegration analysis and the Vector Error Correction (VEC) model proposed by Engle and Granger (1987) have been extensively used. Within the second group, multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are the most commonly employed econometric techniques. One drawback of these models is that the number of parameters often increases rapidly with the dimensions of the model, which limits their scope of application. Recently, some papers have applied the methodology proposed by Diebold and Yilmaz (2009, 2012 and 2014) to explore spillovers in commodity markets. This approach is based on forecast error variance decompositions in a vector autoregressive framework and does not suffer from the curse of dimensionality of multivariate GARCH models. For example, Chevallier and Ielpo (2013), explore volatility spillovers within commodities, between standard assets and commodities and between commodities and commodity currencies, in the U.S.. Zhang and Wang (2014) analyze spillovers between China and world oil markets. Baruník et al. (2015) analyze volatility spillovers across petroleum-based commodities, differentiating between spillovers due to negative and positive returns. Batten et al. (2015) analyze spillovers among the four main precious metals - gold, silver, platinum and palladium. Kang et al. (2017) examine spillover effects among six commodity futures markets – gold, silver, West Texas Intermediate crude oil, corn, wheat, and rice –. Finally, Diebold et al. (2018) measure commodities volatility connectedness using the framework of Demirer et al. (2018), which build on Diebold and Yilmaz (2014). They include in the analysis four energy commodities, two precious metals, four industrial metals, two livestock commodities, four grains, and three so-called “softs” (coffee, cotton, sugar).

In this paper, we also adopt the methodology proposed by Diebold and Yilmaz (2009 and 2012) to uncover the links between energy markets. This approach allows us to dynamically capture the extent of linkages as well as their direction. We use 17 series in our analysis, belonging to the electricity, natural gas, CO2, oil and coal sectors. Our main findings can be summarized as follows. Firstly, we find that own-sector volatility spillovers account for the highest share of forecast error variance. Furthermore, pairwise directional spillovers are higher within, than across, sectors and the highest pairwise spillovers are observed between crude oil series. Secondly, within sectors, the German electricity market is, in overall terms, the main transmitter of volatility spillovers. Over time, the German Netconnect Germany and the Dutch Title Transfer Facility arise as the two reference price series affecting the rest of the natural gas series. There is a change shown in the role of the crude oil series in the later years of the sample, with Brent having become a net receiver of volatility spillovers from West Texas Intermediate, since 2013. Regarding the coal series, the U.S. Central Appalachian and the European API2 index mutually impact upon one another without the former prevailing over the latter. Interestingly, the linkages between natural gas volatility and the rest of the commodity volatilities are shown to be the greatest. In particular, Title Transfer Facility may be on the way to becoming the benchmark price for natural gas in Europe, overtaking National Balance Point. Last but not least, according to our results, natural gas may be replacing crude oil as a global benchmark for energy commodities. Thirdly, regarding the level of integration between European electricity markets, the most integrated markets appear to be those of Germany, France and the Netherlands, distantly followed by Italy, Spain and the Nordic block. Interestingly, spillovers are shown to be time-varying and seem to increase with economic growth as well as during periods of turmoil.

The remainder of the paper is organized as follows. The next section summarizes the literature. Section 3 describes our data. Section 4 lays out the methodology we use to analyze volatility spillovers in European energy markets. Section 5 discusses the empirical results and finally, Section 6 concludes.

2. LITERATURE REVIEW

Interest in energy markets' dynamic relationships has been growing over recent years. The early research on the linkages across energy sectors used cointegration methods. For example, Emery and Liu (2002) analyze the relationship between electricity and natural gas futures prices in the New York Mercantile Exchange, California–Oregon Border and Palo Verde and find that electricity and natural gas futures prices are cointegrated. Interestingly, Asche et al. (2006) report that, in the UK, integration between the wholesale prices of crude oil, natural gas and electricity took place only during that period when the natural gas market had been deregulated but was not yet physically linked to the continental European natural gas market through the interconnector. In a related study, Mohammadi (2009) examines the long-run relations and short-run dynamics among electricity retail prices and fossil fuels (coal, natural gas and crude oil) in the U.S. market. He finds evidence of significant long-run relations only between electricity and coal prices and some evidence of unidirectional short-run causality from coal and natural gas prices to electricity prices.

Return and volatility spillovers have mainly been analyzed by means of Vector Autoregressive (VAR) and multivariate GARCH models. Ewing et al. (2002) examine the transmission of volatility between the oil and natural gas markets using two widely watched indexes, traded on AMEX, that represent the behavior of the stock prices of major companies in the oil and natural gas markets. Their findings indicate that there are significant volatility transmissions between both sectors and that these effects are asymmetric. Efimova and Serletis (2014) explore the interdependence of wholesale oil, natural gas, and electricity market prices and volatilities in the U.S.. The authors show that price spillovers are rather unidirectional, suggesting the existence of a hierarchy of influence, with oil above the gas and electricity markets. Serletis and Xu (2016) search for spillovers and interactions among oil, natural gas and coal in the U.S.. Their results show significant interactions among the three fuel returns, including spillovers from sudden return changes in one fuel to the return volatility of another fuel. Balcılar et al. (2016) examine the risk spillovers between energy futures prices and Europe-based carbon futures contracts and find significant volatility and time-varying risk transmission from energy markets to the carbon market. Finally, Reboredo (2014) examines the dynamics of volatility transmission between the EUA and oil markets using a range-based volatility measure. His findings suggest there are no significant volatility spillovers between these markets.

In the context of the relationships within energy sectors, the early papers also used cointegration techniques.[4] For example, Siliverstovs et al. (2005) suggest that until the beginning of 2004 transatlantic gas markets were not integrated. Using intraday data, Schultz and Swieringa (2013) analyze price discovery in the gas markets of the UK, Belgium and the Netherlands and demonstrate that UK natural gas futures make the greatest contribution to price equilibrium in the longer term. Bunn and Gianfreda (2010) find integration in both spot and forward power markets of France, Germany, Great Britain, the Netherlands and Spain, although, surprisingly, rather less in forward than in spot markets. Finally, De Menezes and Houllier (2016) adopt a time-varying fractional cointegration analysis and find increased convergence in all month-ahead markets, however, overall electricity spot prices are not increasingly converging.

[4] Some of the papers below also employ other techniques such as causality tests or principal component analysis.

Regarding volatility spillovers within energy sectors, Le Pen and Sévi (2010) find evidence of return and volatility spillovers between the German, Dutch and British forward electricity markets. Kao and Wan (2009) study market interactions in the U.S. and UK natural gas spot and forward markets and find asymmetric volatility spillovers in three of the four markets. Jin et al. (2012) analyze the volatility transmission effects among three crude oil markets and observe that Dubai and Brent crude are highly responsive to market shocks, while WTI crude is the least responsive of the three benchmarks.

Finally, fitting Markov Regime Switching models to six European electricity markets, Lindström and Regland (2012) conclude that integration was only partial in the period 2005-2010. In a similar vein, using Granger-causal networks, Castagneto-Gissey et al. (2014) explore time-varying interactions among 13 European electricity markets between 2007 and 2012, and find that a peak in connectivity concurred with the implementation of the Third Energy Package, but conclude that electricity market integration remains to be achieved.

3. DATA

We use daily data covering the period from November 2008 to June 2016 (1990 observations).[5] The data set was obtained from the Thomson Reuters database. As mentioned earlier, this work presents an extensive analysis covering

[5] The starting point of the data set coincides with the first available data for the electricity series of the Netherlands and the Nordic market.

electricity, natural gas, emission allowances, oil and coal forward markets, at an international level. Specifically, we use six electricity price series associated with the following market areas: Germany (GER), France (FR), the Netherlands (NETH), Italy (ITA), the Nordic countries (NORD) and Spain (SPA); six natural gas price series, in particular, National Balance Point (NBP) located in the UK, the Belgian Zeebrugge (ZEE) trading point in Belgium, the Dutch Title Transfer Facility (TTF), the German Netconnect Germany (NCG) and German GASPOOL (GASP), and the Henry Hub (HH) in the U.S.; the European Emission Allowances (EUA); two crude oil price series: West Texas Intermediate (WTI) and North Sea BFOE[6] (Brent) and finally, two coal price series: the API2 index for coal imported into northwest Europe and Central Appalachian (CAPP) for the eastern U.S.. For the analysis in this study, all the price series quoted in a currency other than euros have been converted into euros using the corresponding currency conversion from the Thomson Reuters database. Furthermore, natural gas prices are converted into euros per megawatt hour (MWh). Following APX group, a conversion factor of 29.3071 kilowatt hours (kWh) per therm is used to transform therms into MWh. Figures 1a-1e show the evolution of the 17 series, grouped by sector. Generally, the figures suggest strong comovements within sectors but there are also divergent patterns in particular markets.

[6] The BFOE basket includes Brent, Forties, Oseberg and Ekofisk.

Table 1 presents descriptive statistics for the corresponding return series, computed as the log-difference in daily prices.[7] The mean of each return series is negative. Note that coal return series are the least volatile, as indicated by the standard deviation. Among natural gas series, Henry Hub return series is the most volatile, while NordPool return series is the most volatile of those on electricity. The return series generally exhibit positive skewness, except for the cases of EUA and coal, indicating that there exists an asymmetric tail extending towards more positive values. According to the kurtosis values, most of the distributions are clearly leptokurtic, namely, more peaked than the normal distribution, with just two exceptions: NordPool electricity and Henry Hub natural gas returns. Thereby, the measures for skewness and kurtosis suggest a rejection of the normality hypothesis and the Jarque–Bera statistic confirms this result. Neither the returns follow a t-Student distribution with different degrees of freedom (2,10,20), according to the Kolmogorov-Smirnov test results reported in Table 2A. As a next step we construct the daily volatility series. We compute the daily variance as the natural log of squared returns.

[7] The results in Table 1A show that based on the Augmented Dickey and Fuller (1979) (ADF) test, the null hypothesis of a unit root cannot be rejected except for SPA and HHub series. The results based on the Phillips and Perron (1988) (PP) test show that the null hypothesis of a unit root cannot be rejected except for FRA, NETH, SPA, HHub and CAPP. Finally, the results based on the Kwiatkowski et al. (1992) (KPSS) test show that the null hypothesis of a stationary series is rejected in all cases. When the ADF, PP and KPSS tests are applied to the first difference of individual time series, the conclusion is that all the differenced series are stationary. Given these results, we treat all series as integrated of order one (I(1)) and decide to work with the corresponding return series, computed as the log-difference in daily prices.

Figure 1. Daily price series by sector

Figure 1a. Daily electricity price series

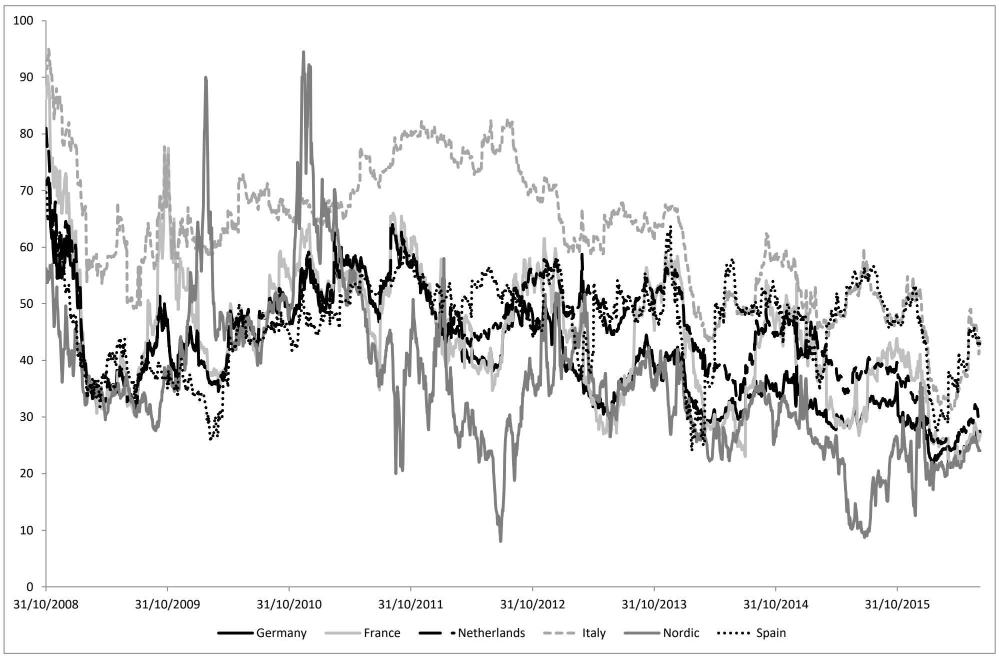


Figure 1b. Daily natural gas price series

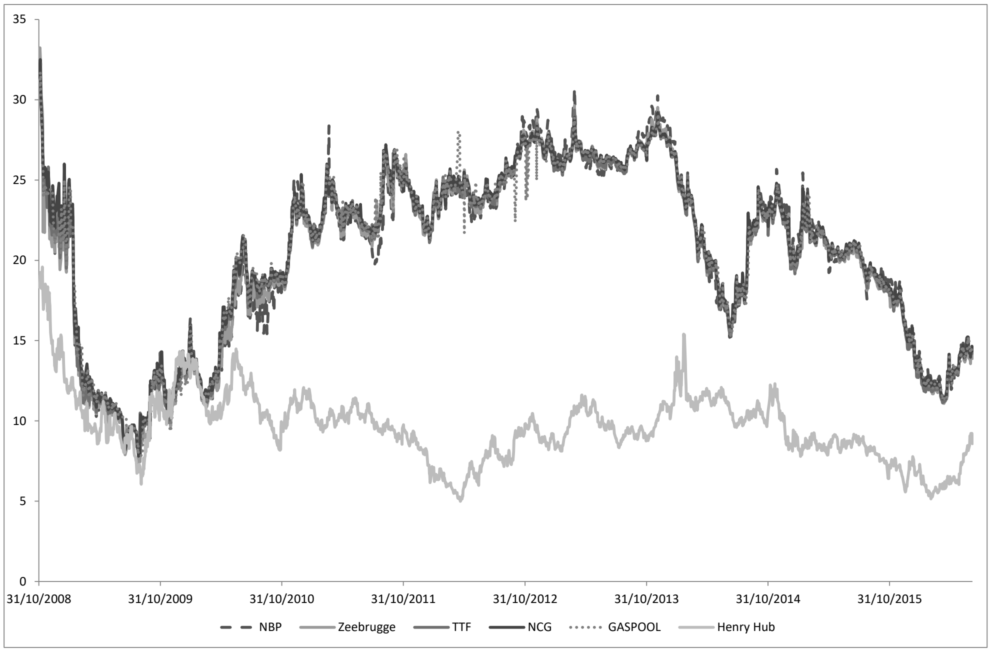


Figure 1c. EUA price series

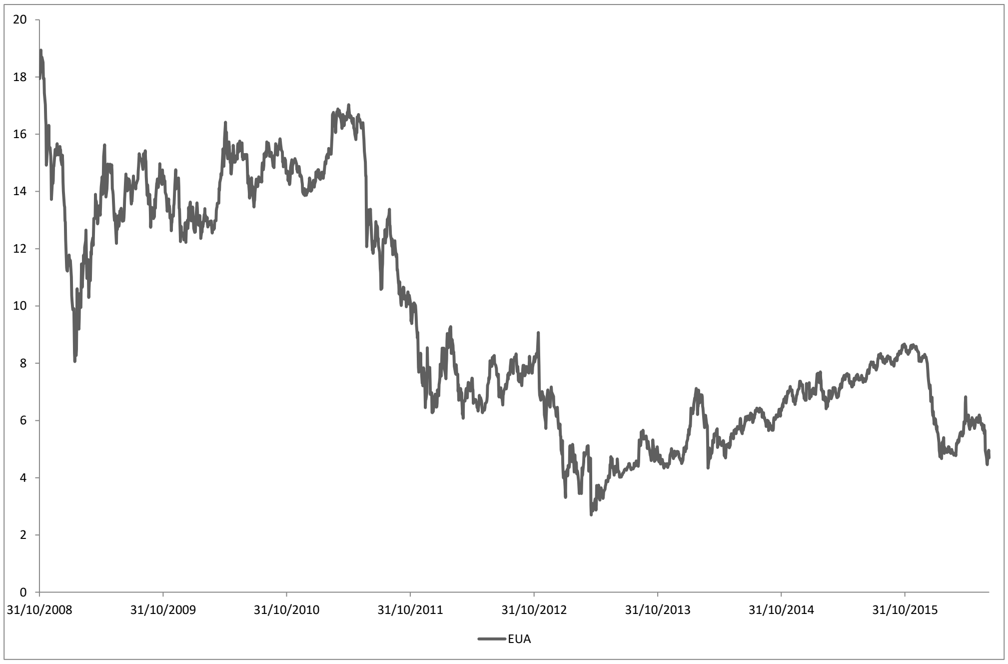


Figure 1d. Crude oil price series

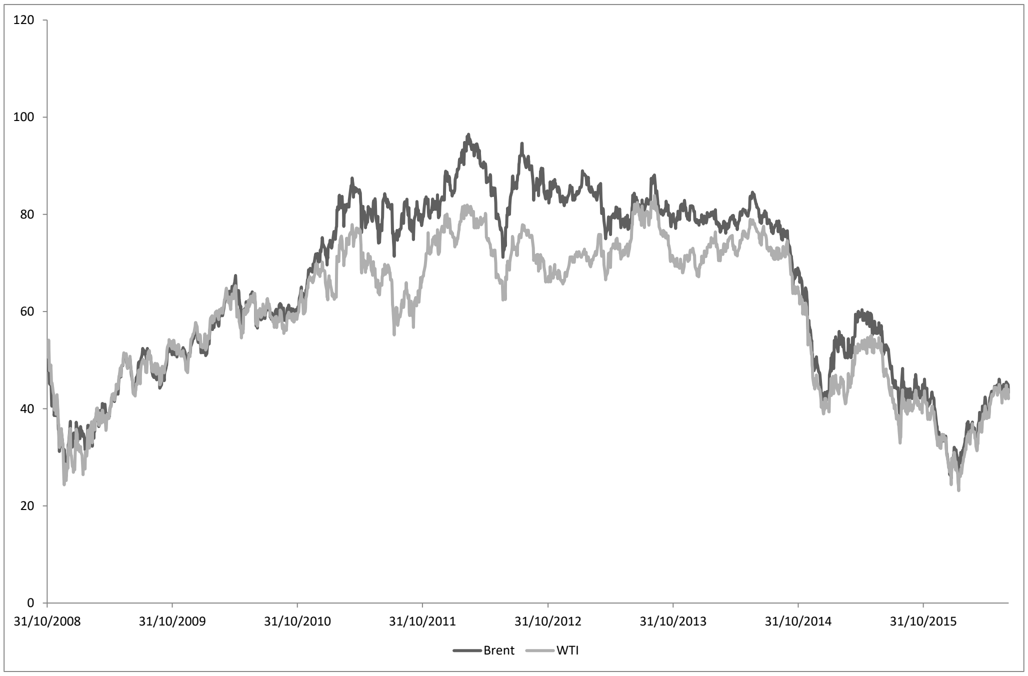


Figure 1e. Coal price series

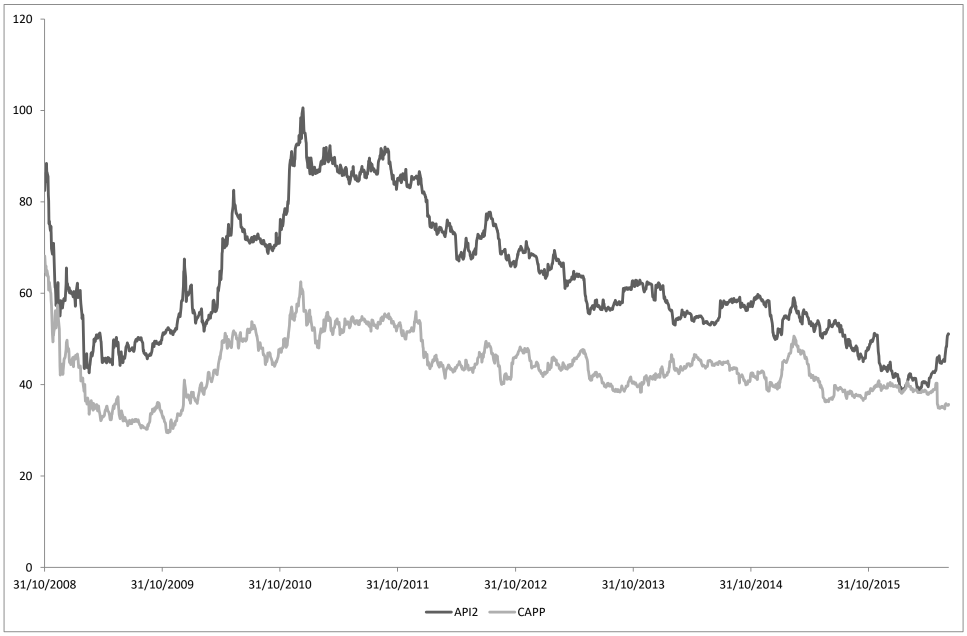


Table 1. Descriptive statistics for returns (%)

	Mean	Std. Dev	Min	Max	Skewness	Kurtosis	JB
GER	-0.06	2.06	-14.42	13.41	0.14	9.56	7608.20***
FRA	-0.09	2.62	-14.60	14.49	0.23	5.94	2953.24***
NETH	-0.05	1.89	-14.27	14.62	0.70	11.71	11559.85***
ITA	-0.02	1.71	-12.86	12.99	0.74	16.25	22124.66***
NOR	-0.15	3.77	-14.97	14.98	0.12	2.97	736.89***
SPA	-0.13	2.36	-14.45	14.87	0.18	7.98	5307.35***
NBP	-0.08	2.58	-13.70	14.85	0.17	5.94	2939.69***
ZEE	-0.05	2.43	-12.60	13.51	0.30	5.26	2334.53***
TTF	-0.05	2.19	-11.65	14.93	0.44	6.69	3786.33***
NCG	-0.07	2.12	-15.57	11.98	-0.10	5.47	2493.71***

GASP	-0.05	2.48	-14.69	14.79	-0.26	9.38	7339.38***
HHub	-0.07	3.01	-11.91	13.93	0.32	1.66	264.541***
EUA	-0.06	2.95	-12.87	13.41	-0.24	2.79	668.01***
Brent	-0.01	2.16	-10.61	13.35	0.06	4.05	1363.80***
WTI	-0.02	2.36	-13.98	13.99	0.07	4.64	1790.41***
API2	-0.01	1.34	-10.12	10.84	-0.21	10.66	9460.44***
CAPP	-0.03	1.38	-11.89	8.32	-0.69	9.05	6961.02***

Note: This table shows the descriptive statistics for returns. The number of observations is 1990. Std. Dev, Min, Max and JB refer to the standard deviation, minimum, maximum and the Jarque-Bera normality test statistic, respectively. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

4. METHODOLOGY

The analysis is based on the spillover index approach introduced by Diebold and Yilmaz (2009 and 2012), which builds on the seminal work on VAR models by Sims (1980) and the notion of variance decomposition. The starting point for the analysis is the following VAR(p):

$$y_t = \sum_{i=1}^{p} \Phi_i y_{i-1} + \varepsilon_t \tag{1}$$

where $y_t = (y_{1,t}, y_{2,t}, \ldots, y_{N,t})$ is a vector of endogenous variables, Φ_i is an *NxN* matrix of parameters to be estimated, and ε_t is a vector of independently and identically distributed disturbances with zero mean, and Σ covariance matrix. If the VAR model is covariance stationary, we can derive the moving average representation of model (1), which is given by:

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \qquad (2)$$

where $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + ... + \Phi_p A_{i-p}$, A_0 is the *NxN* identity matrix and $A_i = 0$ for *i<0*. A transformation of coefficients in the moving average representations can be used to identify variance decompositions. Variance decomposition allows us to decompose the h-step ahead forecast error variance into *own variance shares*, the fraction of the forecast error variance in forecasting y_i due to shocks to y_i , for i=1, 2, …, N, and cross variance shares, or spillovers, the fraction of the forecast error variance in forecasting y_i due to shocks to y_j for j=1, 2, …, N and $j \neq i$.

Diebold and Yilmaz (2009) proposed using Cholesky decomposition to decompose the variance. However, Cholesky decomposition is sensitive to ordering. Diebold and Yilmaz (2012) resolve this ordering problem by exploiting the generalized VAR framework of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998), in which variance decomposition is invariant to the ordering of the variables. Variable *j*'s contribution to *i*'s H-step ahead generalized forecast error variance decomposition is given by:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \qquad (3)$$

where Σ is the estimated variance matrix of the error vector ε, σ_{jj} is the (estimated) standard deviation of the error term for the variable *j*, and e_i is a selection vector with one as the *i*-th element and zeros otherwise. The summation of the own and cross-variable variance contributions shares does not sum to one, thus we normalize each entry of the variance decomposition matrix as:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \tag{4}$$

where $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$.

The normalize variance decomposition allows us to compute the following volatility spillover measures:

(1) The *total volatility spillover index,* which measures the contribution of spillovers of volatility shocks across all markets to the total forecast error variance:

$$S(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \ x\ 100 \tag{5}$$

(2) The *directional spillovers* received by market *i* from all other markets *j*:

$$S_{i\bullet}(H) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \ x\ 100 \tag{6}$$

(3) The *directional spillovers* transmitted by market *i* to all other markets *j* :

$$S_{\bullet i}(H)=\frac{\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ji}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ji}(H)}\,x\,100 \tag{7}$$

(4) The *net spillover*, namely the difference between the gross shocks transmitted to and those received from all other markets, which identifies whether a market is a receiver/transmitter of shocks from/to the rest of the examined markets. The net spillover index from market *i* to all other markets *j* is obtained by subtracting equation (6) from equation (7):

$$NS_i(H)=S_{\bullet i}(H)-S_{i\bullet}(H) \tag{8}$$

(5) The *net pairwise spillover* between markets *i* and *j*, which shows which market is a receiver/transmitter of shocks between two markets:

$$NS_{ij}(H)=\frac{\tilde{\theta}_{ji}(H)-\tilde{\theta}_{ij}(H)}{N}\,x\,100 \tag{9}$$

Overall, the approach by Diebold and Yilmaz (2009 and 2012) provides measures of the intensity of linkages across markets and allows the decomposition of spillover effects.

Spillover measures constructed upon forecasted variance decomposition statistics as the one proposed by Diebold and Yilmaz (2012) have been subject to criticism for example by Fengler and Gisler (2015). The reason is that traditional VAR representations assume marginal univariate volatilities in the data generating process and lack covariances. This in principle could be solved for example by estimating Multivariate GARCH models using LASSO techniques or other strategies for shrinkage and selection, in order to avoid the *curse of dimensionality* of MGARCH models. Nevertheless, if we estimated a MGARCH process instead of our VAR model fitted on volatilities, we would face either of two problems, which indeed would make this alternative unfeasible. On the one hand, if we decided to fit a MGARCH model to our series and then to break down the variance of the forecasted errors into their main components, we would face an important theoretical problem. Namely, after the LASSO reduction of the parameter space we would likely end up (given our huge parameter space) with a non-positive definitive variance-covariance matrix. In other words, our models of the marginal volatilities would not satisfy the basic non-negative constraints that are expected from univariate GARCH processes. On the other hand, if we did not rely on FEVD, but instead we used the MGARCH coefficients to perform our spillover analysis, LASSO would force many of the MGARCH parameters to be zero, making it impossible to analyse the interaction between several pairs of markets in our sample, and possibly it would exclude from the analysis many markets (for example those of power with small interactions with the rest of the system). We acknowledge that our strategy may be potentially underestimating the magnitude of the spillovers by lacking the covariance structure in the estimation process, which deserves to be studied in further research.

5. RESULTS

The spillover measures mentioned in the above section are calculated using a VAR(5) model, based on the Akaike Information Criterion (AIC), and a forecast horizon of ten steps.[8]

5.1. Full sample analysis

Table 2 reports the full sample cross market volatility spillovers. The diagonal elements represent the own-market spillovers while the off-diagonal elements measure the pairwise volatility directional spillovers. As can be observed, own-sector volatility spillovers account for the highest share of forecast error variance, as the diagonal elements receive higher values compared to the off-diagonal elements, and fluctuate between 92.1% for Nordpool electricity (NORD) and 45.3% for Title Transfer Facility natural gas (TTF). Nordpool electricity (NORD), Henry Hub natural gas (HH) and European Union Emission Allowances (EUA) are the most disconnected from the others, as shown by the high percentage of self-generated forecast error variance coming from each and the low contribution from/to others. These results are logical because, on the one hand, the Nordic markets, as opposed to the rest of electricity and natural gas markets considered in the electricity market and the Henry Hub natural gas trading point are non-European energy present study. For the electricity and

[8] This forecast horizon is commonly used in previous literature (see Diebold and Yilmaz (2009 and 2012)).

natural gas sectors, Figures 1a and 1b provide similar intuition. On the other hand, the link between EUA volatility and the rest of the commodities studied is not expected to be as strong as that between electricity and fossil oil volatilities.

Regarding pairwise directional spillovers (the off-diagonal elements) in general, these are higher within than across sectors. Interestingly, the highest observed pairwise spillovers (around 25%) are observed between crude oil series. Consistent with previous literature, this result supports the hypothesis that the two global crude oil markets are integrated (Bachmeier and Griffin, 2006; Bentzen, 2007 and Jin et al., 2012).

Due to the integration of global financial markets and the increasing trend in the use of commodities as investment assets, both eased by advanced technology, crude oil prices have captured the attention of many academics and practitioners. In a globalized context, they are considered to be key to explaining the levels of some related and other *a priori* seemingly unrelated assets, and even the levels of a number of macroeconomic variables. Therefore, crude oil prices have become a relevant variable to watch. The methodology employed in this work allows us to explore the relationships between each of these international reference price series for crude oil and the rest of the commodities involved in this study, in order to find out which one can be considered the benchmark, distinguishing by sector and even by market. Thus, according to the results displayed in Table 2, Brent would be the benchmark price for European electricity *(3.3% volatility spillovers from Brent versus 2.4% from WTI),* natural gas *(2.7% versus 2%),* coal

(2.4% versus 1.9%) and, to a lesser extent, emission allowances *(0.6% versus 0.4%)*. In contrast, WTI would be the benchmark crude oil price for the U.S. Henry Hub natural gas prices *(2.5% volatility spillovers from WTI versus 0.9% from Brent)* and U.S. CAPP coal prices *(3% versus 1.2%)*. These results are consistent with the fact that Brent refers to the crude oil extracted from the North Sea off the coast of the UK whereas WTI crude oil is extracted from the interior of the United States, mainly in Texas.

From the ‘‘contribution to others’’ row and the “contribution from others” column, it is observed that gross directional volatility spillovers are quite different. Four markets belonging to the gas sector (National Balance Point (NBP), Zeebrugge (ZEE), Title Transfer Facility (TTF) and Netconnec Germany (NCG)) are the biggest contributors and receivers of volatility spillovers, meaning that the linkages between natural gas volatilities and the rest of the commodity volatilities are the greatest. In particular, without leaving Table 2, we can observe the following: (i) NBP mainly contributes to TTF (14.4%) and ZEE (13.2%) natural gas volatility, the Netherlands (NETH) electricity volatility (3.8%) and API2 coal volatility (2%); (ii) ZEE mainly contributes to NBP (12.7%) and TTF (11.6%) natural gas volatility, NETH electricity volatility (3.4%) and API2 coal volatility (1.6%); (iii) TTF mainly contributes to NCG (16.7%) and NBP (15.0%) natural gas volatilities, NETH electricity volatility (4.4%) and API2 coal volatility (2.5%), and (iv) NCG mainly contributes to TTF

(15.9%) and NBP (10.7%) natural gas volatility, NETH electricity volatility (4.0%) and API2 coal volatility (2.4%).

Table 2. Full sample volatility spillovers

	Germ.	France	Nether.	Italy	Nordic	Spain	NBP	ZEE	TTF	NCG	GASP.	Henry H.	EUA	Brent	WTI	API2	CAPP	Contribution from others
Germany	61.7	12.1	8.9	2.9	1.0	1.1	2.6	1.4	1.9	1.6	0.5	0.3	1.0	0.8	0.6	1.1	0.5	38.3
France	12.0	66.6	7.7	2.2	0.8	1.5	1.7	0.9	2.1	1.3	0.6	0.3	0.8	0.5	0.3	0.3	0.4	33.4
Netherlands	9.3	8.5	57.8	2.6	0.5	1.1	3.8	3.4	4.4	4.0	1.1	0.6	0.8	0.4	0.5	0.3	0.9	42.2
Italy	4.5	3.9	3.7	74.5	0.3	2.0	2.6	1.3	1.6	1.8	0.3	0.4	0.4	1.2	0.7	0.5	0.3	25.5
Nordic	1.1	0.8	0.4	0.4	92.1	0.2	0.6	0.4	0.4	0.3	1.5	0.2	0.3	0.3	0.1	0.8	0.1	7.9
Spain	1.7	2.6	1.1	1.8	0.3	86.3	1.0	0.6	1.1	0.6	0.6	0.1	0.7	0.1	0.2	0.4	0.6	13.7
NBP	2.1	1.4	2.6	1.6	0.3	0.4	47.2	12.7	15.0	10.7	1.7	0.3	0.5	0.8	0.5	0.9	1.3	52.8
ZEE	1.0	0.8	2.3	1.0	0.3	0.3	13.2	52.0	13.0	10.6	2.0	0.3	0.4	0.5	0.3	0.7	1.1	48.0
TTF	1.0	1.8	2.1	1.3	0.2	0.3	14.4	11.6	45.3	15.9	2.7	0.3	0.7	0.5	0.4	0.6	0.9	54.7
NCG	1.0	1.1	2.6	1.0	0.1	0.4	11.1	9.9	16.7	50.6	2.0	0.3	0.5	0.8	0.4	0.9	0.6	49.4
GASPOOL	0.4	0.6	1.2	0.5	1.3	0.5	3.5	2.8	4.9	4.0	78.3	0.1	0.4	0.1	0.4	0.6	0.2	21.7
Henry Hub	0.3	0.3	0.3	0.5	0.2	0.4	0.4	0.3	0.7	0.5	0.3	87.6	0.5	0.9	2.5	0.7	3.7	12.4
EUA	0.9	0.8	0.6	0.3	1.2	1.1	0.9	0.9	1.5	0.9	0.7	0.5	87.5	0.6	0.4	0.8	0.4	12.5
Brent	0.5	0.4	0.3	1.2	0.5	0.1	1.1	0.5	0.5	0.9	0.2	1.1	0.4	63.9	25.9	1.4	1.1	36.1
WTI	0.4	0.1	0.1	0.6	0.1	0.3	0.5	0.3	0.4	0.6	0.5	2.1	0.3	24.1	66.3	1.1	2.3	33.7
API2	1.7	0.7	0.5	0.6	0.6	0.6	2.0	1.6	2.5	2.4	1.2	0.6	0.9	2.4	1.9	74.4	5.3	25.6
CAPP	0.1	0.4	0.2	0.1	0.2	0.1	0.4	0.9	1.0	0.9	0.3	3.6	0.3	1.2	3.0	4.1	83.1	16.9
Contribution to others	38.0	36.1	34.6	18.7	8.0	10.3	59.9	49.5	68.0	56.8	16.4	11.2	9.1	35.4	38.1	15.2	19.6	Total spillover = 30.9
Net contribution (to-from)	-0.3	2.7	-7.6	-6.8	0.1	-3.4	7.1	1.5	13.3	7.4	-5.3	-1.2	-3.4	-0.7	4.4	-10.4	2.7	

Note: Columns show the market that produces the shock and rows the market that receives the shock. The diagonal elements represent the own-market spillovers while the off-diagonal elements measure the pairwise volatility directional spillovers. The model was estimated using the generalized variance decomposition on a daily frequency and 10-day step ahead forecast. The lag length was set at 5, following the AIC criterion. Volatility series were calculated as the natural log of squared returns. The total spillover equals the grand off-diagonal column sum, relative to the grand column sum including diagonals.

The "*Net* contribution" row, which indicates whether a market is a net receiver or transmitter of volatility spillovers, shows that TTF is the main net transmitter, followed by NCG and NBP (all natural gas markets). However, most of the spillovers of these net contributors are in fact given to other markets belonging to the same sector. Thus, TTF is shown to be the main transmitter of volatility spillovers to the rest of European natural gas hubs involved in the study with the only exception of Zeebrugge (which receives slightly more volatility spillovers from NBP than from TTF) being the corresponding index values of 15, 16.7, 4.9 and 13, respectively for NBP, NCG GASPOOL and Zeebrugge. Additionally, TTF is the main transmitter to Henry Hub (0.7), too. These results confirm the idea that TTF is well on the way to becoming the benchmark price for natural gas in Europe, after having overtaken the long-established NBP market in trading volume. The volumes traded on the Dutch TTF surpassed those on the UK NBP already in 2014 and since then continued to gradually gain share in Europe. At the end of the third quarter of 2016, TTF is clearly ahead of the UK hub (EU, 2015; EU 2016a; EU 2016b).

On the other hand, the API2 coal price index appears to be the main net receiver of volatility spillovers – mostly from the other coal series considered in this study, namely the U.S. CAPP, and, at a certain distance, from the TTF and NCG natural gas prices series. Following API2 as the main volatility spillover net receiver, we find electricity prices from the Netherlands (NETH) and Italy (ITA), which are mainly affected by electricity prices from Germany (GER) and

France (FR). It makes sense that these markets become the main net receivers of volatility spillovers given the typically regional nature of coal and electricity markets, as opposed to natural gas or crude oil markets which are much more globalized.

According to the spillover effect results between the European electricity markets, the highest level of integration is shown to be among Germany, France and the Netherlands, followed distantly by Italy, Spain and, lastly, the Nordic market. These results can be explained by the fact that in 2008 the power spot markets for Germany[9], France and Switzerland merged, establishing a company (PEX SPOT SE) under European law, based in Paris, France, with a branch in Leipzig, Germany.

Finally, the total volatility spillover, appearing in the lower right corner of Table 2, indicates that on average, across our entire sample, 30.9 percent of volatility forecast error in all markets comes from spillovers; which gives an idea of the global integration level.

5.2. Rolling sample analysis

The static analysis provides a good characterization of the spillovers over the full sample period. However, it is not helpful for understanding how spillovers

[9] Germany and Austria formed one price zone.

change over time. In order to assess the time-varying nature of both total and directional spillovers, we estimate the VAR using a 200-day rolling window and 10 days as the predictive horizon for the underlying variance decomposition.[10]

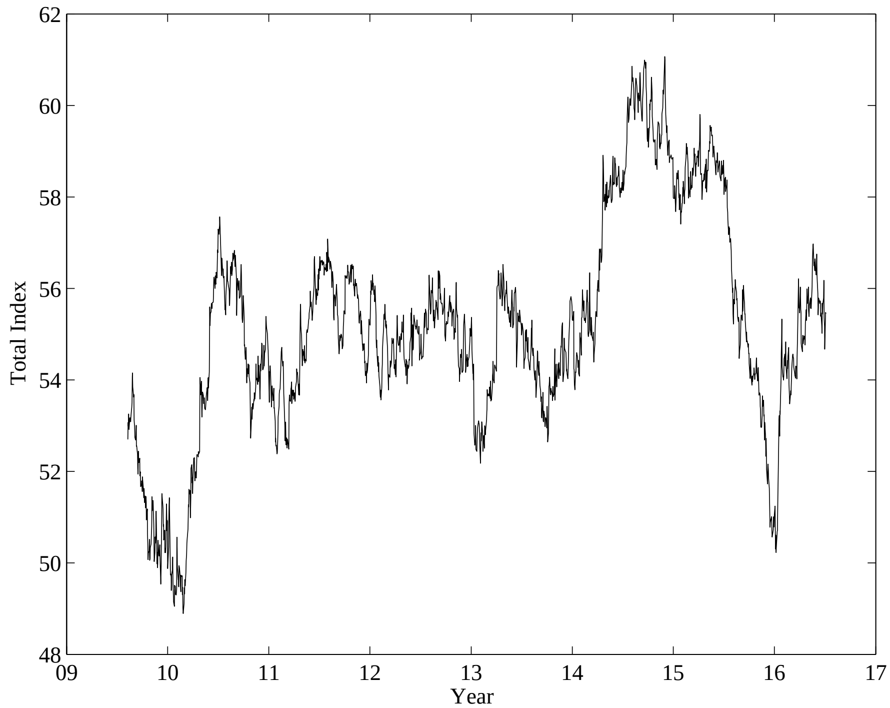
Figure 2 displays the time-varying total spillover index. The plot reveals a large variability in the index and quite a high level of volatility spillovers across energy markets, fluctuating mostly between 49% and 61%.[11] We observe some important jumps in volatility spillovers. To start with, volatility spillovers decrease from around 54% to 49% during the second half of 2009 and early 2010, coinciding with the reduction of electricity demand due to the global economic crisis. The crisis impact started during the last quarter of 2008 and increased in 2009, with a 4.2% drop in the EU27 GDP, which led to a 4.7% drop in European electricity consumption: the first reduction since 1982 (Lewiner, 2010). During economic growth periods, the demand for power generally increases, propelling electricity and fuel prices up together. In contrast, in a context of low economic growth, the links between types of fuel

[10] One alternative to using rolling windows for generating dynamics in our system, would have been to directly introduce the dynamics on the parameters of the system, for example within a Bayesian framework that considers a certain dynamic for the slope coefficients of the VAR representation. This would require, however, the selection of an a-priori distribution to shrinkage the parameter space of the Time-Varying VAR in the estimation process, due to the curse of dimensionality that would arise given our relatively large system (17 series).

[11] Notice that nothing prevents that the cross-spillover index remains below the total spillover statistic during the full period analyzed. The total spillover statistic comes from a VAR model fitted on the full sample, while the total spillover index consists of variance decomposition statistics extracted from VAR models fitted on subsamples. Naturally, the set of VAR models fitted on the subsamples fit the data better than the total sample VAR. For this reason the variance share of every series explained by others is larger in the dynamic exercise than in the static one. In the static case most of the explanation comes from the own variance share, and this means that the VAR model fits to a lesser extent compared to the subsample VARs. There is not contradiction in this finding.

weaken with power demand reduction. Aloui et al. (2014) provide evidence of an asymmetric dependence structure between crude oil and natural gas markets as they tend to comove during bullish periods but not during bearish periods. From 2010, when the worst of the global economic crisis appears to be over, spillovers increase towards almost 58% and stabilize in the 53-58% band until early 2014. The spillover index increases again during 2014 and early 2015, after which it declines sharply to around 50%. At the end of the sample, volatility spillovers are again around 55%. The notable increase of spillovers during 2014 and early 2015 coincides with the oil price drop, plummeting by about a third in June 2014 as U.S. shale oil and gas production increased and demand for oil from Europe and China decreased. Given that the commodities involved in this study are close substitutes for each other, it makes sense that in moments of turmoil, big shocks in one market affect other markets.

Figure 2. Rolling Total Volatility Spillover Index



Note: Daily total cross-spillover index. Window length equals 200 days.

We then analyze the net spillovers, defined as the difference between the directional spillovers of one series transmitted to and received from all the other series, over time (see Equation (8)). Figure 3 shows that many series frequently switch between a net transmitting and a net receiving role. Confirming previous results, Italian electricity, Spanish electricity, EUA, Brent and both coal series (API2 and CAPP) are net receivers whereas French electricity, TTF natural gas and NCG natural gas are net transmitters, on average. It is noteworthy that GASPOOL clearly changes its role from a net transmitter to a net receiver in 2014. The reason behind this is the difference in terms of liquidity, which encourages traders to choose to hedge their physical German positions at the Dutch hub. Liquidity attracts liquidity and it seems to have stagnated at the German GASPOOL since 2014, growing at a much lower rate than the rest of the gas trading hubs.

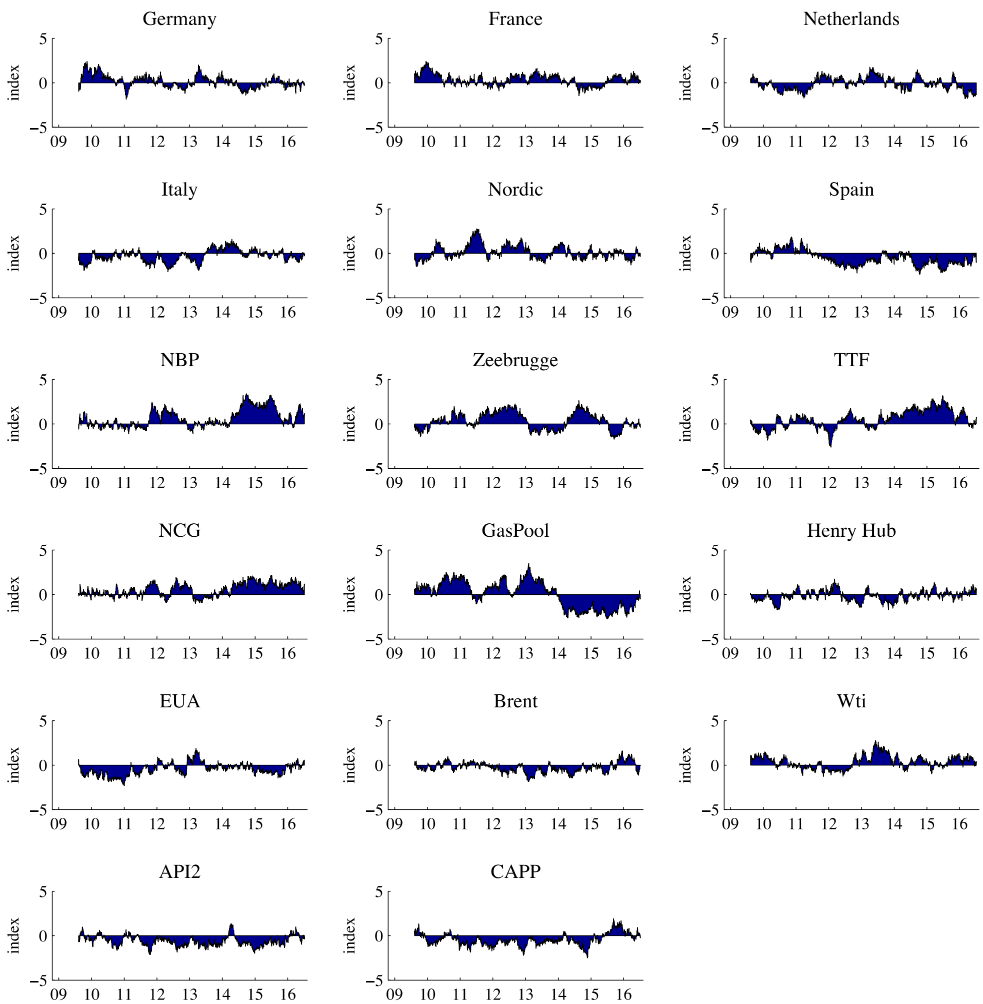
Figures 1A-1C in Appendix display net spillovers within sectors. Focusing on the power market, the German electricity market is, in overall terms, the one which seems to have most influence on the other European electricity markets, with the exception of the Nordic market. The markets with a mutual influence across the sample are shown to be Germany, the Netherlands and France, in line with their previously highlighted highest level of integration (Figure 1A).

So-called risk management natural gas hubs, which are those providing the opportunity to trade all along the forward curve, are more likely to become benchmark hubs, having an influence on the others. From Figure 1B, only the Dutch TTF and the UK NBP have clearly become net transmitters of spillovers within the gas sector, particularly since 2014. It is precisely these hubs that trade quarters, seasons and years forward contracts in any quantity, beyond the month-ahead forward contract, which is the most commonly negotiated.

Within the oil sector, Figure 1C shows a greater number of volatility spillovers from WTI to Brent than vice-versa, mainly occurring since 2013. Regarding the coal sector, as shown in the same Figure 1C, the European API2 and the U.S. CAPP have a mutual impact on each other, alternating the role of net volatility spillover transmitter, over time.

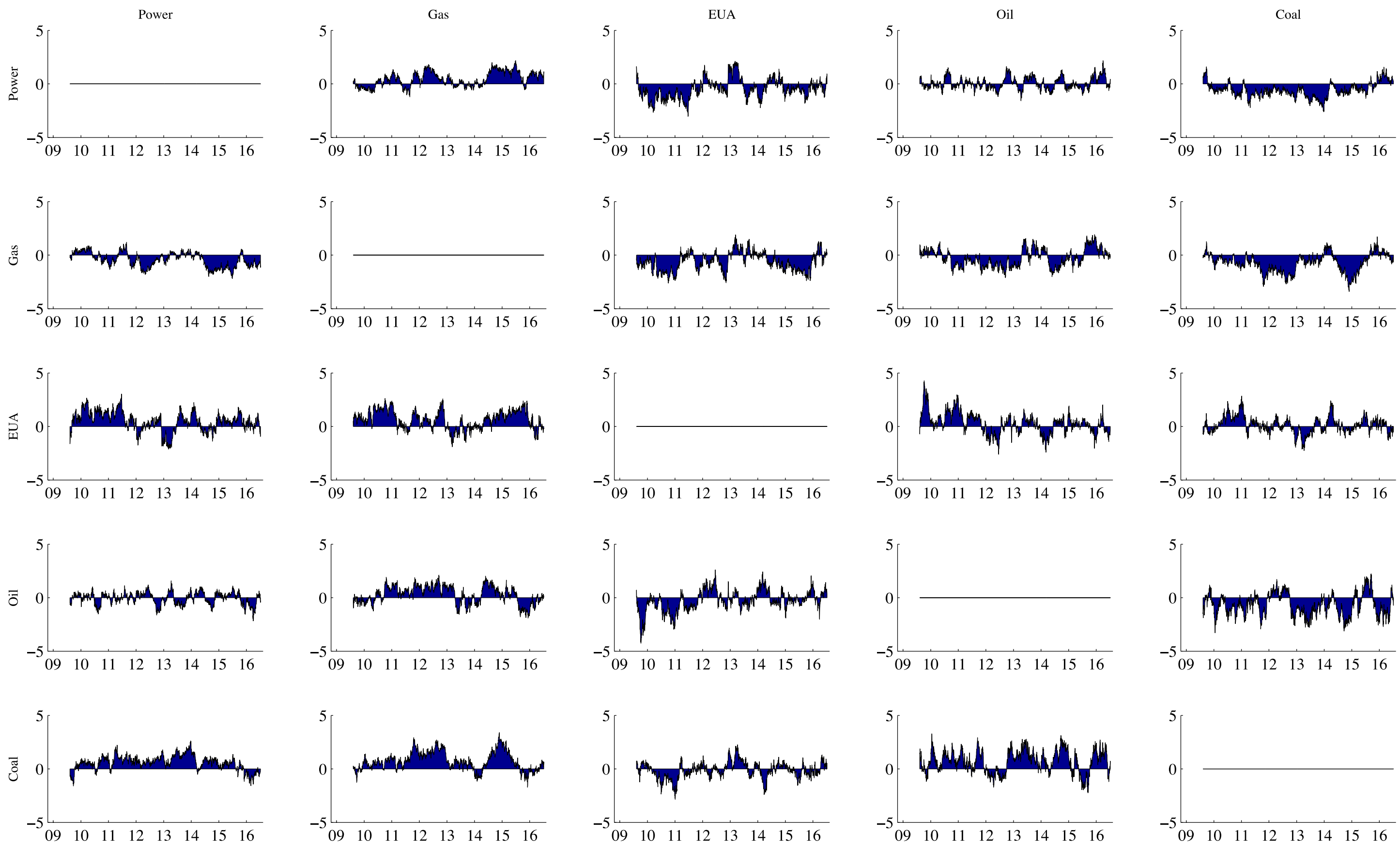
Finally, Figure 4 shows how the dynamic behavior, in net terms, evolves over time for each sector, i.e. tending towards transmitting (positive values) or receiving (negative values) volatility spillovers. There are four important observations one can make. Firstly, we see that positive net spillovers from coal are a rare occurrence. In fact, the coal sector is a net importer of volatility from other sectors for most of the sample period. Secondly, EUA switches between being a net receiver and a net transmitter, but, in general, it adopts a net receiving role. Thirdly, far larger net spillovers are transmitted by the gas sector than by the other sectors, followed by the power sector. Interestingly, the oil sector becomes primarily a net receiver from the gas sector and a net exporter to the EUA and coal sectors. Lastly, note the predominant role of natural gas markets in transmitting volatility spillovers to the others. The natural gas market, above all in the form of liquid natural gas, has grown considerably in recent years, which may explain how natural gas is becoming a global energy commodity, capable of affecting the price behavior of the rest of the power commodities.

Figure 3. Net volatility spillovers from the market *i* to the total



Note: Daily net dynamic spillovers from each market to the total. The time axis is presented in years. A positive number means that the market is a net transmitter of shocks in this period, while a negative number means it is a net receiver.

Figure 4. Net volatility spillovers between sectors



Note: Daily net dynamic spillovers between energy sectors. The time axis is presented in years. A positive number means that the market is a net transmitter of shocks in this period, while a negative number means it is a net receiver.

6. CONCLUSIONS

This study carries out an extensive analysis of the links between energy markets. In particular, it examines the extent and evolution of spillover effects between some major price references of electricity, natural gas, crude oil, coal and emission allowances, both across and within sectors. A total of 17 forward price series are used in the analysis, covering electricity (from Germany, the Netherlands, France, Italy, Spain and the Nordic market), natural gas (NBP from the UK, ZEE from Belgium, TTF from the Netherlands, NCG and GASPOOL from Germany and Henry Hub from the U.S.), crude oil (WTI from the U.S. and Brent from Europe), coal (API2 index from Europe and CAPP from the U.S.) and emission allowances (EUA from Europe), for the period from November 2008 to June 2016. The methodology employed allows us to embrace a joint comparison of all the above-mentioned series together with a pairwise analysis. A number of relevant results derived from this study are summarized as follows.

Firstly, own-sector volatility spillovers account for the highest share of forecast error variance. Among all the commodity series, Nordic electricity, Henry Hub natural gas and EUA are the most disconnected from the others. Pairwise directional spillovers are higher within than across sectors and the highest observed pairwise spillovers are observed between crude oil series.

Secondly, under the assumption that crude oil prices have been traditionally considered the benchmark price for the rest of the commodities, Brent is shown to be the crude oil benchmark for European electricity, natural gas, coal and emission allowances, whereas WTI is so for U.S. natural gas and coal.

Furthermore, when comparing sectors, the linkages between natural gas volatility and the other commodity volatilities are shown to be the greatest. Given the typically regional nature of coal and electricity markets, some electricity and coal series are shown to be the main receivers of volatility spillovers, as opposed to some crude oil and natural gas series which, as a result of belonging to much more globalized markets, become the main net transmitters. Interestingly, TTF might be on the way to becoming the benchmark price for natural gas in Europe, after having overtaken NBP in trading volume.

In addition, the results achieved indicate that spillovers are time-varying and seem to increase with economic growth as well as during periods of turmoil. Within sectors, the German electricity market is, in overall terms, the main volatility spillovers transmitter. Over time, NCG and TTF arise as the two reference price series, affecting the rest of the natural gas series. It is clear that GASPOOL changes its role, after 2014, from net volatility spillovers transmitter to net volatility spillovers receiver, in favor of TTF and NCG. There is also a role change shown in the crude oil series during the later years of the sample. In particular, Brent becomes a net receiver of volatility spillovers from WTI after 2013. Regarding the coal series, CAPP and API2 have a mutual impact upon one another without the former prevailing over the latter. Another relevant conclusion is that natural gas seems to be overtaking crude oil as a global benchmark for energy commodities.

Political implications are derived in terms of the level of integration between energy markets in the UE. Thus, the most integrated markets appear to be Germany, France and the Netherlands, followed distantly by Italy, Spain and the Nordic market. Greater efforts, in terms of harmonizing rules, increasing interconnections and designing new coupling initiatives, should be made to further integrate the Nordic market, Italy and Spain, whose low level of interconnection with France has led some analysts to refer to Spain as an *"energetic island"* in Europe (Knodt and Piefer, 2015).

Furthermore, our results are of relevance to practitioners, as a correct valuation of the risks being assumed crucially depends on a proper knowledge of the shock-transmission mechanisms across markets and the way the information flows from one market to the others. If volatility is transmitted across markets in a a quite systematic way when arriving new information, this should be taken into account when devising trading strategies and particularly for risk hedging purposes.

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APPENDIX

Table 1A. Unit Root tests

	Prices			Returns		
	ADF	PP	KPSS	ADF	PP	KPSS
GER	-2.386	-3.074	1.993	-27.939	-42.312	0.063
FRA	-3.218	-4.014	0.556	-22.252	-43.657	0.045
NETH	-2.752	-3.899	2.369	-26.777	-42.871	0.111
ITA	2.733	-2.486	2.965	-31.963	-46.567	0.056
NOR	-2.969	-3.152	0.908	-12.047	-40.645	0.015
SPA	-3.768	-4.289	1.279	-8.056	-45.769	0.061
NBP	-1.650	-2.296	3.594	-28.257	-48.347	0.162
ZEE	-1.675	-2.250	3.737	-16.623	-48.731	0.163
TTF	-1.563	-2.280	3.717	-16.386	-41.882	0.185
NCG	-1.745	-2.202	3.618	-9.518	-44.603	0.181
GASP	-1.685	-2.200	3.681	-27.287	-49.449	0.156
HHub	-4.336	-4.269	0.958	-16.620	-49.655	0.085
EUA	-1.571	-1.973	2.523	-11.378	-43.681	0.051
Brent	-1.308	-1.152	5.065	-9.940	-47.182	0.222
WTI	-1.558	-1.501	4.485	-25.666	-45.761	0.118
API2	-1.308	-1.881	3.588	-15.444	-41.189	0.097
CAPP	-2.485	-3.851	1.939	-9.612	-37.133	0.132

This table shows the Augmented Dickey and Fuller (ADF), Philips Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests. The number of lags in the ADF test is determined following the Akaike Information Criteria. The critical values at 1%, 5% and 10% significance level of Mackinnon (1991) for the ADF and PP tests (process with intercept but without trend) are −3.43, −2.86 and −2.56, respectively. The critical values at 1%, 5% and 10% significance level for the KPSS test (process with intercept but without trend) are 0.739, 0.463 and 0.347, respectively

Table 2A. Kolmogorov-Smirnov Statistic

	df=2	df=10	df=20
GER	0,477	0,476	0,467
	(<0.01)	(<0.01)	(<0.01)
FRA	0,457	0,449	0,453
	(<0.01)	(<0.01)	(<0.01)
NETH	0,484	0,465	0,484
	(<0.01)	(<0.01)	(<0.01)
ITA	0,483	0,481	0,480
	(<0.01)	(<0.01)	(<0.01)
NOR	0,458	0,446	0,441
	(<0.01)	(<0.01)	(<0.01)
SPA	0,472	0,466	0,468
	(<0.01)	(<0.01)	(<0.01)
NBP	0,491	0,471	0,466
	(<0.01)	(<0.01)	(<0.01)
ZEE	0,473	0,470	0,476
	(<0.01)	(<0.01)	(<0.01)
TTF	0,474	0,471	0,478
	(<0.01)	(<0.01)	(<0.01)
NCG	0,470	0,477	0,474
	(<0.01)	(<0.01)	(<0.01)
GASP	0,465	0,466	0,462
	(<0.01)	(<0.01)	(<0.01)
HHub	0,468	0,467	0,463
	(<0.01)	(<0.01)	(<0.01)
EUA	0,458	0,456	0,480
	(<0.01)	(<0.01)	(<0.01)
Brent	0,481	0,468	0,466
	(<0.01)	(<0.01)	(<0.01)
WTI	0,477	0,466	0,466
	(<0.01)	(<0.01)	(<0.01)
API2	0,476	0,482	0,496
	(<0.01)	(<0.01)	(<0.01)
CAPP	0,482	0,479	0,505
	(<0.01)	(<0.01)	(<0.01)

This table shows the Kolmogorov-Smirnov statistic to test weather each series follows a t-student distribution with different degrees of freedom (df). P-values in brackets.

Figure 1A. Net volatility spillovers within sectors (power)

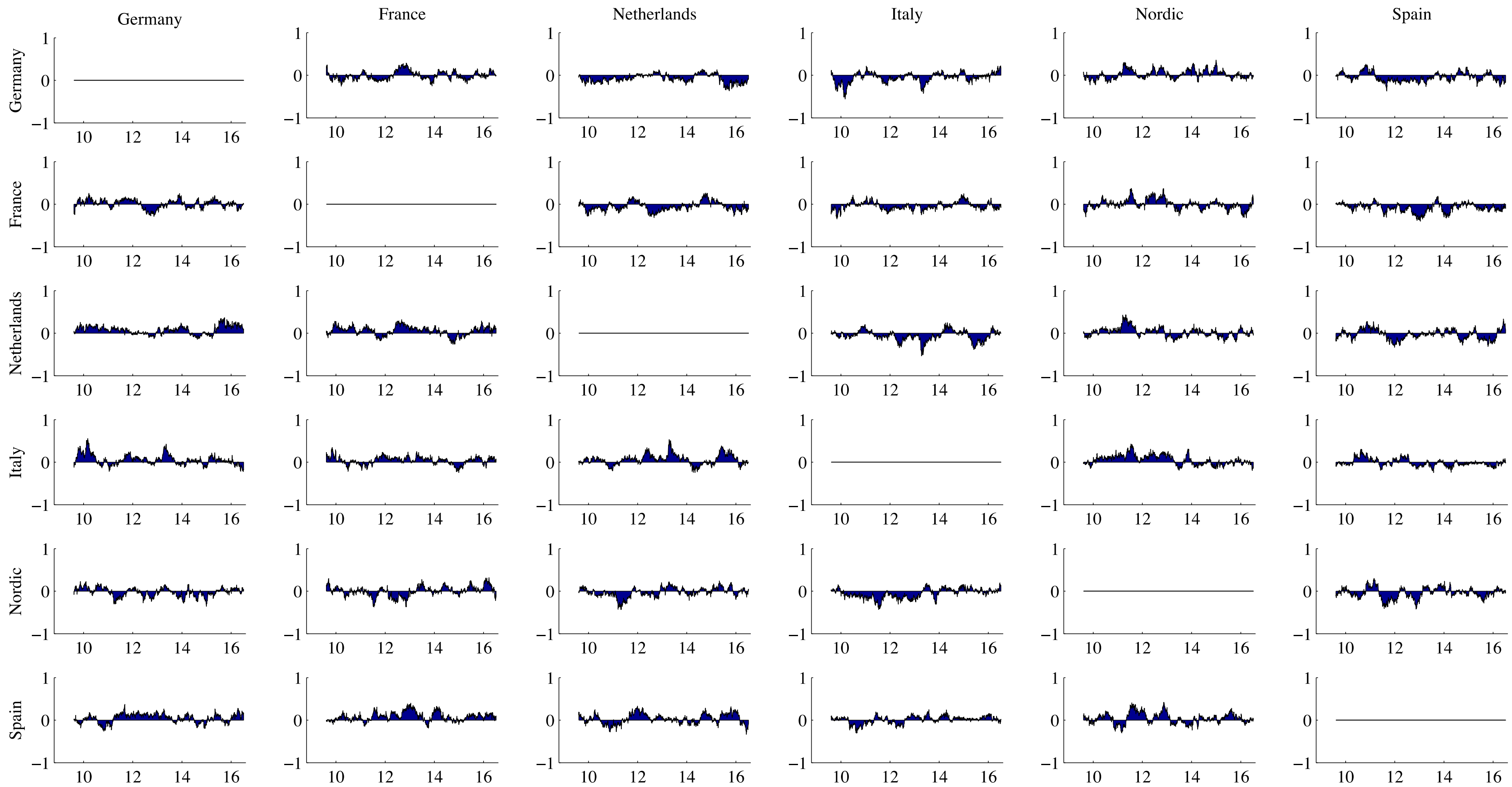


Figure 1B. Net volatility spillovers within sectors (gas)

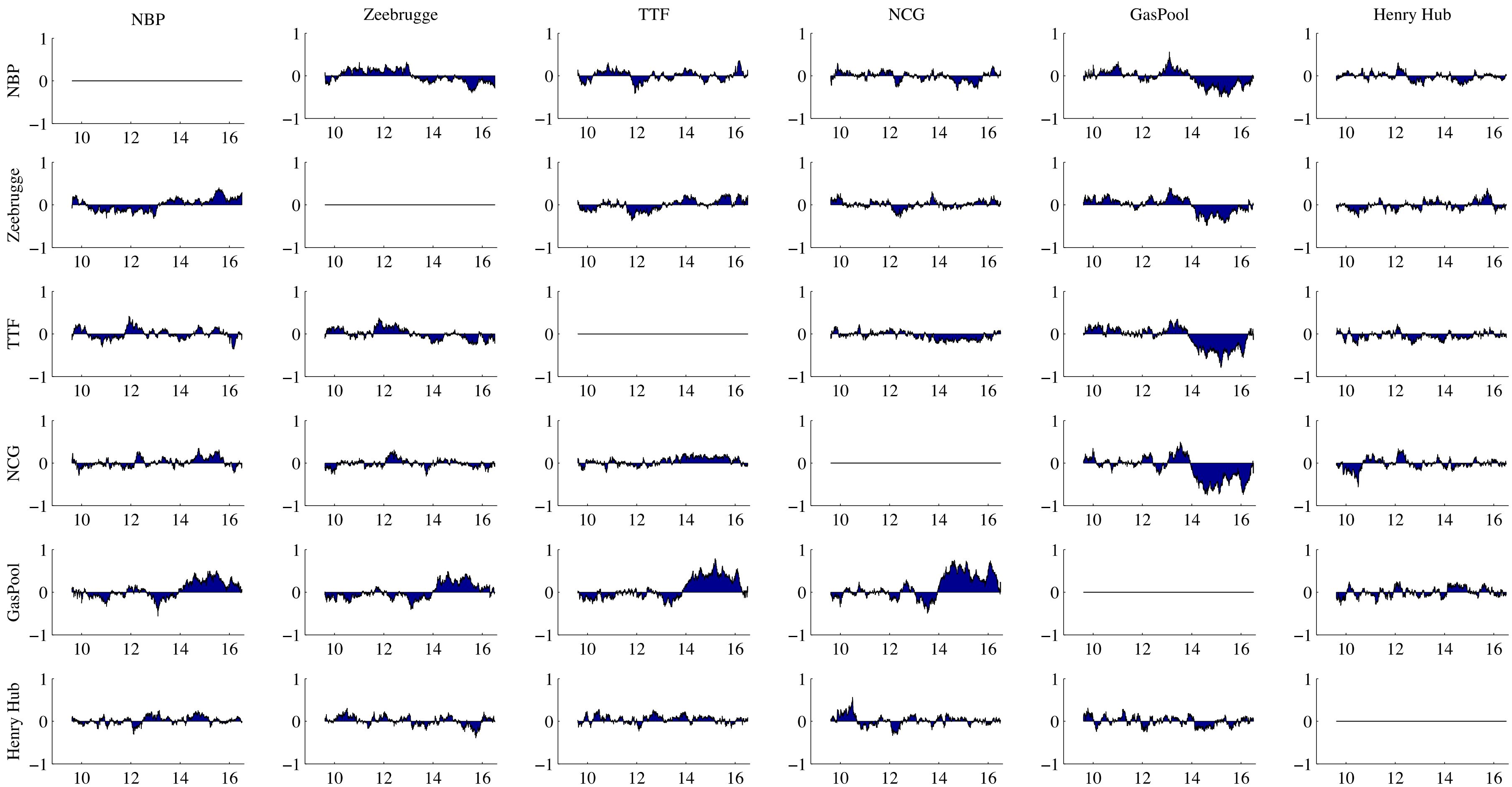
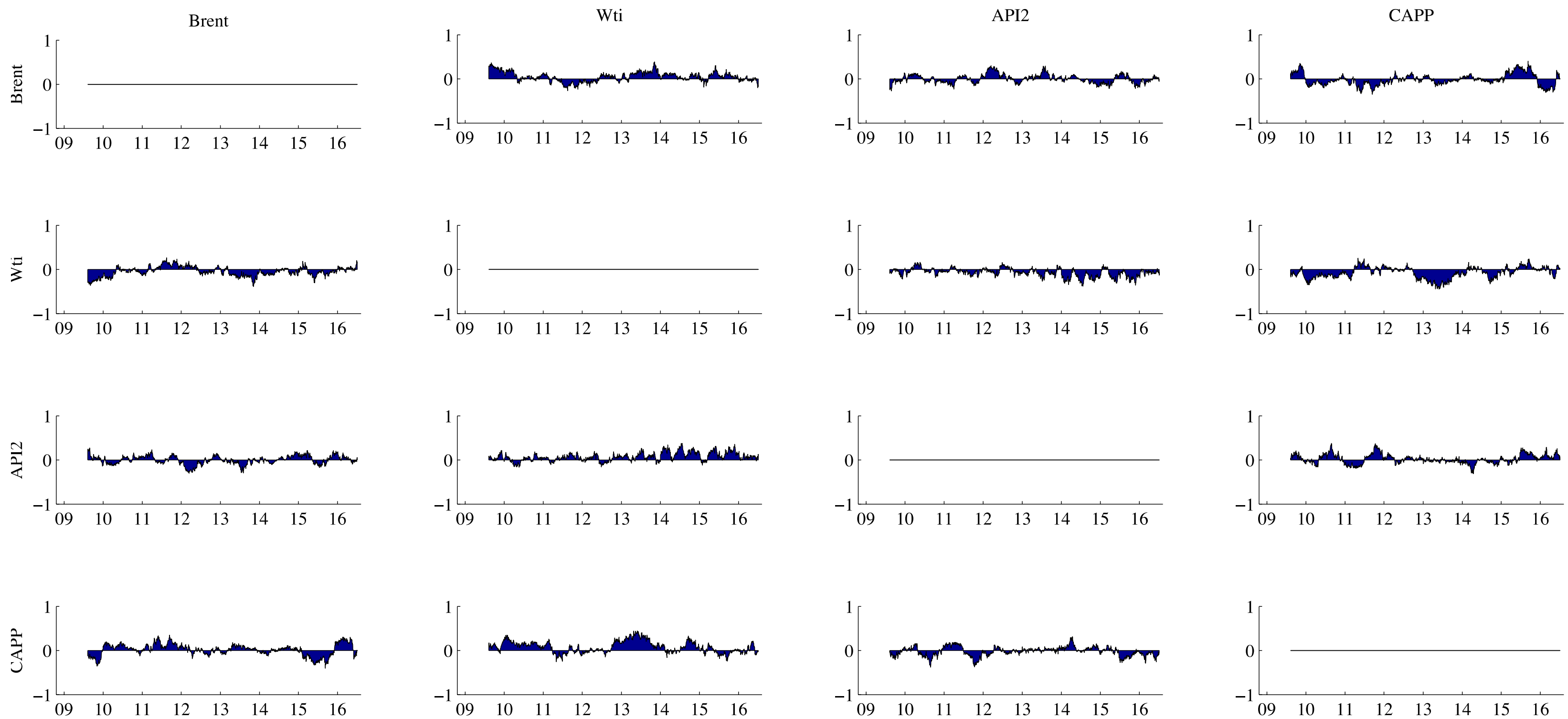


Figure 1C. Net volatility spillovers within sectors (oil and coal)



Note: Daily net dynamic spillovers within sectors. The time axis is presented in years. A positive number means that the market is a net transmitter of shocks in this period, while a negative number means it is a net receiver.