Germany´s energy transition and its effect on European electricity spot markets

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ABSTRACT

Germany´s so called *Energiewende* (energy transition) of the summer 2011 induced the closure of all its nuclear plants by 2022, while ambitious medium and long term targets for renewable energy sources (RES-E) were being pursued. Germany's energy transition is yet unique for a major industrial country and is therefore closely observed worldwide because of its viability and challenges.
This paper empirically examines the potential impact of electricity generated by RES-E in Germany on other electricity spot markets, by employing MGARCH (multivariate generalized autoregressive conditional heteroscedasticity) models with constant and time-varying correlations for daily data. The interrelationship of electricity spot prices of APX-ENDEX (UK and Netherlands), Belpex (Belgium), EPEX (Germany, Switzerland), OMEL (Spain), Nordpool (Finland, Denmark, Norway) and Powernext (France) with wind as well as solar penetration induced by the German system is studied from November 2009 to May 2011. There are indications of positive cross-market and lagged spillover. Positive time-varying correlations between spot markets are present for those markets with substantial shares of interconnector capacity. With increasing wind penetration, there is significant reduction in electricity spot prices, especially for well-connected markets.

Keywords: electricity spot markets, energy transition, MGARCH, renewable energies, volatility analysis

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Introduction

The promotion of renewable energies in Germany was first legislated by the Renewable Energy Source Act (RESA) in 1991.[1] Since then renewable electricity generation has shown considerable growth rates. In 2010, the German government enforced their energy policy by presenting the *Energiekonzept* (Energy Concept) a long term energy strategy that directs Germany´s Energy Transition with the goal that Germany becomes one of the most energy efficient and environmentally friendly economies (Bundesregierung, 2011).

Germany´s renewable energy policy experienced an unexpected impetus following the multiple reactor meltdowns in Fukushima on 11th of March 2011, which prompted a broad consensus within the German government to put into action the *Atomaustiegsgestz* (Nuclear Phase-Out Act), by shutting down eight nuclear power plants and the successive closures of the remaining nine nuclear plants until 2022 (Bundesregierung, 2011).[2] At the same time, the German government emphasized it's committed to existing plans for RES-E. The Renewable Energy Source Act 2012 aims to increase the electricity generated from RES-E to at least 35% until 2020 and then gradually to at least 80% by the year 2050 (RESA, 2012). The RESA also reaffirmed the basic principles of the feed-in policy, which prioritizes renewable energy sources, a commitment to connect all renewable producers to the grid and guarantee a favorable unit price (RESA, 2012). However, studies such as Gross et al. (2006), Holttinen at al. (2009) and Smith et al. (2007) highlight the challenges associated with increased wind penetrations. There is, for example, a significant risk that a system with high wind capacity will have a shortage of power. If there is a large amount of wind in one system, external trade can be used to balance the variable wind output (Denny et al, 2010).

Other studies have shown that electricity spot market prices decrease to varying extents with the in-feed of wind generated electricity (see for example: Jacobson and Zvingilaite (2010), Sensfuß et al (2008), Neubarth et al. (2006), Gil et al. (2012), Bode and Groscurt (2006), Saenz de Miera et al. (2008)). The reduction of electricity spot prices (also known as *merit order effect*) is attributed to the increase of wind generation, which displaces technologies with higher marginal costs (Sensfuß et al. 2008, Woo et al. 2011). Nevertheless, studies have also shown that positive effects of increased RES-E on electricity spot price level may come at the cost of an overall increase in spot price volatility (Woo et al., 2011; Milstein and Tishler, 2011; Green and Vasilakos, 2010).

Woo et al. (2011) used quarter hourly electricity price data and explanatory variables (quarter hourly nuclear generation, daily Henry Hub Gas price, quarter hourly loads as well as binary variables to account for time effects) from Texas between January 2007 and May 2010. Via a regression analysis, they inferred that wind generation tends to reduce the level of electricity spot prices and enlarge spot price variance. Milstein and Tishler (2011) analyzed the relationship between intermittently renewable energy and optimal endogenous generating capacity mix, energy production by technology, and market prices in a Cournot market with CCGT and PV generation. Their solution to a two-stage game using real world data for Israel shows that a rising adoption of PV can increase price volatility. Green and Vasilakos

[1] Erneuerbare Energien Gesetz
[2] In 2010 Germany consumed almost 530TWh of electricity of which more than 26% (140TWh) were generated by nuclear power plants (country factsheet 2012).

(2010) examined the impact of intermittent wind generation on British hourly equilibrium prices and output, using data on expected wind generation capacity and demand for 2020. They found that the volatility of prices increases and significant yearly variation in generators' profits.

Despite the fact that the integration of electricity markets is a promising instrument to manage intermittent RES-E, the few studies that assess the volatility interrelationships among liberalized electricity spot markets have neglected the potential impact of different generation technologies.[3] For example, Worthington et al. (2005) employed the multivariate GARCH (MGARCH) and BEKK (Baba, Engle, Kraft and Kroner) models to capture the source and magnitude of price and volatility spillovers among five spot electricity markets in Australia. Their results indicate positive lagged mean spillovers in only a small number of markets and no mean spillovers between markets. Higgs (2009) employs a Constant Conditional Correlation and two Dynamic Conditional Correlation models to four Australian electricity markets from 1999 to 2007 to analyze the inter-relationships of electricity spot prices and levels. They concluded that the less direct the interconnection between regions, the lower the volatility spillovers between these regions, which suggests that the key to interactions between electricity markets is geographical proximity and interconnector capacity.

Le Pen and Sévi (2010) used daily data from March 2001 to June 2005 and estimated a VAR-BEKK model and Volatility Impulse Response Functions. They found evidence of return and volatility spillovers in forward electricity markets (German, Dutch and British); their estimated impacts are significant, especially when shocks are large and/or decay rapidly.

Veka et al. (2012) employed a MGARCH model to examine returns of price derivates from Nordpool and EEX with several energy commodities (ICE gas, Brent crude oil, coal and carbon emission contracts). They found significant time-varying relationships for all commodities included in the analysis, with the exception of oil. Their data suggests that the strongest relationship between Nordic energy futures and German electricity futures. Moreover, they discovered that the relationship appears to be stronger the longer the maturity of the contracts.

This paper assesses the potential effects of Germany´s energy transition on level and volatility of electricity spot prices in Germany and in other European countries. In contrast to previous studies, a multivariate framework is adopted. Germany serves as a statuary example, because of its radical approach to substituting nuclear energy with renewables, the prominent role wind generated electricity already holds in its energy mix, as well as the size and importance of its electricity market in Europe.

The following section reviews trading arrangements and price setting mechanisms in European electricity markets. The third section outlines the summary statistics of the data. In the fourth section the methodology is introduced. The empirical results are presented in the fifth section. The paper concludes with a discussion of the findings.

[3] Bosco et al. (2007) remark that *"[...] post-reform European price series have generally been studied in isolation and the issue of the interdependency in the price dynamics of neighboring markets has largely been ignored."* (p. 2).

Price setting mechanisms and trading arrangements

In 1988, the principles for a single European "internal market" for goods and services were established in the Single Electricity Act. After nearly ten years of debate, the EU Directive 96/92/EC defined a set of common rules for generation, transmission and distribution of electricity and aimed to create a supranational market to increase efficiency and competition in the electricity sector (Gebhardt and Höffler, 2007). Since then, several directives followed (e.g. 2003/54/EC, 2009/72/EC), which do not only address the original aims but also specify paths to the integration of renewable energy in electricity markets and security of supply in member states.

Prior to the *liberalization,* little trade was observed in Germany: its excess electricity export was rarely more than 5TWh per anno (see Figure 2); interconnection with other countries had the main function of securing stable operation of the European electricity network rather than facilitating trade (Creti et al., 2010). After liberalization, electricity flows have been more and more dictated by market mechanisms and, especially in Germany, have increased significantly (BDEW, 2012).

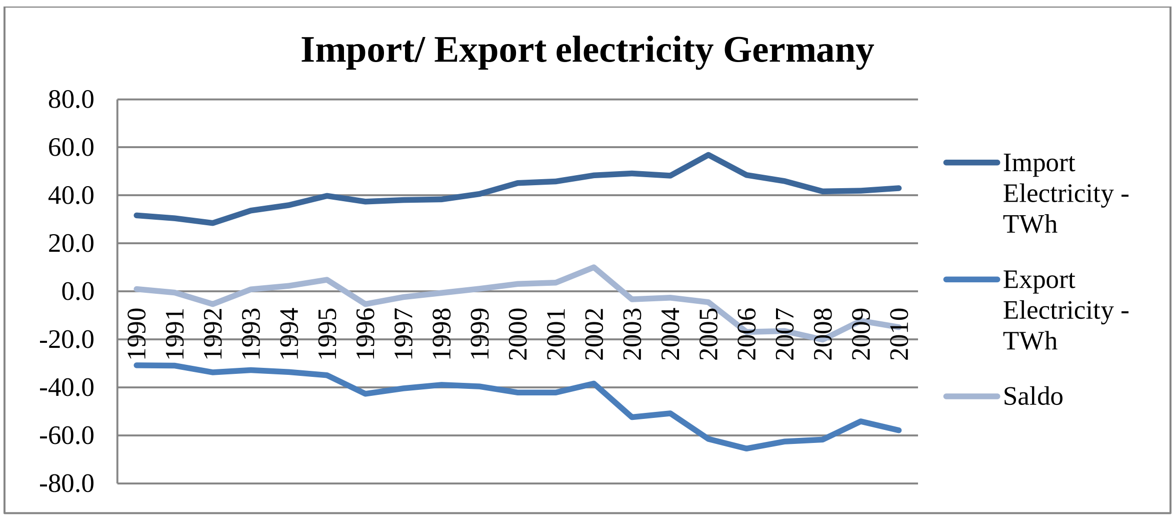

Figure 1: Import-Export of electricity in Germany in MWh since 1990. Source: European Commission 2012

Since November 21st 2006, France, Belgium and the Netherlands have coupled their day-ahead markets through their national power exchanges and transmission system operators (TSO). The *Trilateral Market Coupling* (TLC) realizes a joint, simultaneous, allocation of energy and interconnector capacity between the individual markets in cooperation with the TSO's.[4] As of November 2010, the Central Western European Market Coupling (CWE) has extended the TLC to Luxembourg and Germany (Belpex, 2012). The connection of NorNed to the CWE Market Coupling started in January 2011, thus linking the liquid Norwegian day-ahead market to the wider Central West European power market (APX-ENDEX, 2012).

[4] Via market coupling, the daily cross-border transmission capacity between countries is made through implicit and explicit energy transactions at the power exchanges. The purpose of market coupling is to maximize the total economic surplus of all participants: cheaper electricity generation in one country can meet demand and reduce prices in another country and supply fluctuations can be balanced of (Belpex, 2012). If there is sufficient Available Transmission Capacity (ATC) prices will converge across adjacent countries (price convergence). If the ATC is too small, prices cannot be equalized.

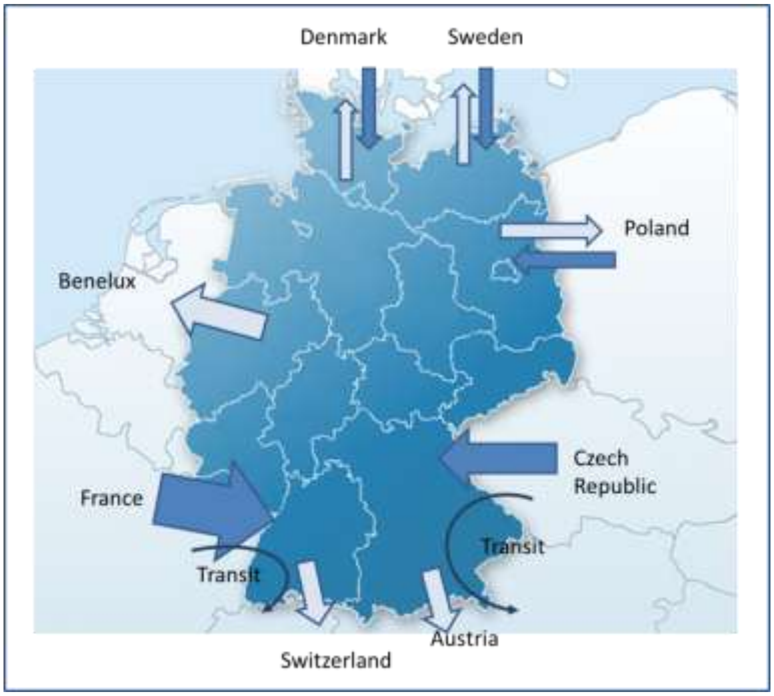

Figure 2: Import- Export of electricity between Germany and its neighboring European countries. Source: European Commission, 2012

Currently, Germany is well connected to its neighboring countries and is a net exporter with relatively stable import/ export relationships with its bordering countries. It exports electricity to the Benelux countries, which have high shares of variable peak electricity supply such as coal and gas fired plants.[5] Most of the times electricity is imported from France, which has a stock of base-load nuclear plants (428.5TWh or 75.3% of electricity in 2010 has been produced by nuclear power) and the Czech Republic, which also has relatively high shares of nuclear (32.6% or 28TWh in 2010) and fossil fuel based generation (47.1TWh which equals 54.8%) (European Commission, 2012). Imports and exports with Denmark, Sweden and Poland are highly wind dependent (BDEW, 2012).

The development of Germany´s Energy mix since 1991 is illustrated in Figure 3. Electricity generated from solid fuels had the highest share, almost 263MWh (42%) in 2010, and was followed by nuclear (140.6MW or 22%). Figure 4 shows the quantity of wind generated electricity comparing to neighboring countries (2010 as base year): in Germany 37.8MW electricity was generated by wind, which is only surpassed by Spain with 44.2MWh (European Commission, 2012).

[5] In 2010 22.6TWh (19.1%) of electricity in the Netherlands was produced from solid fuels and 77.4TWh (65.5%) from gas. In Belgium 4.4% which equals 4.2TWh of the total electricity has been produced by solid fuels and 33.2TWh (34.9%) by gas (European Commission, 2012).

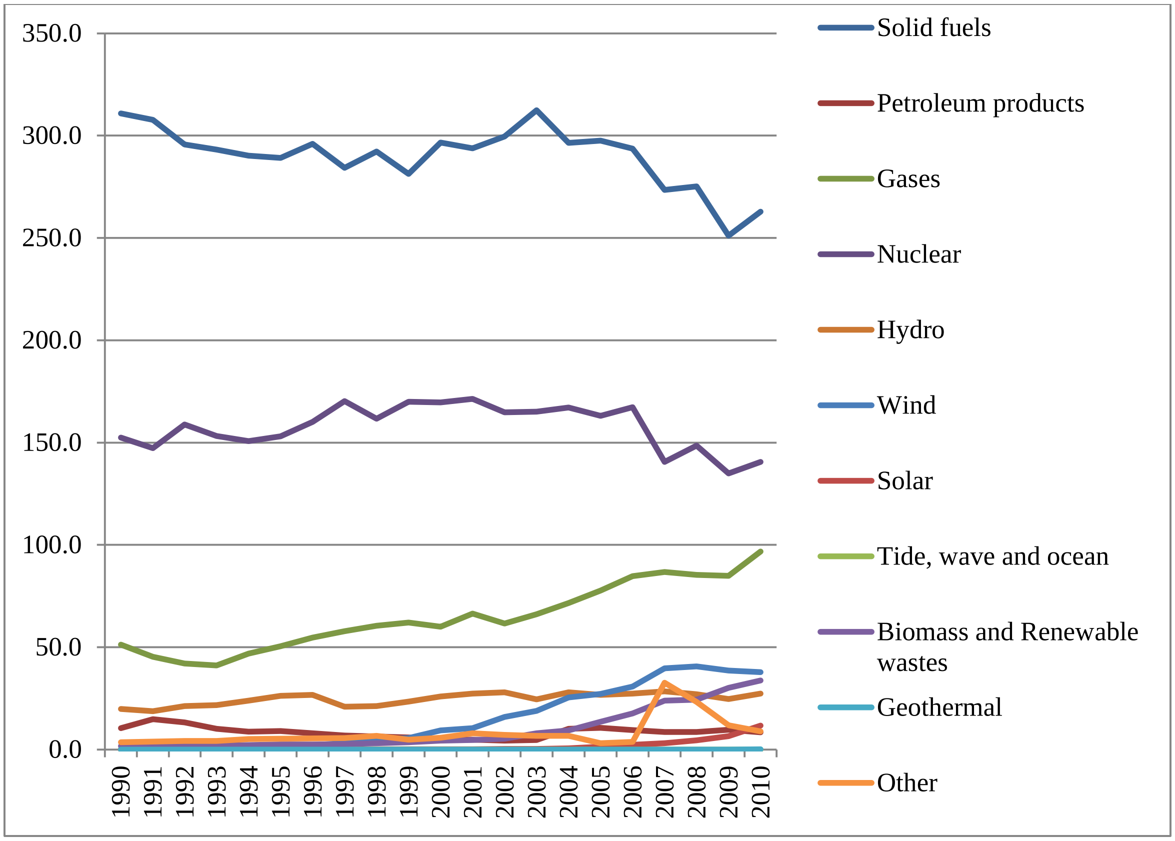

Figure 3: Energy Mix Germany in MWh 1990-2010. Source: European Commission, 2012

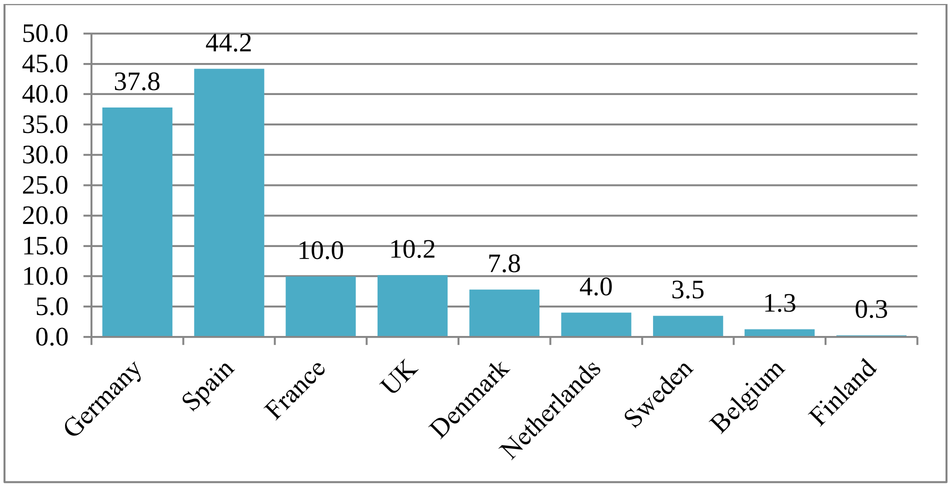

Figure 4: Installed wind capacity in MWh for 2010. Source: European Commission, 2012

Modeling Volatility Spill Overs

There has been considerable interest in examining whether or not volatility is transmitted from one financial market to another. GARCH (generalized autoregressive conditional heteroscedasticity) models (Bollerslev (1986)) have been widely applied to model the volatility dynamics, and applications to spot electricity markets may be found in Knittel and Roberts (2001), Hadsell et al. (2004), Higgs and Worthington (2005) and Chan and Gray (2006).

The Multivariate Framework

Bollerslev et al. (1988) provided the VEC specification for a multivariate GARCH model (Vec-GARCH), a straightforward extension of univariate GARCH models. Since then several parameterizations have been proposed in the econometric literature. In order for a multivariate GARCH model to be feasible, the variance- covariance matrix must be positive definite for all values of disturbances in the model. To ensure this, Engle and Kroner (1995) proposed a quadratic formulation of the VEC model, which is the BEKK representation:

$$\sum = C_0 C_0^I + \sum_{k=1}^{K} \sum_{i=1}^{q} A_{ki}^I \varepsilon_{t-1} \varepsilon_{t-1}^I A_{ki} + \sum_{k=1}^{K} \sum_{i=1}^{p} B_{ki}^I \sum_{t-i} B_{ki^I} \tag{1}$$

Where c_{ij} are elements of a n x n symmetric matrix of constants C, the elements a_{ij} of the symmetric n x n matrix A measuring the innovation from market I to market j and the elements b_{ij} of the symmetric n x n matrix B indicates the persistence in conditional volatility between market i and j.

The parameters c_{ij} , a_{ij} and b_{ij} cannot be interpreted individually, as they are functions of the intercept terms and the coefficients of the lagged variance, covariance and error terms (Kearney and Patton, 2000). Although a positive semi-definite covariance matrix is ensured, there is the drawback of rapidly increasing the number of unknown parameters. Consequently, these models are rarely used with more than four parameters (Minović, 2009).

Constant Conditional Correlation

Bollerslev (1990) proposed a Constant Conditional Correlation MGARCH model (CCC), which has been preferred in empirical research because of its computational simplicity. This model is based on the decomposition of the conditional covariance matrix into conditional standard deviation and correlations. The conditional correlation matrix is time invariant and can be written as:

$$H_t = D_t P D_t = \rho_{ij} \sqrt{h_{iit} h_{jjt}} \tag{2}$$

Where

$$D_t = diag(h_{11t}^{\frac{1}{2}} \dots h_{KKt}^{\frac{1}{2}}), \tag{3}$$

$$R = \rho_{ij}$$

h_{iit} is defined as the conditional variance of the univariate GARCH model and R is the symmetric positive definite constant conditional correlation matrix with $\rho_{ii} = 1$.

Dynamic Conditional Correlation

Although the CCC model overcomes the shortcomings of the BEKK and VEC models, the assumption of constant correlations may be too restrictive (Minović, 2009). Tse and Tsui (2002) and Engle (2002) therefore extended the CCC models to *dynamic* conditional correlation models (DCC), by including a time dependent conditional correlation matrix:

$$H_t = D_t R_t D_t \tag{4}$$

Where D_t is defined as in equation (4) and h_{iit} is defined as any univariate GARCH process. Tse and Tsui (2002) assume a conditional correlation matrix, R, as follows:

$$R_t = (1 - \theta_1 - \theta_2)R + \theta_1 \Psi_{t-1} + \theta_2 R_{t-1} \tag{5}$$

Where $\theta_1 + \theta_2 < 1$ and non-negative, R is the KxK symmetric and positive definite constant parameter matrix with $\rho_{ii} = 1$ for all i, R_t is a weighted average of R, R_{t-1} and Ψ_{t-1}, and Ψ_{t-1} is the KXK correlation matriy of ε_t for $\tau = t - M, t - M + 1, \ldots . t - 1$ (Higgs 2009).

For the bivariate case we write the correlation coefficient for Tse and Tsui (2002):

$$\rho_{12t} = (1 - \theta_1 - \theta_2)\rho_{12} + \theta_2 \rho_{12,t-1} + \theta_1 \frac{\sum_{m=1}^{M} e_{1,t-m} e_{2,t-m}}{\sqrt{(\sum_{m=1}^{M} e_{1,t-m}^2)(\sum_{m=1}^{M} e_{2,t-m}^2)}} \tag{6}$$

Engle (2002) proposed:

$$\rho_{1,2t} = \frac{(1-\theta_1-\theta_2)\bar{q}_{12} + \theta_{1 e_{2.t-1} e_{1,t-1}} + \theta_2 q_{12,t-1}}{\sqrt{((1-\theta_1-\theta_2)\bar{q}_{11} + \theta_1 e_{1,t-1}^2 + \theta_2 q_{11,t-1})((1-\theta_1-\theta_2)\bar{q}_{22} + \theta_1 e_{2,t-1}^2 + \theta_2 q_{22,t-1}))}} \tag{7}$$

The DCC models are estimated in two steps: first the univatiate GARCH models are estimated thereafter the correlation coefficients are estimate. A basic requirement is the removal of the predictable component to produce the disturbance e_t, with a conditional mean of zero before the GARCH equation is specified for the variance (Higgs 2009). This procedure is computationally less expensive than multivariate GARCH models and allows for the estimation of very large correlation matrices (Engle, 2002).

Data

The dataset used in the present study consists of hourly electricity spot prices from seven major European wholesale markets: APX-NL (Netherlands), Belpex (Belgium) EPEX (Germany), Nordpool (Denmark, Finland and Sweden), APX-UK (UK), OMEL (Spain) and Powernext (France). In total 16935 hourly observations covering the period from 02.11.2009 to 06.10.2011 are available. Since hourly data have multiple seasonalities, we focus on the week-daily mean average prices, thus reducing the sample to 504 observations. This is a common approach in the literature (De Vany and Walls (1999), Robinson (2000), Wolak (2000), Lucia and Schwartz (2002), Escribano et al. (2002), Higgs and Worthington (2005), Worthington et al. (2005), Chan and Gray (2006), Koopman et al. (2007) and Becker et al. (2007), Higgs (2011)), especially as the influence of wind forecast on spot prices has been described as being more relevant on a daily basis, when compared to an hourly basis (Neubarth et al., 2006).

We obtained hourly forecasts and actual electricity output generated by wind from the Transparency in Energy Markets EEX database to produce the wind penetration variable. We transformed it to daily frequency and divided it by the volumes traded on the spot market. Table 1 presents the summary statistics of electricity spot prices and wind penetration variables.

	Min	*Mean*	*Max*	*Std.Dev*	*Skewness*	*Excess Kurt.*	*JB*	*ADF*
France	15.13	50.51	89.83	9.90	0.31	1.61	62.76	-1.13
Germany	7.21	49.47	72.06	8.21	-0.47	1.23	50.10	-0.90
NL	21.04	49.96	73.04	7.96	-0.37	0.62	19.45	-0.82
Nordpool	0.00	55.26	134.80	19.86	0.46	1.21	48.57	-0.12
Spain	3.13	41.83	67.35	10.53	-0.90	1.10	93.41	-0.61
Switzerland	15.66	54.86	80.33	8.75	-0.32	1.03	30.98	-1.04
UK	27.10	44.47	110.92	8.28	1.93	10.83	2774.00	-1.03
Belgium	15.11	50.03	206.10	11.74	4.72	60.80	79497.00	-1.58
Wind Penetration actual	0.00	0.01	0.13	0.01	4.75	33.85	25960.00	-8.51
Wind Penetration planned	0.00	0.03	0.25	0.02	2.90	17.33	7011.40	-6.15

Table 1: Minimum (Min), mean, maximum (Max), standard deviation (Std. Dev) shown in EUR/MWh; skewness, excess kurtosis, Jarque Bera statistic (JB), Augmented Dickey Fuller Test (ADF)

The distributions of the spot prices and wind penetration variables are non-normal, as shown by the Jarque-Bera statistics which exceed their critical values. France, Nordpool, the UK and Belgium exhibit positive skewness, whereas Germany, the Netherlands, Spain and Switzerland are negatively skewed. Kurtoses are generally very large with the largest value of 60.80 for Belgium. The UK also has a comparably high excess kurtosis (10.83). Thus fat-tailed distributions are observed, which are common in financial markets and in the specific case of electricity prices reflect the many spikes in the data.

Estimation results

First, the univariate models are estimated. The coefficients, standard errors and t-values are displayed in Table 2.[6] The lagged models show significant positive lagged mean spill overs for all markets; for example, an increase of 1 EUR/MWh in France may cause an increase of 1.70EUR (exp(0.534)) of prices in the following day. There are also cross-country mean spill overs: a 1EUR/MWh increase in Switzerland's price can result in 0.63EUR/MWh (exp-0.474) decrease in

6 The assessment of solar generated electricity did not yield significant results, possibly because the time series were shorter. We therefore only report the results related to wind.

Spanish prices. Similarly, a 1EUR/MWh increase of price in the Nordpool may lead to a 0.43 EUR/MWh (exp(-0.84)) decrease in spot prices in Spain.

The planned penetration level has a significant (5% significance level) negative impact on German, Dutch and Swiss electricity spot prices. That means, the higher the planned wind penetration levels in the German system, the lower the electricity spot prices.

	FR		**GER**		**NL**		**NP**		**ES**		**CH**		**UK**		**BEL**	
FR_1	**0.53 (0.09)**	**6.02**	0.04 (0.06)	0.64	0.05 (0.06)	0.78	0.01 (0.05)	0.19	0.18 (0.12)	1.55	0.05 (0.07)	0.65	-0.06 (0.06)	-1.02	**0.25 (0.09)**	**2.66**
GER_1	-0.02 (0.10)	-0.16	**0.31 (0.07)**	**4.53**	**0.21 (0.07)**	**3.04**	-0.09 (0.06)	-1.49	-0.02 (0.14)	-0.11	0.05 (0.08)	0.63	0.09 (0.07)	1.34	0.06 (0.11)	0.58
NL_1	-0.05 (0.13)	-0.39	**0.21 (0.08)**	**2.52**	**0.33 (0.08)**	**4.03**	0.07 (0.08)	0.97	**0.51 (0.17)**	**3.09**	-0.08 (0.10)	-0.79	0.18 (0.09)	2.15	-0.07 (0.13)	-0.56
NP_1	**0.09 (0.03)**	**3.16**	**0.07 (0.02)**	**3.56**	**0.08 (0.02)**	**4.49**	**1.02 (0.02)**	**58.30**	**-0.08 (0.04)**	**-2.24**	**0.08 (0.02)**	**3.54**	0.08 (0.02)	3.96	**0.10 (0.03)**	**3.50**
ES_1	0.05 (0.03)	1.91	**0.07 (0.02)**	**3.98**	**0.07 (0.02)**	**3.95**	0.01 (0.02)	0.40	**0.70 (0.03)**	**21.00**	0.02 (0.02)	1.01	0.06 (0.02)	3.57	**0.08 (0.03)**	**3.16**
CH_1	**0.16 (0.07)**	**2.23**	0.02 (0.05)	0.35	-0.01 (0.05)	-0.13	-0.05 (0.04)	-1.17	**-0.47 (0.09)**	**-5.15**	**0.65 (0.06)**	**11.60**	-0.09 (0.05)	-1.90	0.13 (0.07)	1.77
UK_1	0.10 (0.06)	1.67	**0.13 (0.04)**	**3.36**	**0.12 (0.04)**	**3.18**	-0.04 (0.04)	-1.11	0.15 (0.08)	1.93	0.03 (0.05)	0.75	**0.57 (0.04)**	**14.70**	**0.12 (0.06)**	**2.06**
BEL_1	0.00 (0.09)	-0.04	-0.02 (0.06)	-0.30	-0.01 (0.06)	-0.22	0.00 (0.05)	-0.06	-0.12 (0.12)	-1.02	-0.01 (0.07)	-0.15	0.00 (0.06)	-0.02	**0.21 (0.09)**	**2.33**
Pl. pntr..	-0.23 (0.13)	-1.79	**-0.72 (0.09)**	**-8.51**	**-0.61 (0.08)**	**-7.22**	**-0.17 (0.08)**	**-2.09**	0.02 (0.17)	0.12	**-0.22 (0.10)**	**-2.14**	-0.12 (0.09)	-1.34	-0.21 (0.13)	-1.56

Table 2: Univariate Model estimate. FR_1 lagged French spot price; GER_1: 1 lagged German spot price; NL_1 1 lagged Netherlands spot price; NP_1 1 lagged Nordpool spot price; ES_1 1 lagged Spain spot price; CH_1 1 lagged Switzerland spot price; UK_1: 1 lagged UK spot price; BEL_1 1 lagged Belgium spot price; Pl. pntr.: Planned wind penetration level. Standard errors in parentheses; significant values are printed in bold.

The results of the CCC model suggest that 92% (33 of 36 for planned penetration) and 89% (32 of 36 for actual penetration) conditional correlations are significant. Moreover, significant correlations between spot prices volatilities are positive.[7] According to the CCC model the correlations are highest between the Belgium and France (.94) and lowest between Spain and Germany (0.11). Spain exhibits the least number of significant correlations with the other European countries. These findings are consistent with the physical interconnector linkage between these countries: countries that are directly connected by means of an interconnectors exhibit positive volatility spill overs.

The wind penetration variables display negative correlations with electricity spot prices, which are stronger and generally more significant with planned penetration, when compared to actual penetration. This is intuitive as electricity prices are set before actual power delivery, therefore forecasts (centralized or received from participating wind farms), rather than actual metered output are more likely to affect the market clearing process (Gil et al., 2012).

Likelihood ratio tests assess the fit of the two models and test $H_0: \theta_1 = \theta_2 = 0,$ i.e. the model with constant conditional correlations versus time varying conditional correlations alternative. The critical 5% value for 23 degrees of freedom of the Chi square statistic is 35.17: we reject hypothesis of constant correlations. According to the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC), Engle´s Dynamic Conditional Correlation model is the best on the data.

The TTDCC and EDCC models suggest similar correlation coefficients, with positive correlations between electricity spot price levels and negative correlations between wind penetration and electricity spot prices. However, there are less significant correlation coefficients, when compared to the CCC model. The strongest correlation estimate is found for Germany and the Netherlands (.81), whereas the lowest for Nordpool and the UK (.15). They are depicted in Figure 4 (EDCC model).[8]

7 The log-likelihood with a Student's t-distribution yields higher log likelihood than with a normal. We therefore employed the Student's t distribution in the subsequent analysis.

8 We only report the results of the EDCC model, as the results of the TTDCC model only differ marginally.

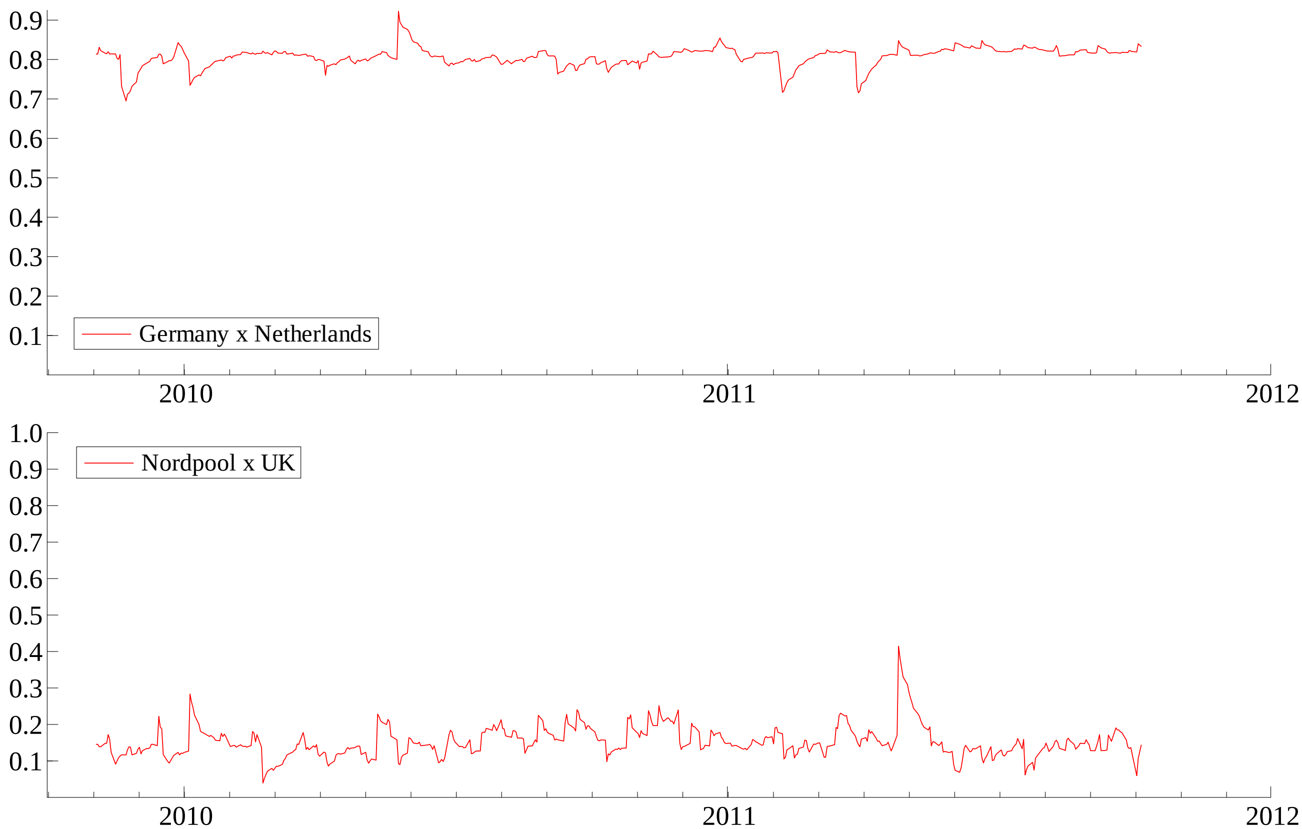

Figure 5: Dynamic Conditional Correlataion (EDCC) for Germany and Netherlands as well as Nordpool and UK

The EDCC model indicates significant conditional correlation between planned wind penetration and all electricity spot price series, except for Spain. Concerning actual wind penetration level, we do not find a relationship in the cases of France, Spain and Belgium. Again, throughout the sample, the correlation estimates for planned wind penetration are larger (or at least the same) in magnitude, when compared to actual wind penetration. The time varying conditional correlation coefficients ($\boldsymbol{\theta_1}$, $\boldsymbol{\theta_2}$) for both the TTDCC and EDCC models sum to less than one; thus suggesting that the dynamic conditional correlations are mean-reverting.

	Coefficient	Std. Error	t-value	Coefficient	Std. Error	t-value
$\boldsymbol{\rho_{21}}$	**0.68**	**0.03**	**21.00**	**0.66**	**0.03**	**19.38**
$\boldsymbol{\rho_{31}}$	**0.75**	**0.02**	**35.75**	**0.75**	**0.02**	**34.26**
$\boldsymbol{\rho_{41}}$	**0.22**	**0.05**	**4.10**	**0.21**	**0.05**	**4.21**
$\boldsymbol{\rho_{51}}$	**0.18**	**0.05**	**3.47**	**0.17**	**0.05**	**3.23**
$\boldsymbol{\rho_{61}}$	**0.61**	**0.04**	**17.09**	**0.60**	**0.04**	**16.35**
$\boldsymbol{\rho_{71}}$	**0.28**	**0.04**	**6.22**	**0.27**	**0.04**	**6.39**
$\boldsymbol{\rho_{81}}$	**0.94**	**0.01**	**127.70**	**0.94**	**0.01**	**120.20**
$\boldsymbol{\rho_{91}}$	**-0.12**	**0.04**	**-2.75**	-0.08	0.05	-1.64
$\boldsymbol{\rho_{32}}$	**0.80**	**0.02**	**47.31**	**0.79**	**0.02**	**44.49**
$\boldsymbol{\rho_{42}}$	**0.36**	**0.05**	**7.76**	**0.36**	**0.04**	**8.08**
$\boldsymbol{\rho_{52}}$	**0.11**	**0.05**	**1.98**	0.08	0.06	1.50
$\boldsymbol{\rho_{62}}$	**0.57**	**0.03**	**16.79**	**0.56**	**0.03**	**15.99**
$\boldsymbol{\rho_{72}}$	**0.26**	**0.04**	**6.12**	**0.26**	**0.04**	**6.10**
$\boldsymbol{\rho_{82}}$	**0.67**	**0.04**	**18.31**	**0.65**	**0.04**	**17.18**
$\boldsymbol{\rho_{92}}$	**-0.35**	**0.04**	**-8.80**	**-0.24**	**0.04**	**-5.54**
$\boldsymbol{\rho_{43}}$	**0.30**	**0.04**	**6.97**	**0.29**	**0.04**	**6.95**
$\boldsymbol{\rho_{53}}$	**0.16**	**0.04**	**3.64**	**0.15**	**0.04**	**3.36**
$\boldsymbol{\rho_{63}}$	**0.63**	**0.03**	**21.72**	**0.62**	**0.03**	**20.78**
$\boldsymbol{\rho_{73}}$	**0.30**	**0.04**	**7.99**	**0.30**	**0.04**	**7.94**
$\boldsymbol{\rho_{83}}$	**0.72**	**0.02**	**31.13**	**0.72**	**0.02**	**29.75**
$\boldsymbol{\rho_{93}}$	**-0.29**	**0.04**	**-7.54**	**-0.19**	**0.04**	**-4.76**
ρ_{54}	-0.02	0.04	-0.54	-0.03	0.04	-0.66
$\boldsymbol{\rho_{64}}$	**0.20**	**0.04**	**4.84**	**0.19**	**0.04**	**4.73**
$\boldsymbol{\rho_{74}}$	**0.16**	**0.04**	**4.26**	**0.16**	**0.04**	**4.15**
$\boldsymbol{\rho_{84}}$	**0.21**	**0.06**	**3.72**	**0.21**	**0.05**	**3.85**
$\boldsymbol{\rho_{94}}$	**-0.14**	**0.04**	**-3.72**	**-0.08**	**0.04**	**-2.10**
$\boldsymbol{\rho_{65}}$	**0.22**	**0.04**	**4.87**	**0.20**	**0.05**	**4.41**
$\boldsymbol{\rho_{75}}$	0.01	0.04	0.19	0.01	0.04	0.20
$\boldsymbol{\rho_{85}}$	**0.19**	**0.06**	**3.39**	**0.18**	**0.06**	**3.10**
ρ_{95}	-0.01	0.04	-0.28	-0.05	0.05	-1.10
$\boldsymbol{\rho_{76}}$	**0.23**	**0.04**	**5.69**	**0.22**	**0.04**	**5.46**
$\boldsymbol{\rho_{78}}$	**0.59**	**0.04**	**15.17**	**0.58**	**0.04**	**14.58**
$\boldsymbol{\rho_{79}}$	**-0.15**	**0.04**	**-3.97**	**-0.09**	**0.04**	**-2.20**
$\boldsymbol{\rho_{87}}$	**0.26**	**0.05**	**5.46**	**0.26**	**0.05**	**5.53**
$\boldsymbol{\rho_{97}}$	**-0.11**	**0.04**	**-3.08**	**-0.09**	**0.04**	**-2.52**
$\boldsymbol{\rho_{98}}$	**-0.12**	**0.04**	**-2.65**	-0.07	0.05	-1.41
AIC			**-24.78**			**-26.20**
SIC			**-24.16**			**-25.59**
Log likelihood			**6304**			**6663.25**

Table 3: Constant conditional correlations estimation results - ρij is the correlation between variable i and j. (1 for France; 2- Germany; 3-Netherlands; 4- Nordpool; 5- Spain; 6-Switzerland; 7-UK; 8- Belgium; 9: planned penetration(left column)/ actual penetration (right columns), standard errors and p-values for the conditional correlations: AIC and SIC are the Akaike Information Criterion and Schwartz Criteria, respectively. LnL is the log likelihood, LR test: θ 1 =θ 2 =0 (constant correlation assumption); significant values are printed in bold.

	Coefficient	Std. Error	t-value	Coefficient	Std.Error	t-value
ρ_{21}	**0.72**	**0.03**	**22.61**	**0.70**	**0.03**	**20.66**
ρ_{31}	**0.79**	**0.02**	**33.06**	**0.78**	**0.02**	**31.79**
ρ_{41}	**0.24**	**0.06**	**4.17**	**0.23**	**0.05**	**4.21**
ρ_{51}	**0.19**	**0.06**	**3.46**	**0.18**	**0.06**	**3.23**
ρ_{61}	**0.64**	**0.04**	**17.70**	**0.63**	**0.04**	**16.44**
ρ_{71}	**0.27**	**0.05**	**5.26**	**0.26**	**0.05**	**5.42**
ρ_{81}	**0.96**	**0.01**	**189.20**	**0.96**	**0.01**	**179.80**
ρ_{91}	**-0.12**	**0.05**	**-2.38**	-0.10	0.05	-1.80
ρ_{32}	**0.81**	**0.02**	**42.50**	**0.81**	**0.02**	**40.09**
ρ_{42}	**0.37**	**0.05**	**7.37**	**0.37**	**0.05**	**7.62**
ρ_{52}	0.12	0.06	1.94	0.09	0.06	1.52
ρ_{62}	**0.60**	**0.04**	**16.89**	**0.58**	**0.04**	**15.92**
ρ_{72}	**0.26**	**0.05**	**5.21**	**0.26**	**0.05**	**5.30**
ρ_{82}	**0.71**	**0.03**	**21.24**	**0.69**	**0.04**	**19.76**
ρ_{92}	**-0.35**	**0.05**	**-7.69**	**-0.24**	**0.05**	**-4.96**
ρ_{43}	**0.31**	**0.05**	**6.31**	**0.30**	**0.05**	**6.21**
ρ_{53}	**0.16**	**0.05**	**3.22**	**0.15**	**0.05**	**3.00**
ρ_{63}	**0.66**	**0.03**	**21.18**	**0.65**	**0.03**	**20.14**
ρ_{73}	**0.29**	**0.04**	**6.47**	**0.29**	**0.04**	**6.51**
ρ_{83}	**0.76**	**0.03**	**28.92**	**0.75**	**0.03**	**27.61**
ρ_{93}	**-0.28**	**0.04**	**-6.30**	**-0.19**	**0.05**	**-4.01**
ρ_{54}	-0.02	0.05	-0.38	-0.03	0.05	-0.56
ρ_{64}	**0.22**	**0.05**	**4.71**	**0.21**	**0.05**	**4.57**
ρ_{74}	**0.15**	**0.04**	**3.40**	**0.14**	**0.04**	**3.26**
ρ_{84}	**0.24**	**0.06**	**4.08**	**0.23**	**0.06**	**4.10**
ρ_{94}	**-0.12**	**0.04**	**-2.78**	-0.07	0.04	-1.61
ρ_{65}	**0.21**	**0.05**	**4.29**	**0.20**	**0.05**	**4.01**
ρ_{75}	0.01	0.04	0.29	0.01	0.04	0.32
ρ_{85}	**0.20**	**0.06**	**3.38**	**0.18**	**0.06**	**3.11**
ρ_{95}	-0.01	0.05	-0.15	-0.06	0.05	-1.20
ρ_{76}	**0.23**	**0.05**	**4.95**	**0.22**	**0.05**	**4.75**
ρ_{78}	**0.63**	**0.04**	**16.27**	**0.62**	**0.04**	**15.11**
ρ_{79}	**-0.16**	**0.04**	**-3.59**	**-0.11**	**0.05**	**-2.25**
ρ_{87}	**0.26**	**0.05**	**4.88**	**0.25**	**0.05**	**4.96**
ρ_{97}	**-0.10**	**0.04**	**-2.47**	**-0.09**	**0.04**	**-2.26**
ρ_{98}	**-0.12**	**0.05**	**-2.30**	-0.09	0.06	-1.62
θ_1	**0.02**	**0.01**	**4.17**	**0.02**	**0.01**	**3.81**
θ_2	**0.84**	**0.04**	**20.22**	**0.83**	**0.05**	**17.44**
AIC	**-25.03**	**LnL**	**6370.52**	**-26.4**	**LnL**	**6729.79**
SIC	**-24.40**	**LR test**	**133.04**	**-25.83**	**LR test**	**133.08**

Table 4: dynamic conditional correlations—Engle's (2002). $\boldsymbol{\rho_{ij}}$ is the correlation between variable i and j. (1 for France; 2- Germany; 3- Netherlands; 4- Nordpool; 5- Spain; 6-Switzerland; 7-UK; 8- Belgium; 9: planned penetration(left column)/ actual penetration (right columns), standard errors and p-values for the conditional correlations: AIC (Akaike Information Criterion) and SIC (Schwartz Information Criteria), LnL is the log likelihood, LR test: $\boldsymbol{\theta_1}$ =$\boldsymbol{\theta_2}$=0 (constant correlation assumption); significant values are printed in bold

Summary and Conclusions

European electricity markets are likely to become increasingly integrated, and much planning will necessarily happen at the European level (BMBF, 2011). This study provides evidence that the choices made by one State in the European Union inevitably can impact on the energy security of its neighbors. The univariate models suggest that high levels of wind penetration in Germany have had a direct bearing on other European electricity prices, even before the major phasing out of German nuclear plants. The influence was more noticeable when forecasted wind penetration was considered: high levels of forecasted wind penetration in Germany appeared to be linked to price reducing effects in three other countries as well as within Germany. Negative associations between forecasted wind penetration levels were confirmed in all countries except Belgium and Spain. When time varying correlations (TTDCC) were considered the correlation with French spot prices also became insignificant.

The findings are consistent with the physical interconnector linkage between the countries under study and the energy mixes.[9] To begin with, the significant associations between variance of forecasted wind penetration and spot price volatility can be explained by the fact that German wind generated electricity enjoys priority dispatch and sets the prices in the merit order curve. [10] Countries that are well connected by means of an interconnector exhibit positive volatility spill overs: Spain is relatively isolated with lower interconnection capacity, whereas especially Germany, France, Belgium and the Netherlands are connected through market coupling. The insignificant correlation between volatilities of French electricity prices and actual wind penetration volatility may be explained by the fact that Germany is a net-importer of French electricity.

To guarantee security of supply as well protection against price risks, balancing mechanisms need to be in place to manage the intermittency of RES, for example through *"outsourced reserve capacity"* i.e. trade with other countries. However, many of Germany´s trade partners generate electrical power using nuclear technologies or rely on fossil fuels, some of which are likely to be phased out, thus illustrating the challenge faced by its Energy Concept and the viability of its environmental and energy policy objectives.

A limitation of the study may be seen in the possibility that some of the findings could be overestimated due to omission of wind generation levels in other markets which are likely to be correlated. This would exacerbate balancing mechanisms. For future research we plan to examine leverage effects (differences between positive and negative deviations), the potential impact of demand level, winter versus summer effects as well as the influence of oil and, especially, gas prices.

[9] See appendix for major European interconnector lines.
[10] All electricity produced by wind in Europe must be given priority access to the grid by the transmission system operator (European Commission 2001).

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Appendix

Cable	***Connecting***	***Capacity***
NorNed	*Norway-Netherlands*	*700MW*
IFA	*France UK*	*2000MW*
Kontek	*Germany-Denmark*	*600MW*
Baltic	*Germany –Sweden*	*600MW*
BritNed	*UK-Netherlands*	*1000MW*