Time-Varying Convergence in European Electricity Spot Markets and their Association with Carbon and Fuel Prices

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ABSTRACT

Long-run dynamics of electricity prices are expected to reflect fuel price developments, since fuels generally account for a large share in the cost of generation. As an integrated European market for electricity develops, wholesale electricity prices should be converging as a result of market coupling and increased interconnectivity. Electricity mixes are also changing, spurred by a drive to significantly increase the share of renewables. Consequently, the electricity wholesale price dynamics are evolving, and the fuel-electricity price nexus that has been described in the literature is likely to reflect this evolution. This study investigates associations between spot prices from the British, French and Nordpool markets with those in connected electricity markets and fuel input prices, from December 2005 to October 2013. In order to assess the time-varying dynamics of electricity spot price series, localized autocorrelation functions are used. Electricity spot prices in the three markets are found to have stationary and non-stationary periods. When a trend in spot prices is observed, it is likely to reflect the trend in fuel prices. Cointegration analysis is then used to assess co-movement between electricity spot prices and fuel inputs to generation. The results show that British electricity spot prices are associated with fuel prices and not with price developments in connected markets, while the opposite is observed in the French and Nordpool day-ahead markets.

KEYWORDS

Energy markets; electricity markets; price convergence; cointegration; localized autocorrelation function

1. Introduction

In Europe, natural gas, coal and carbon prices have been found to be associated with electricity price movements (Aatola et al., 2013; Asche et al., 2006; Bollino et al., 2013; Castagneto-Gisey, 2014, Mjelde and Bessler, 2009), as the costs of generation are a large share of electricity prices. Most European states, however, have limited fossil fuel resources that can be used for electricity generation at the required scale. In recent years, concerns over the dependency on fuel imports have increased, despite growing shares of electricity from renewable energy sources (RES-E), as conventional back-up capacities are needed to secure supply. Depending on the strength of association between electricity and fuel prices, uncertainty about the latter could impair Europe's economic competitiveness, as the cost of electricity is an important input factor in almost every industry. In fact, electricity-intensive industries have already moved from the EU to regions where it is less costly (Reinaud, 2008).

In order to achieve cost-efficient electricity prices, a well-functioning internal European electricity market has been advocated. A pan-European electricity market implies regional integration, harmonization of trading rules, increased cross-border electricity transmission and trade (European Commission, 2013). Therefore, from the perspective of assessing electricity market integration in the EU, strong associations between fuel and electricity prices could affect electricity price convergence and vice versa.

The aim of this study is to link research on electricity market integration with studies of associations between electricity, fuel and carbon prices. A time-variant framework is adopted in order to understand dynamics that might have been neglected, possibly leading to the mixed findings reported in the literature. We examine long-run dynamics and convergence in three large European markets, where the reliance on fossil fuels for electricity generation varies: APX-UK (Britain), EPEX-FR (France) and Nordpool (Norway, Denmark, Sweden, Finland, Estonia, Latvia and Lithuania). Figure 1 provides a summary of the electricity generation mix in these markets, as well as in Germany and Netherlands, whose markets are connected to at least two of the three main ones and are also considered in the analysis. A more detailed description of the generation mix is provided in section 1.2.1. For assessing long-run dynamics, a two-stage analysis is developed: (1) stationary and non-stationary periods of electricity spot prices are identified via local autocorrelation functions (Cardinali and Nason, 2013), (2) convergence with fuel, carbon and other electricity markets is assessed in a cointegration analysis (Johansen, 1988, 1991).

The paper is structured as follows. First, the literature on electricity market integration and assessments of fuel, carbon and electricity price associations is reviewed; the contextual framework is introduced, and the research question is outlined. The second section describes the methods and dataset used. Section three reports results, while findings are discussed in section four. Section five concludes the paper and outlines policy implications.

1.1. Literature Review

Within a growing literature on common long-run dynamics in energy markets, a subset of studies have focused on the integration of fossil fuel and electricity prices. In general, integration is demonstrated by establishing price convergence over time, which is then interpreted as efficiency gains obtained when the marginal costs of production are equal in different regions (Engle and Rogers, 2004). Related studies can be classified as follows: (1) investigations of electricity market integration, (2) assessments of electricity and fuel price convergence and (3) investigations of electricity and energy market integration. The next sub-sections review each category and their implications for the present investigation.

1.1.1. On Electricity Market Integration

The Law of One Price (Fetter, 1924) has been the core theoretical foundation in assessing common long-run dynamics in liberalized electricity markets. Following the initial evaluations (Bower, 2002; Boisselau, 2004), several studies (e.g. Armstrong and Galli, 2005; Böckers and Heimeshoff, 2012; Bunn and Gianfreda, 2010; Robinson, 2008; Zachmann, 2008; Pellini, 2012) have examined electricity price convergence in the EU. Their assessments suggest decreasing price differences in several cases, greater convergence in peak-load periods (with the exception of Bunn and Gianfreda, 2010). Interconnection and geographical distances between markets were found to be crucial for price convergence. Yet, several authors concluded that the integration of European electricity markets has *"still a way to go"* (Pellini, 2012:1). However, most studies on electricity market integration neglected the potential relevance of the electricity generation mix, which could impact on convergence. Studies assessing relationships between electricity and fuel prices are therefore reviewed in the following section.

1.1.2. On Associations between Fuel and Electricity Prices

Since seminal evaluations by Serletis and Herbert (1999), several studies addressed the associations between generation fuels (such as natural gas, coal, crude oil and uranium) and electricity prices. For example, Brown and Yücel (2008), Emery and Liu (2002), Mjelde and Bessler (2009), Nakajima and Hamori (2013) and Woo et al. (2006) analyzed different U.S. markets and observed positive correlation between natural gas and electricity prices, which was also more pronounced during peak periods.

In the specific case of European markets, Asche et al. (2006) analyzed the British market and used cointegration analysis for monthly crude oil, natural gas and electricity wholesale prices in the period from 1995 to 2002. Interestingly, the authors found an integrated energy market only during 1995 to 1998, when the natural gas market was deregulated, but not yet physically linked to continental Europe by an interconnector. They inferred that prices could have decoupled in the second period, because of an incomplete regulatory structure or insufficient transmission capacity. Bollino et al. (2013) reasoned that even if from a physical viewpoint the possibility to exercise arbitrage is limited, it is conceivable that fuel price information available at the strategic decision center of a big multinational electricity generation company can be shared throughout its subsidiaries in different markets, thus stimulating market integration.

Moutinho et al. (2011) used daily prices from 2002 to 2005 and established cointegration between the Spanish electricity spot and natural gas prices, as well as for coal prices, but not for oil prices. By contrast, Furió and Chuliá (2012), using data from 2005 to 2011 found full integration of fuel (oil and natural gas) and electricity prices in the month-ahead market. Their findings support Munoz and Dickey's (2009) claim that natural gas, coal and oil, in this order, were the main components of Spanish electricity prices. Bencivenga et al. (2010) linked the research conducted in the US and the EU by comparing the associations between crude oil, natural gas and electricity prices in both markets. Using daily data from 2001 to 2009, their results suggest differences in convergence behavior. The authors concluded that despite the efforts of the European Commission, integration in the EU was lower than in the US and attributed their finding to incomplete deregulation in the European market, exercise of market power and self-governing gas price behavior.

Simpson and Abraham's (2012) study added to the literature by assessing electricity market and energy sector decoupling (regulation) versus convergence (deregulation/liberalization). They compared the electricity and energy markets in several countries within OECD, Latin America and Asia from 2000 to 2011. They reason that the strength of the integrating relationship between fuel and electricity prices should be indicative of greater progress of electricity market liberalization. Their results showed that larger economies, whether developed or undeveloped, demonstrated stronger relationships between fuel and electricity prices. Thus a greater degree of liberalization was due to less price manipulation through monopolies. In addition, they suggested that heavy use of renewable sources and their regulatory cost reduced convergence.

Together these studies demonstrate that associations between fuel and electricity prices are relevant for long-run dynamics in electricity prices, and should therefore be considered when assessing electricity market integration.

1.1.3. On Electricity Market Integration and Fuel and Carbon Price Associations

Among evaluations of electricity market integration, few researchers have addressed dependencies with fuel prices. For example, Kalantzis and Milonas' (2010) analysis of eight EU electricity spot markets between 2006 and 2009 concluded that rising oil prices indirectly exert a positive impact on price convergence, due to substitution with indigenous energy sources. This effect is more pronounced during off-peak hours, when the interconnection capacity was not fully utilized and congestion was less frequent.

Including renewables (wind electricity production and water reservoir levels) in their assessment of convergence between fuel and electricity prices, Ferkingstad et al. (2011) investigated dynamics between Nordpool and German electricity prices, major fuel sources (oil, natural gas and coal), from 2002 to 2008. Similar to single-market studies, their findings confirmed strong correlation between natural gas and electricity prices, whereas the price of coal did not play an important role. Bosco et al. (2010) found strong evidence of common long-run dynamics between electricity and natural gas prices in four European markets between 1999 and 2007. Bollino et al. (2013) could not find any association with oil prices, concluding instead that natural gas, the common marginal generation source, prevails in the determination of long-run relationships of electricity prices in the UK, Germany, Austria and France.

The introduction of the EU Emissions Trading Scheme (EU ETS) in 2005 marked an important change in EU energy policy. Several researchers (e.g. Fezzi and Bunn, 2010; Sjim et al., 2006; Pinho and Madaleno, 2011) analyzed how carbon costs are linked to electricity prices. Pinho and Madaleno (2011) used monthly data from 2005 to 2009 and examined associations between carbon, electricity and fuel prices in Germany, France and Nordpool by means of a Vector Error Correction Model. They found the impact of carbon prices to depend on the countries' energy mixes. Aatola et al. (2013) assessed the effect of carbon prices on the integration of European electricity markets using Granger causality, correlation and cointegration analysis. Comparing three sub periods, their findings support the association with energy mixes, but also indicate that there is variation with time and plant technology. They observed that carbon prices had a positive but uneven effect on electricity market integration.

In summary, the reviewed literature mainly focuses on one aspect of price convergence: either with prices in other electricity markets, or with generation input costs. Despite possible associations between these aspects, a link between the papers does not appear to have been formally established. Since assessments of electricity market integration found more convergence during peak-load periods, when conventional gas/coal generation are likely to be needed, some convergence of electricity wholesale prices could therefore have been driven indirectly by fuel prices.[1]

Furthermore, the findings reported above indicate that convergence should be time-varying, as associations depend on the local electricity mix, the degree of regulation and the size of the market. Cointegration analysis was broadly applied to assess convergence and was at most employed to three sub-periods to capture changes in time (Aatola et al., 2013). Cointegration analysis requires non-stationarity of the time series; in order to meet this criterion researchers either aggregated the data (e.g.

[1] With more interconnections, and more cross-border movements of electricity, additional imported power reflects its marginal production cost in the country of origin, which ultimately depends on the fuel used for its generation.

Bosco et al. 2010; Ferkingstad et al., 2011; Mjelde and Bessler, 2009) or employed price indices, such as consumer prices (e.g. Simpson and Abraham, 2012). The present study addresses potential implications for and from electricity market integration that have been neglected in earlier assessments, in a time-varying framework.

1.2. Contextual Background of European Electricity Markets

1.2.1. Electricity Mix in European Markets

The local electricity mix is likely to be relevant for electricity market integration because of the price setting mechanism and the possibility for arbitrage in case of complementary generation portfolios (Teusch, 2012). The bid of a conventional electricity generator to the exchange reflects the variable cost of the fuel that is used for production and the carbon price. This is the case even if the allowances are granted for free as they represent opportunity costs (Sjim et al, 2006).

The system operator dispatches the generators with the lowest marginal generation cost and then moves up the dispatch curve, calling on generators with higher marginal costs until demand is satisfied. Thus, if there were no constraints in transmission lines, the electricity spot price is set by the marginal producer. In a cost-reflective market, input prices in electricity generation should at least be partially reflected in electricity prices and, for markets with a large share of a specific marginal fuel in its electricity mix, associations are expected to be stronger (Furió and Chuliá, 2012).

Figure 1 and Table 1 present gross electricity generation between 2005 and 2012 in the five markets (France, Britain, Germany, Nordpool and the Netherlands) considered here. The French electricity mix is characterized by the highest share of nuclear generation among these markets. The share fluctuated between 76% and 80% between 2005 and 2012. In 2012, 11% of the domestic electricity was generated by hydro, 4% by gas, followed by wind and coal-generated electricity (3% each). In Britain, large but declining quantities of gas were used to generate electricity between 2005 and 2012. The share of coal on the other hand increased from 30% in 2011 to 40% in 2012. Nuclear generation contributed around one fifth of gross electricity output between 2005 and 2012. The largest component in the German electricity mix is coal, with a share of 45% in 2012. More than 16% of the local electricity mix in 2012 consisted of nuclear, which declined from 167TWh in 2006 to 100TWh in 2012. This decrease is due to the implementation of Atomgesetz[2]. The implementation of EEG[3] (Renewable Energy Sources Act) in 2000 has led to rapid growth in renewables, especially biomass, photovoltaics and wind.

Nordpool has a large share of seasonal hydro-generated electricity, about 130TWh hydro capacity, of which 63% is installed in Norway, 26% in Sweden and 11% in Finland (NordpoolSpot, 2014). In the Netherlands, gas and coal have the highest shares in the local electricity mix, which vary over time.

In summary, we observe changing electricity mixes and significant differences across countries, reflecting local and EU energy policies that aim at decarbonizing the electricity sector and increasing the share of RES-E.

FIGURE 1

TABLE 1

1.2.2. Electricity Trade in the EU

In addition to decarbonizing the electric system, some electricity markets have become integrated via coupling, which is the use of implicit auctioning involving two or more power exchanges. For example, the Trilateral Market Coupling couples the Belgian, Dutch and French electricity markets since November 2006. The Interim Tight Volume Coupling links the Belgian, Dutch, French and German electricity markets with Nordpool since November 2010. The British market, though interconnected with three other markets, was not coupled to any other European market in the period covered by this study.

Different levels of interconnectivity are also reflected in Figure 2, where the ratio of imports to total electricity generation and exports to total electricity generation from 2005 to 2012 are depicted. The Netherlands is a major electricity transit country and this can be seen in the values of import and export

[2] This is detailed at http://www.bmub.bund.de/bmub/parlamentarische-vorgaenge/detailansicht/artikel/atomgesetz-atg-gesetz-ueber-die-friedliche-verwendung-der-kernenergie-und-den-schutz-gegen-ihre-gefahren/

[3] This is detailed at http://www.bmub.bund.de/en/service/publications/downloads/details/artikel/renewable-energy-sources-act-eeg-2012/

shares of the total Dutch electricity generation, which reached almost 32% and 15% respectively. In the German and Nordpool markets, imports and exports fluctuated around 10% of the overall generated electricity between 2005 and 2012. In France, exports ranged between 9% and 13% in the same period, however imports were much smaller with the highest value of only 4% in 2009 and 2010. The British market stands out as the one with the lowest shares of imports and exports expressed as a share of total domestic electricity generation: exports were less than 1% and imports at most 3% between 2005 and 2012.

FIGURE 2

1.2.3. Electricity Spot Price Dynamics

Electricity spot prices have often been found to be stationary mean-reverting processes (e.g. Escribano et al., 2002; Haldrup and Nielsen, 2006; De Jong and Huisman, 2002; Huisman and Mahieu, 2003), unlike most fuel price series that tend to follow trends. Mean reversion implies stationarity. With each successive movement away from the long-run average, the likelihood that the next price movement will be toward the average increases (Marshall, 2000). One aim of electricity market integration is to increase the speed of mean reversion of prices, which would indicate greater market resilience against unexpected supply or demand shocks. A quick speed of mean reversion or strong stationary behavior implies robustness and flexibility of the electric system, in the sense that additional capacities are brought online quickly and prices revert to their normal levels as expensive plants are swiftly replaced. By contrast, persistent prices indicate that shocks are less easily overcome.

Any assessment of price convergence via standard cointegration analysis (Johansen, 1988, 1991), requires that the time series are at least integrated of order one (*I(1)*). This long-run price behavior contradicts the aim of electricity market integration, which implies faster mean reversion. With increasing market integration, long-run behaviors of electricity spot prices could be changing: from non-stationarity due to associations with mainly non-stationary fuel prices towards increasing periods of mean-reversion facilitated by the availability of local and neighbor market capacities.

All in all, the differences in local electricity mixes and cross-border flows suggest that fuel, carbon and electricity prices in neighboring markets may differ in relevance for price dynamics and convergence in the markets described. This study therefore revisits the question "How do fuel and carbon prices associate with electricity prices?", within the context of the integration of electricity markets and, therefore, attempts to link the different streams of literature.

2. *Methods*

2.1. Analysis Procedure

Prior to the empirical analysis, outliers are replaced with the average over a four-week period. An outlier is defined as a value exceeding three standard deviations of the mean average over a four-week window. The time series behavior is then summarized and assessed for stationarity and trends, via unit root tests and estimates of the order of integration. The methods are described in 2.1.1. Serial correlation of the electricity spot price time series are examined via estimates of the localized aurocorrelation function (LACF), as detailled in section 2.1.2.. Having identified potential non-stationary periods as those where the absolute values of LACF of lags 1 to 20 are greater than 0.8 – i.e. close to 1 - a unit root test is used to confirm or reject non-stationarity. Within periods where a unit root is confirmed, a cointegration analysis of neighbouring electricity spot prices, fuel inputs and carbon prices is performed, as described in section 2.1.3. We differentiate between peak and off-peak hours, because they have different price dynamics, as the more expensive generation units would normally be allocated at peak periods. It could also be argued that during peak periods, the competition between generators is greater.

2.1.1. Assessing Trends: Tests for Integration and Fractional Integration

The Augmented Dickey Fuller (ADF) and the Phillips and Perron tests (PP), which were proposed by Dickey and Fuller (1979, 1981) and Phillips and Perron (1988) respectively, are used to test the alternative hypothesis of a mean-reverting against the null hypothesis of a trended, *I(1)*, time series. The tests are conducted up to lag length l which in this study is selected based on the Akaike Information Criteria (AIC). The order of integration of the time series (d) is also estimated by employing the semi-parametric two-step Feasible Exact Local Whittle (FELW) estimator by Shimotsu (2006) with bandwidth equal to 0.75, as suggested by Lopes and Mendes (2006), and the GPH (Geweke and Porter-Hudak, 1983) estimator.

2.1.2. Identifying Time-varying Dynamics: Localized Autocorrelation Functions (LACF)

A locally stationary process is a non-stationary time series that has a time-varying spectrum. This kind of process is useful in describing time series whose properties change over time, thus allowing for the identification of periods that are locally stationary as well as other periods that are locally non-stationary. Following Nason et al. (2000), a stationary time series X_t can be represented as:

$$X_t = \int_{-\pi}^{\pi} A(\omega) e^{i\omega t} dz(\omega) \quad (2)$$

Where $A(\omega)$ is an amplitude function, $e^{i\omega t}$ is a system of harmonic exponentials and $dz(\omega)$ is an orthogonal increment process. The amplitude function, $A(\omega)$, controls the variance of the time series. The usual spectrum $f(\omega) = |A(\omega)|^2$ and the spectrum and autocovariance are a Fourier transform pair.

Several extensions to the basic stationary model have been proposed to address non-stationarity of time series, such as the general class of models that are *locally stationary*. These models replace the time invariant $A(\omega)$ term with an expression that explicitly depends on time, e.g. $A_t(\omega)$ (see for example Priestley (1983), Dahlhaus (1997); Dahlhaus and Polonik (2006) or Dahlhaus and Polonik (2009)).The localized autocovariances, $c(z, \tau)$ are computed following Nason et al. (2000):

$$c(z, \tau) = \sum_{j=1}^{J} S_j(z) \psi_j(\tau), \quad (3),$$

where $\psi_j(\tau) = \sum_k \psi_{j,k}$ is the autocorrelation wavelet of the discrete non-decimated wavelet $\psi_{j,k}$ and $c(z, \tau)$ is the autocovariance of X_t at lag τ and at rescaled time $z = t/T$ for time points *t=1, ….T* where *T* is the length of the time series (Cardinali and Nason, 2013). The LACF estimates are computed with the *costat* package available in *R* (Nason, 2013). The method requires the time series to be of a length that is a power of two; we therefore consider the longest possible sample length of 2048 observations.

Standard ACF can be used to determine stationarity. If the ACF falls immediately from 1 to 0, the series is stationary. If the ACF declines gradually from 1 to 0 over a prolonged period of time, then it is non-stationary. We identify periods in the LACF of at least 20 consecutive days and the estimated coeffficients from the first to the 20th lag are greater than 0.8. This indicates that the time series are more likely to be non-stationary, since these estimates are not declining immediately. After a unit root is confirmed, cointegration analysis is carried out for that period.

2.1.3. Assessing Co-movement with fuel prices: Tests for Cointegration

Two time series x_t and y_t, integrated of order *d*, are said to be cointegrated of order (*d, b*) if the error correction term represented by the linear combination $z_t = y_t - \beta * x_t$ is integrated of order $d - b$, where $0 < b \leq d$. This study uses the VAR approach, which was developed by Johansen (1988, 1991) and Stock and Watson (1988) to assess cointegration. The general VAR (*k*) model can be written as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{j=1}^{k-1} \Gamma_j \Delta y_{t-j} + \varepsilon_t \quad (4)$$

where y_t is a vector of *I(1)* variables. The variables are said to be cointegrated if Π has less than full rank and is not equal to zero. In this case Π can be written as $\Pi = \alpha\beta^T$, where α and β are $n \, x \, r$ matrices. The rank of Π determines the number of independent rows in Π and therefore the number of independent cointegrating vectors (number of significant eigenvalues). Each significant eigenvalue represents a stationary relation. If Π is equal to zero, there is no cointegration. For a given *r*, the maximum likelihood estimator of β defines the combination of y_{t-1} that yields the largest canonical correlation of Δy_t with y_{t-1}.

The trace and maximum eigenvalue tests in the bivariate case the null hypothesis of *r=0* cointegrating vectors (*not cointegrated*) against the alternative hypothesis of *r=1 (cointegrated*) cointegrating vectors (Johansen (1988), Stock and Watson (1988)).

2.2. Data

Three electricity spot markets are considered: APX-UK, Nordpool and EPEX-FR . In each case, two other electricity markets (Germany and the Netherlands for Britain; France and the Netherlands for Nordpool; Germany and Britain for France) as well as API2 Coal, UK NBP Natural Gas[4] and EU-ETS (carbon) prices are included in the analysis. Figures 3 and 4 depict electricity base-load prices, fuel and

[4] Although the use of other European natural gas prices (such as TTF in the Netherlands) could be justified, these prices have been found to be cointegrated, see for example Schultz and Swieringa (2013).

carbon prices as well as electricity peak-load prices and fuel and carbon prices in the day-ahead market, respectively. Base-load prices are the mean average of 24 hourly price observations for weekdays only[5]. Peak prices are averages covering the hours from 7am to 7pm for weekdays (APX, 2013).

FIGURE 3

FIGURE 4

Table 2 contains the summary statistics of the data, covering the period from the 12.12.2005 to 16.10.2013 for all series except coal, which began on the 17.07.2006. The electricity base- and peak-load spot prices for Britain (APX-UK), France (EPEX-FR), Germany (EPEX-DE), Netherlands (APX-NL), Nordpool (NP) and prices for natural gas, coal and carbon emissions have been obtained from Thomson Reuters Datastream. We exclude oil from the analysis as gas increasingly serves as a substitute for oil and both are highly correlated (Moutinho et al., 2011, Furió and Chuliá, 2012).

Estimated means in the second row show that on average electricity prices share a similar price level, with the lowest average prices observed in Nordpool (41.83€/MWh for base-load and 44.43€/MWh peak-load periods) and the highest in France (52.31€/MWh for base-load and 63.06€/MWh for peak-load periods) during both peak- and base-load periods. Volatility in all markets is larger during peak- compared to base-load periods, which is consistent withe the convexity of the merit order curve.

Carbon prices are quoted in €/EUA and ranged between 0.01-29.78 €/EUA with an average of 8.24 €/EUA. Coal and natural gas prices are reported in €/MWh. The former ranged between 17.81-58.22 €/MWh and the latter between 16.90-101.00 €/MWh during the period studied.[6]

TABLE 2

3. Results

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[5] Base-load power refers to electricity produced throughout the day, whether at night or during the day. Prices do change during the day as demand for electricity fluctuates in any 24-hour period. The daily prices used here are averages of the 24 hourly slots for this tier of electricity.

[6] Coal prices have been converted from £/ton to €/MWh assuming a heat rate of 35%. Gas prices were originally reported in Pence/Therm and have been converted to €/MWh assuming a heat rate of 50% (EIA, 2014)

3.1. Tests for Integration and Fractional Integration

The *p-values* of the PP and ADF unit root tests are reported in rows two to five of Table 2 for each time series and its first difference. The optimal lag lengths *l* used in the tests are reported in brackets behind the test statistics. The tests for the series strongly reject the hypothesis of a unit root for all electricity base- and peak-load as well as natural gas prices. The coal and carbon price series, on the other hand, are non-stationary since their *p-value* is larger than .05. The ADF and PP unit root tests on the differenced series reject the unit root hypothesis for all series. Hence, carbon and coal prices are integrated of order one (*I(1)*).

The semi-parametric GPH estimates for the order of integration *d*_GPH in row six of Table 3 confirms non-stationary *I(1)* behavior of carbon and coal because the estimates of *ds* are close to 1. The estimated order of integration *d*_2 step ELW, which can be found in row seven of Table 2 is similar to the values obtained via the GPH estimator, thus confirming that carbon and coal prices are non-stationary, integrated *I(1)* process. All electricity spot price series, on the other hand, appear to be fractionally integrated process with quicker speeds of mean reversion because the order of integration *d* is significantly smaller than one. Furthermore, lower values of *d* are observed for peak-load.

TABLE 3

3.2. LACF and non-stationarity

Figures 5 and 6 depict the LACF of lags 1-20 for APX-UK, EPEX-FR and Nordpool during base- and peak-load periods between December 2005 and October 2013. When comparing LACF estimates during peak- and base-load periods, we observe that values of peak prices have a larger range. Furthermore, LACF estimates indicate non-stationary periods for peak as well as base-load prices. For example, for Britain between the end of November 2006 until end of May 2007 (on the x-axis 200 to 400) LACF values are close to one. But there may also be stationary periods, where the LACF decline quickly implying decreasing associations between lags.

A similar observation holds true for EPEX-FR (France), though there seem to be fewer non-stationary periods compared to the Brittish market. The Nordpool LACFs seem to have increased in variance over time. At the beginning of the time series of Nordpool (both base-load and peak-load prices) the LACF values were high (close to one) and showed little variability, however from the second quarter in 2008 variability seems to have increased.[7]

FIGURE 5

FIGURE 6

According to the identification criteria based on the LACF values, there are 10 periods for British base-load electricity spot prices that are likely to be non-stationary. The periods and their duration are listed in Table 4 in the first and second column, respectively. The unit root test results confirm that four (printed in bold) of the ten identified periods of British base-load prices are non-stationary. For six periods, the null hypothesis of a unit root was rejected at 5% significance level. For the four periods for which a unit root was confirmed, the ADF test was also conducted for coal, carbon and natural gas prices, as well as Dutch and French base-load electricity prices. The unit root test results are reported in columns four to eight. Coal prices and carbon prices were found to be non-stationary during the same four periods as British base-load prices. Natural gas prices shared non-stationarity with British base-load prices during two periods. Electricity base-load prices in the Netherlands were non-stationary during the first period. The French electricity market did not share any non-stationary periods. For the periods where the other variables shared a unit root with British base-load prices, a cointergation analysis was carried out which will be detailed in 3.6.2.

For British electricity peak-load prices, nine periods could be non-stationary according to the LACF criteria. They are listed in the first column of Table 5. The periods are similar to British electricity base-load periods but shorter. The null hypothesis of a unit root was rejected at 5% significance level for six periods. For three periods the hypothesis of a unit root was not rejected. British base- and peak-load prices mainly contained a unit root during winter and spring months. The other time series (natural gas,

[7] Figures similar to 5 and 6 are available for EPEX-FR and Nordpool, but are omitted here in the interests of brevity.

coal, carbon and French electricity) were assessed for a unit root during the same periods for which a unit root in British electricity peak-load prices was confirmed. Results are reported in columns four to seven of Table 5. Again, coal and carbon prices shared non-stationary behavior during the same three periods. French electricity spot prices were non-stationary only during the first period in Autum 2006, and natural gas was non-stationary during the last period in the first quarter of 2010.

TABLE 4

TABLE 5

For Nordpool electricity base- and peak-load prices, eight potentially non-stationary periods were identified by means of the LACF criteria in each case. The periods are listed in the first column in Tables 6 and 7, respectively. The length of the potentially non-stationary periods range between 20 to 197 days for base-load and 23 to 121 day for peak-load prices as detailled in the second columns. The ADF test statistics in the third columns show that four base-load and three peak-load periods were found to contain a unit root according to the ADF statistics. There appears to be no clear pattern regarding seasons and non-stationarity in Nordpool base-load prices.

Natural gas prices show non-stationary behavior during the same four periods as Nordpool base-load prices. Coal prices are non-stationary only during one (the last) period from 15.06.2010 to 26.07.2010. Carbon prices show non-stationary behavior during three periods from 12.12.2005 to 6.3.2006 as well as from 29.10.2009 to 25.11.2009 and 15.06.2010 to 26.07.2010. The interconnected German and Dutch electricity markets' prices contain a unit root between July and September 2008 (31.07.2008- 02.09.2008). The periods that have been found to be non-stationary for peak-load prices are dissimilar to the identified base-load periods (the first non-stationary period is from 08.11.2006 to 24.01.2007; the second is between 31.07.2008 and 29.08.2008 and the third between 16.06.2010 and 27.07.2010). Natural gas prices are non-stationary during the same period as electricity peak-load prices in Nordpool. Coal and carbon prices share non-stationary behavior during two periods and prices in Germany are non-stationary at the same time with Nordpool electricity peak prices only once (the second non-stationary period).

TABLE 6

TABLE 7

For French electricity base-load prices, two periods lasting 68 and 70 days from February to May in 2007 and in 2009 confirmed a unit root (Table 8, column 1). However, only natural gas shared non-stationary behavior during the first period. For French peak-load prices four non-stationary periods were possible, but the ADF test statistics reported in the third column of Table 9 only confirmed a unit root from 17.06.2011- 09.08.2011 for all variables (natural gas, coal and carbon prices, British and German electricity peak-load prices).

TABLE 8

TABLE 9

All in all, there is evidence that EU electricity spot prices are locally stationary processes as they show periods of non-stationarity, as well as periods where prices revert to their mean more quickly. In the following section we assess convergence during the identified non-stationary periods.

3.3. Analysis of Convergence

Only the identified non-stationary periods are investigated concerning common long-run dynamics, as detailed below.

3.3.1. Britain

The cointegration analysis for British electricity base-load and peak-load prices are summarized in Tables 10 and 11, respectively. The periods that have been found to contain a unit root in the previous section are listed in the first column. The second column lists the variables for which cointegration is assessed as a unit root for the respective period. The Maximum Eigenvalue (λ_{eigen}) and Trace (λ_{trace}) test statistics are stated in columns three and four, respectively, with *p-values* reported in brackets.

For British electricity prices, four cointegrating relationships for base prices (Table 10) and three for peak-load periods (Table 11) were found. For the first period in autumn 2006 (26.09.2006 to 08.11.2006) carbon prices are integrated with British electricity base-load prices according to the Maximum Eigenvalue statistics (5% significance level). The λ_{eigen} test statistics surpass their critical values and we reject the hypothesis *not integrated*. Cointegration with coal, and Dutch electricity base-load prices was rejected.

TABLE 10

TABLE 11

In the second non-stationary period (rows five and six) there is also an association between carbon and base-load prices during the winter months 2006/2007 (28.11.2006 to 31.05.2007). Despite non-stationary behavior of base-load prices for the third period (11.03.2009 to 19.05.2009), we do not find co-movement with any other variable under study.

During the last non-stationary period, from December 2009 to late spring 2010 (21.12.2009-14.5.2010), the Trace as well as the Maximum Eigenvalue statistics suggest cointegration between natural gas and base-load prices as the test statistics are larger than the critical value. Furthermore, the two statistics suggest cointegration between base-load and coal prices.

For British electricity peak-load periods, results are reported in Table 11. Just as in the case of base-load prices for the first non-stationary period during autumn 2006 (29.09.2006- 07.11.2006), Peak-load prices and carbon prices are cointegrated according to the Maximum Eigenvalue statistic at 5% significance level. Peak-load prices also moved with carbon prices between the end of November 2006 to end of May 2007. The last non-stationary period of peak-load prices coincides with the fourth non-stationary period of base-load prices but is significantly shorter. Peak-load prices and coal, as well as peak-load prices and carbon prices, were found to be cointegrated.

All in all, peak-load prices were found to be integrated with the same variables as base-load prices, but for shorter periods. The British electricity market did not show any signs of convergence with interconnected electricity markets.

3.3.2. Nordpool

Table 12 presents the four non-stationary periods (first column) and cointegration test statistics (columns four and five) for Nordpool electricity base-load prices with the variables (listed in the second column), which also contain a unit root in the respective period. The results of the cointegration analysis using the Trace and Maximum Eigenvalue test statistics confirm only one of ten possible cointegrating relationships for Nordpool base-load prices. Between the end of July and the beginning of September 2008 (31.07.2008- 02.09.2008), German base-load prices appear to be integrated with Nordpool base-load prices at 5% significance level according to both test statistics. The Dutch electricity prices series during the same period did not share a cointegrating relationship with Nordpool base-load prices.

For Nordpool peak-load periods (Table 13) a cointegrating relationship was confirmed only with German peak-load prices at 5% significance level according to the Trace as well as the Maximum Eigenvalue statistics. The period is similar to base-load prices from 31.07.2008-29.08.2008. For all other variables we reject the hypothesis of cointegrating relationships with Nordpool peak prices.

We do not find associations between Nordpool prices and any fuel or carbon prices.

TABLE 12

TABLE 13

3.3.3. France

For French base-load prices, non-stationary behavior was confirmed for only one period between 07.02.2007 and 11.05.2007, listed in the left column of Table 14. Natural gas was the only variable that was also found to be non-stationary during that period and we found strong evidence for cointegration for the pair according to the Trace as well as Maximum Eigenvalue Statistics.

For French peak-load prices, the period from 17.06.2011 to 09.08.2011 was assessed regarding convergence with other electricity markets, fuel or carbon prices. Columns three and four of Table 15 contain the test results of the Trace and Maximum Eigenvalue statistics for peak-load periods with natural gas, coal and carbon prices and adjacent electricity markets in Britain and Germany. For the single period that was found to be non-stationary, cointegration of peak-load prices with fuel and carbon prices was rejected. The hypothesis of no cointegration with German and British peak-load prices, on the other hand, was rejected at 5% significance level using the Trace test statistics.

TABLE 14

TABLE 15

4. Discussion

In the first part of the analysis, whilst electricity spot and natural gas prices were found to be fractionally integrated mean reverting processes in the long run, coal and carbon prices follow trends. The LACF estimates confirmed that electricity spot prices in the three markets (Britain, Nordpool and France) are time-varying processes. Periods that appeared highly persistent were tested for a local trend; peak- and base-load price periods are similar in all three markets. LACF estimates are subject to uncertainty, possibly due to small sample sizes, and there is a need for further investigation concerning their reliability. For example, rolling-window unit-root tests with varying window sizes could be computed and results compared. It could also be that the threshold of 0.8 was too conservative, thus leading to greater rejections of unit roots, yet the aim of this study was to identify periods of non-stationarity and the combination of methods was fit for purpose, especially since the low power of the ADF test in smaller samples would have favored the acceptance of unit roots.

Non-stationary peak-load periods are fewer and generally shorter in comparison to base-load prices. This shows that market responses to shocks are quicker for peak load. This finding is consistent with the higher estimate for the order of integration *d* observed in the base- compared to peak-load periods, thus indicating slower mean reversion of base-load prices. This slower response to shocks could be due to the fact that the lower end of the merit order curve consists of less flexible generation, which might have been traded in forward contracts. In addition, power plants may not be willing to produce electricity at lower prices, which are common during base hours.[8] Hence, changes in weather conditions and unexpected events mean that generators and suppliers need to adjust their base-load position thus leading to a more volatile market. This is cause for concern with increasing levels of wind power and greater market integration, as it suggests that shocks to base load may be transmitted across borders.

In the British market a seasonal pattern was identified: non-stationarity mainly occurred during winter and spring months, when heating demand is high. LACF estimates for Nordpool showed a break in its behavior apparently due to the commissioning of the NorNed Interconnector in May 2008, which physically linked Norway with the central European market. LACF values before the commissioning of NorNed showed less variability and values closer to 1. LACF values thereafter were much less persistent. Unit root tests in Nordpool revealed that after 2009 non-stationary periods coincided with high hydro reservoir levels, as illustrated by Figure 7. Prices during these periods are more resilient against demand or supply shocks due to availability of highly responsive hydro-powered plants.

FIGURE 7

The least non-stationary periods were identified in the French market. Cointegration tests were then used to assess co-movement with natural gas, coal and carbon prices as well as with other interconnected or coupled electricity spot markets during the identified non-stationary periods. The results show that electricity spot price movements in the different markets are influenced by the electricity mix and cross-border trade. Spot prices in the British market are found to be more associated with carbon, natural gas and coal prices and independent of other spot markets. These observations are not surprising given the

[8] For this last comment, we are grateful to an external anonymous reviewer.

limited interconnection and trade with other markets and an electricity mix that relies heavily on coal and gas generators.

Figure 8 illustrates the changing electricity mix in Britain between 2009 and 2013, while Figure 9 compares the British electricity mix during the non-stationary period in spring 2009 and one year after. Similarly, Figure 10 displays a similar comparison for the non-stationary period from December 2009 to May 2010. For both these periods when convergence of electricity and natural gas prices was found, the share of natural gas in the electricity mix was higher than in other periods. For the latter period, the finding is possibly due to extreme meteorological conditions: in the first quarter of 2010, two balancing alerts from the National Grid due to production problems in Norway provoked a brief reduction of gas flow (European Commission, 2010). Electricity prices were therefore soaring in the second quarter of 2010 and strongly associated with its marginal cost of production.

FIGURE 8

FIGURE 9

FIGURE 10

The French and Nordpool electricity markets have a low share of conventional thermal electricity, as detailed in section 1.2.1. Unsurprisingly, there is only one period of common long-run dynamics between natural gas and French base-load prices, which can be explained by the long warm spell from January to August 2007. The hot weather limited nuclear electricity output due to reduced cooling capacity and demanded alternative sources of generation. Interestingly, in 2011, a similar incident in the 2nd and 3rd quarter decreased availability of nuclear power and led to price convergence between France and adjacent electricity markets (Britain and Germany), but not with fuel prices (European Commission, 2011a, 2011b). This confirms the importance of a policy that supports electricity market integration, since capacity shortfalls can be compensated via imports.

When assessing integration with adjacent electricity markets, there are noteworthy additions to existing literature. The results do not support Bosco et al.'s (2010) conclusion that Nordpool did not share a common trend with other markets due to individual peculiarities in the technology structure, and suggest that there have been changes since 2007. For example, in the summer of 2008, Nordpool was integrated with the German electricity market. All in all, market integration may reduce associations between fuel and electricity prices.

A limitation of this study is the low power of trace and maximum eigenvalue statistics in small sample sizes, which led to some conflicting results. A less restrictive method, such as fractional cointegration, might be more reliable. Another limitation of the study is that the assessment was not conducted for all bordering or interconnected markets, as for some markets (e.g. Spain) prices were not available in peak and base-load resolution. Furthermore, the use of UK NBP Natural Gas as an indicator of natural gas prices as well as API2 coal for coal prices in Europe could be questioned. Other indices might have led to different results; however, the variation should be marginal due to the liquidity in the natural gas market and the predominance of API2 coal traded.

5. *Conclusion and Policy Implications*

Our results showed that electricity spot prices in all markets have a time-varying behavior, with periods of longer mean reversion, during which there may be stronger associations with fuel and carbon prices. In addition, where there is stronger interconnection or market coupling, there is greater association with neighboring markets for some periods. Consequently, local electricity mix and market integration are relevant for spot price formation. The results support the reasoning that Europe's fuel price dependency can be reduced not only by increasing the share of domestic RES-E, but also by increasing interconnection and electricity market coupling. The electricity-fuel price nexus was weaker in well-connected markets, as supply and demand could be managed more flexibly with cross-border trading. On the one hand, this is encouraging and reinforces the policy of electricity market integration, as a consequence of the liberalization process. On the other hand, the time-varying nature of spot prices and the local changes that were observed are also cause for concern.

First, it was observed that base-load spot prices may be subject to longer periods of volatility clustering; in interconnected markets this may lead to volatility transmission between markets. Second, the time-varying behavior of spot prices confirms that not only risk-premiums but also their differences, based on which the direction of the power flow in interconnectors should be determined, are also time-varying. Consequently, historical time series of spot prices are not very reliable for the assessment of future investments and interconnector flows. Indeed, there is greater complexity in the markets, which calls for policies that encourage greater sharing of information between market operators. Third, weather conditions may explain a significant proportion of changes in the nature of spot prices. Given national energy policies that aim to increase renewable generation, spot markets' dependency on weather forecasts is likely to increase, thus making forward and future contracts more attractive, but also with the potential to increase risk-premium and the cost to consumers. Indeed, the lack of transparency in these bilateral contracts has already resulted in regulations at European level (REMIT) since December 2011, so that trade data are now available for regulators to better monitor the market and investigate market abuse.

In Britain, for example, the regulator (Ofgem) has recently established specific slots of two hours, when the eight biggest market players are obliged to trade. As shown in this study and previous literature, there is stronger association between gas and electricity prices in Britain, thus the regulator should also be assessing whether the greater trading on these slots has an impact on the natural gas market. A strong association between energy markets with a limited number of big players may lead to confusing signals and affect competition. This could become problematic for policy makers, who target investments in flexible gas powered generation.

At present, the British market is less associated with other markets, reflecting the fact that the island is less interconnected with electricity trade flow patterns that tend to be unidirectional (exports to Ireland, imports from France). However, new interconnectors are planned. Given the observed link between carbon prices and electricity prices in Britain, in order to discourage the use of coal and encourage cleaner energy, it is not surprising that the British Electricity Market Reform of 2013 included a carbon price floor. As confirmed by this study, so far British electricity spot prices are less associated with those in neighboring markets, but with the planned increases in interconnection price differentials should influence the trade flow. In this case, the policy of having a different (greater) price for carbon may mean that price floors may be required in neighboring electricity markets.

The findings also indicate that previous studies of electricity market integration may have overestimated the strength of market integration, if they have not controlled for common price drivers that may result from having similar electricity mixes. All in all, the present study highlights the time-varying nature of spot prices and its link with a changing electricity mix in Europe. It shows that local electricity markets, in spite of market coupling and similar designs, may face different challenges in their path to decarbonization that stem from the local electricity mix. Potential volatility spillovers from different markets should be monitored by policy makers and regulators.

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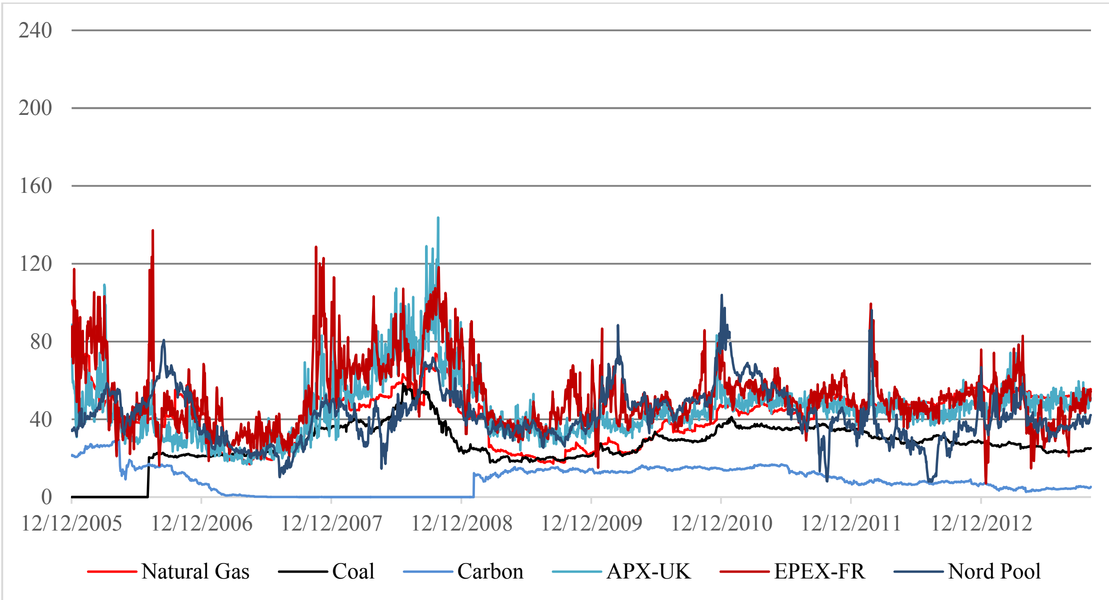
Figure 1: Gross electricity generation mix from 2005 to 2012

Source: Eurostat, 2014

Figure 2: Import and export as a ratio of total electricity generation from 2005 to 2012

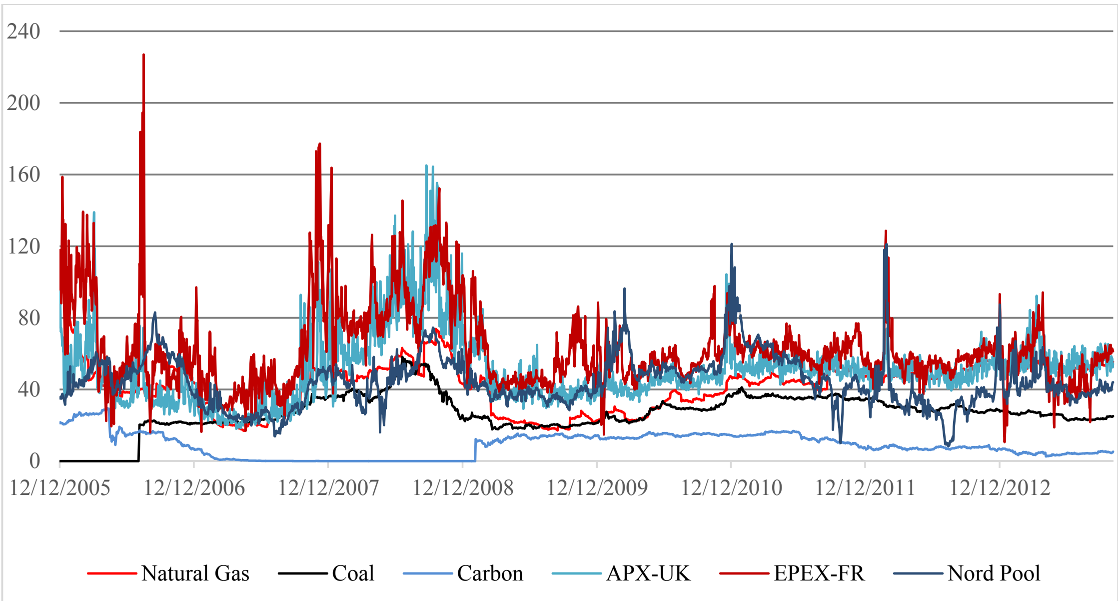
Source: Eurostat, 2014

Figure 3: Electricity base load, natural gas, coal and carbon prices



Electricity base load, natural gas and coal prices in €/MWh, carbon prices in €/EUA from 12.12.2005 to 16.10.2012.

Figure 4: Electricity peak load, natural gas, coal and carbon prices



Electricity peak load, natural gas and coal prices in €/MWh, carbon prices in €/EUA from 12.12.2005 to 16.10.2012.

Figure 5: LACF APX-UK base

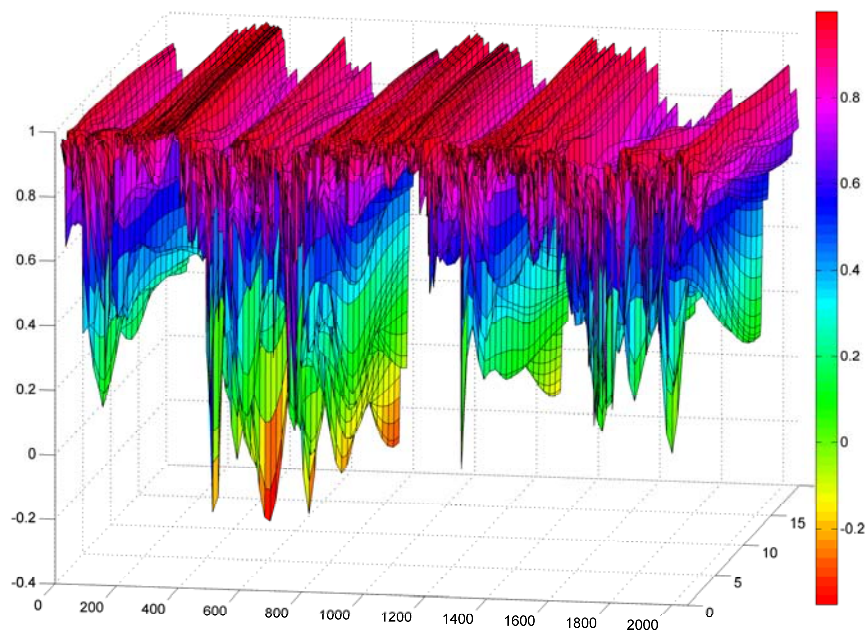


Figure 6: LACF APX-UK peak

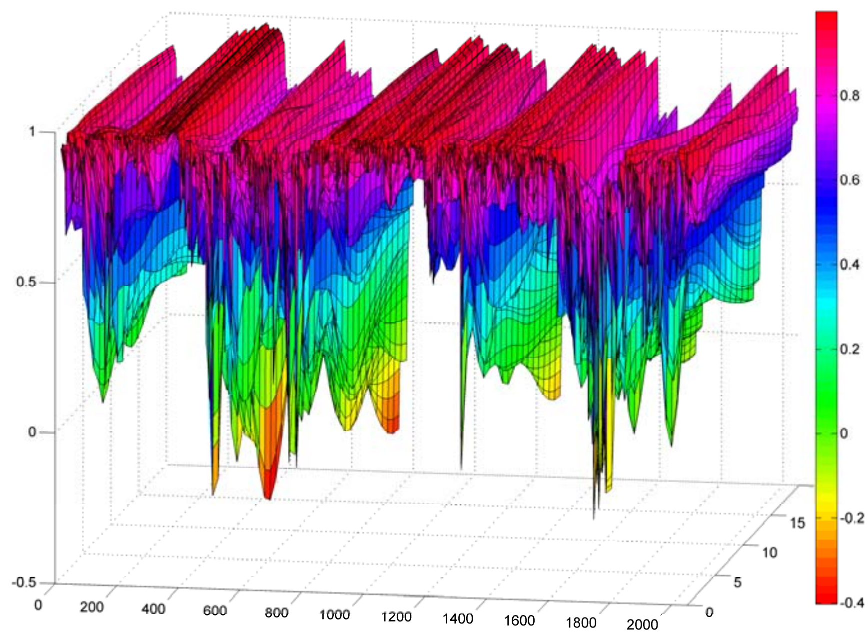
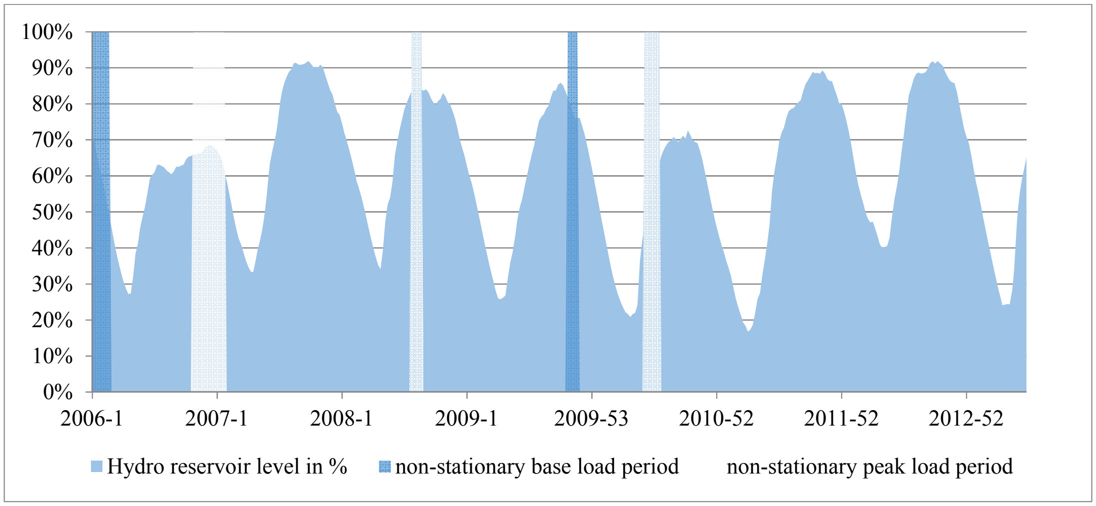


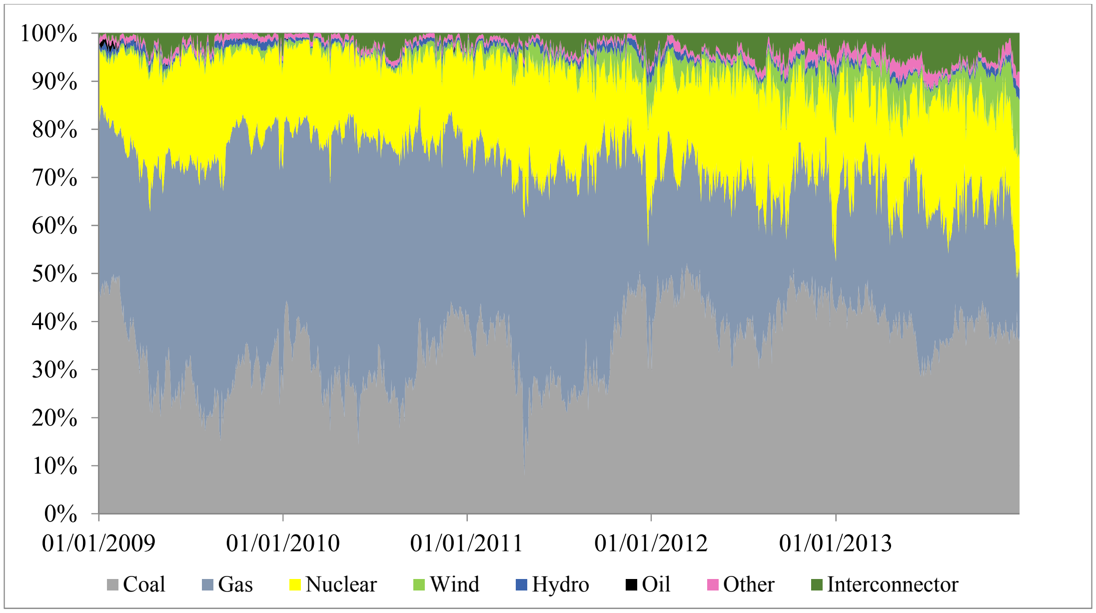
Figure 7: Hydro reservoir level and non-stationary periods in Nordpool



Hydro reservoir level for Nordpool and non-stationary base and peak load periods from January 2006 to June 2013 [Source: NordpoolSpot, 2014]

NordpoolSpot, 2014, Nordpool Spot. [online]. Available from: http://www.nordpoolspot.com/ [last accessed 02/01/2014]

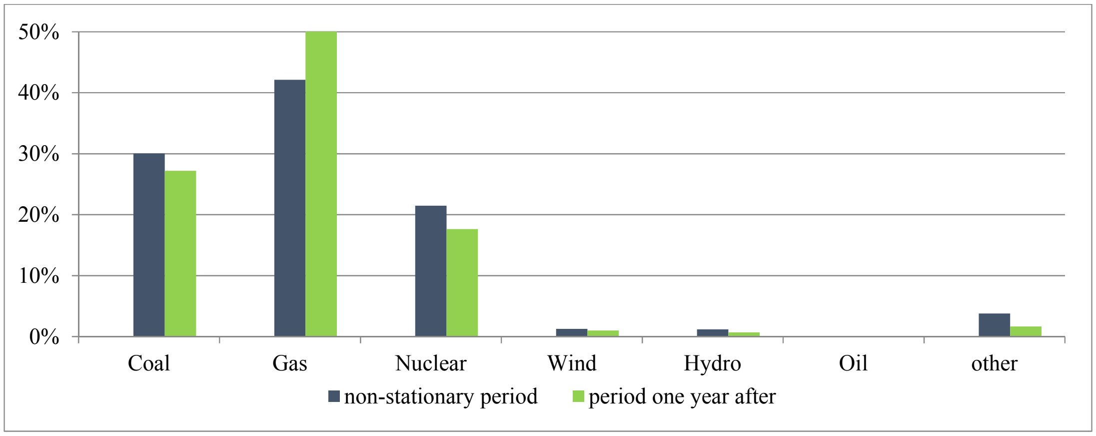
Figure 8: Time-varying electricity mix GB



Weekday daily British electricity generation by fuel and supply by interconnector from 1.1.2009- 31.12.2013 [Source: Elexon, 2014]

Elexon, 2014. Elexon Portal. [online]. Available from: https://www.elexon.co.uk/ [last accessed 25/03/2015]

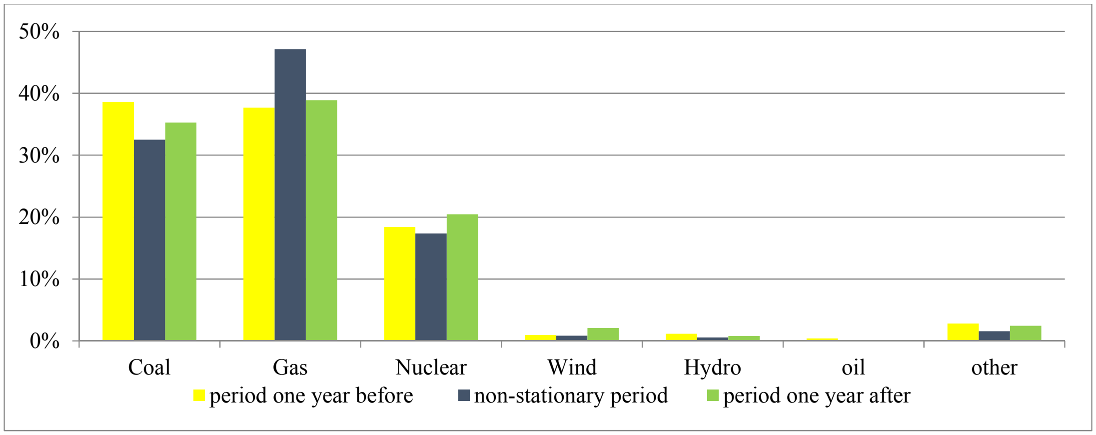
Figure 9: British electricity mix comparison A



British fuel mix during the non-stationary period (11.03.2009-19.05.2009), and one year after (11.03.2010-19.05.2010). Own calculation [Source Elexon, 2014**]**

Elexon, 2014. Elexon Portal. [online]. Available from: https://www.elexon.co.uk/ [last accessed 25/03/2015]

Figure 10: British electricity mix comparison B



British fuel mix during the non-stationary period (21.12.2009-14.05.2010), one year before (21.12.2008-14.05.2009) and one year after (21.12.2010- 14.05.2011). Own calculation [Source Elexon, 2014]

Elexon, 2014. Elexon Portal. [online]. Available from: https://www.elexon.co.uk/ [last accessed 25/03/2015]

Table 1

France

	2005	2006	2007	2008	2009	2010	2011	2012
Gas	5%	5%	5%	5%	4%	5%	5%	4%
Coal	5%	4%	4%	4%	4%	4%	3%	3%
Oil	1%	1%	1%	1%	1%	1%	0%	1%
Hydro	9%	10%	10%	11%	11%	11%	8%	11%
Solar	0%	0%	0%	0%	0%	0%	0%	1%
Wind	0%	0%	1%	1%	1%	2%	2%	3%
Nuclear	79%	79%	78%	77%	77%	76%	80%	76%
Other	1%	1%	1%	1%	1%	1%	1%	1%

Great Britain

	2005	2006	2007	2008	2009	2010	2011	2012
Gas	39%	37%	43%	47%	45%	47%	41%	28%
Coal	34%	38%	35%	32%	28%	28%	30%	40%
Oil	1%	1%	1%	1%	1%	1%	0%	1%
Hydro	1%	1%	1%	1%	1%	1%	2%	1%
Solar	0%	0%	0%	0%	0%	0%	0%	0%
Wind	1%	1%	1%	2%	2%	3%	4%	5%
Nuclear	21%	19%	16%	14%	19%	16%	19%	20%
Other	3%	3%	3%	3%	3%	4%	4%	5%

Nordpool

	2005	2006	2007	2008	2009	2010	2011	2012
Gas	4%	4%	4%	4%	5%	6%	5%	3%
Coal	3%	7%	6%	4%	5%	6%	5%	3%
Oil	1%	1%	0%	0%	0%	1%	0%	0%
Hydro	61%	56%	59%	61%	60%	56%	57%	62%

Solar	0%	0%	0%	0%	0%	0%	0%	0%
Wind	0%	1%	1%	1%	1%	1%	2%	2%
Nuclear	26%	26%	25%	24%	22%	23%	24%	23%
Other	5%	6%	6%	6%	6%	7%	7%	7%

Germany

	2005	2006	2007	2008	2009	2010	2011	2012
Gas	14%	14%	15%	16%	15%	16%	16%	14%
Coal	47%	46%	47%	44%	43%	42%	43%	45%
Oil	2%	2%	1%	1%	2%	1%	1%	1%
Hydro	3%	3%	3%	3%	3%	3%	3%	3%
Solar	0%	0%	0%	1%	1%	2%	3%	4%
Wind	4%	5%	6%	6%	7%	6%	8%	8%
Nuclear	27%	27%	22%	24%	23%	23%	18%	16%
Other	3%	4%	5%	5%	6%	7%	7%	8%

Netherlands

	2005	2006	2007	2008	2009	2010	2011	2012
Gas	63%	62%	63%	63%	64%	67%	65%	58%
Coal	24%	24%	24%	22%	21%	19%	19%	24%
Oil	1%	1%	1%	1%	0%	0%	0%	0%
Hydro	0%	0%	0%	0%	0%	0%	0%	0%
Solar	0%	0%	0%	0%	0%	0%	0%	0%
Nuclear	4%	4%	4%	4%	4%	3%	4%	4%
Wind	2%	3%	3%	4%	4%	3%	5%	5%
Others	7%	7%	5%	6%	7%	7%	8%	9%

Table 2: Summary statistics for coal, carbon, natural gas and electricity base and peak prices

	API2 COAL	EU ETS	Natural gas	FR BASE	FR PEAK	GER base	GER peak	NL base	NP base	NP peak	GB BASE	GB PEAK
Mean	29.06	8.89	42.36	52.31	63.06	50.70	60.65	54.10	41.83	44.43	45.28	51.06
Maximum	58.22	29.78	101.00	137.22	226.94	127.08	181.67	191.81	103.93	121.26	143.78	165.06
Minimum	17.81	0.01	16.90	7.11	10.67	5.80	6.76	17.00	7.94	8.46	16.84	18.12
Std. Dev.	7.72	6.86	13.67	17.49	22.94	15.49	20.68	16.41	13.63	14.34	15.61	19.15
observations	1893	2048	2048	2048	2048	2048	2048	2048	2048	2048	2048	2048

Table 3: Assessments of long-run dynamics

	1 API2 COAL	2 EU ETS	3 Natural gas	4 FR BASE	5 FR PEAK	6 GER base	7 GER peak	8 NL base	9 NP base	10 NP peak	11 GB BASE	12 GB PEA
1 PP level	0.389*	0.2209*	0.007	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2 PP first differences	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.001	0.001
3 ADF level	0.2687 (*l*= 9)*	0.2192 (*l* = 1)*	0.0006 (*l* = 0)	0.000 (*l* =3)	0.000 (*l* =8)	0.000 (*l* =3)	0.001 (*l* =13)	0.000 (*l* =4)	0.040 (*l* =9)	0.001 (*l* =9)	0.0203 (*l* = 10)	0.0025 (*l* = 9)
5 ADF first differences	0.000 (*l*=8)	0.000 (*l* =0)	0.000 (*l* =0)	0.000 (*l* =12)	0.000 (*l* =12)	0.000 (*l* =12)	0.000 (*l* =12)	0.000 (*l* =13)	0.000 (*l* =8)	0.000 (*l* =8)	0.000 (*l* =9)	0.000 (*l* =13)
6 *d*_GPH	1.009 (0.0247)	1.001 (0.0247)	1.039 (0.0247)	0.6514 (0.0247)	0.6035 (0.0247)	0.6168 (0.0247)	0.5896 (0.0247)	0.6754 (0.0247)	0.8956 (0.0247)	0.8421 (0.0247)	0.658 (0.0247)	0.6064 (0.0247
7 *d*_ 2 step ELW	1.25983	0.87970	1.14830	0.6511	0.6525	0.60981	0.6074	0.6227	0.8385	0.7565	0.77872	0.77614
8 Observations	1893	2048	2048	2048	2048	2048	2048	2048	2048	2048	2048	2048

Assessments of long run dynamics for coal, carbon, natural gas as well as electricity base and peak prices. l is the lag length that has been chosen to carry out the ADF test based on the AIC. The ADF test has been conducted including an intercept. d_GPH is the Geweke and Porter-Hudak (1983) order of integration estimator and d_2 step ELW the two step exact local whittle estimator (Shimotsu and Phillips, 2005). * indicate 5% significance level.

Geweke, J., Porter-Hudak, S., 1983. The estimation and application of long memory time series models. Journal of time series analysis, 4(4), 221-238.

Shimotsu, K., Phillips, C.B. 2005. Exact local whittle estimation of fractional integration. Annals of Statistics, 33(4), 1890-1933

Table 4: Unit root test for British base-load price periods

	GB base		EU ETS	Natural gas	API2 coal	FR
Period	Number of days	ADF	ADF	ADF	ADF	AD
26.09.2006-08.11.2006	**32**	**-0.978 (*l*=1)**	**0.573 (0)**	3.137 (*l*=1)*	**-1.445 (0)**	-2.8
28.11.2006-31.05.2007	**133**	**-2.026(*l*=6)**	**-1.691 (4)**	-3.081 (*l*=0)*	**-2.371 (0)**	-4.5
11.03.2009-19.05.2009	**50**	**-1.994(*l*=5)**	**--1.100 (0)**	**-1.253 (*l*=0)**	**-1.337 (0)**	-3.9
08.07.2009-13.08.2009	27	-3.087(***l***=6)*	-	-	-	-
17.08.2009-14.12.2009	86	-3.961(***l***=5)*	-	-	-	-
21.12.2009-14.5.2010	**105**	**-2.194(*l*=4)**	**-0.345 (0)**	**-0.585 (*0*)**	**-0.345 (0)**	-3.9
18.01.2011-24.02.2011	28	-4.1201(***l***=1)*	-	-	-	
11.03.2011-28.04.2011	35	-4.165 (***l***=0)*	-	-	-	
02.05.2011-04.08.2011	69	-3.8178(***l***=1)*	-	-	-	
02.05.2011-04.08.2011	69	-3.8178(***l***=1)*	-	-	-	

ADF test with intercept and lag l selected with AIC for adjacent energy markets. H0: series has a unit root. * indicate rejection at 5%.Test statistics that indicate that the series contains a unit root are printed in bold.

Table 5: Unit root test for British peak-load price periods

	GB peak		Natural gas	API2 Coal	EU ETS	FR peak
Period	Number of days	ADF	ADF	ADF	ADF	ADF
29.09.2006-07.11.2006	**28**	**-1.533(*l*=1)**	-1.882 (*l*=0)*	**-0.895 (*l*=0)**	**0.930 (*l*=0)**	**-0.012 (*l*=1)**
29.11.2006-31.05.2007	**132**	-2.827(*l*=6)*	-3.087 (***l***=0)*	**-2.247 (*l*=0)**	**-2.357 (*l*=5)**	-4.726 (*l*=0)*
11.03.2009-13.05.2009	42	-5.09(*l*=0)*	**-**	-	-	-
08.07.2009-02.09.2009	41	-3.699(***l***=0)*	-	-	-	-
04.09.2009-14.12.2009	72	-5.782(***l***=0)*	-	-	-	-
19.01.2010-14.05.2010	**84**	**-2.031(*l*=4)**	**-0.763 (*l*=2)**	**0.590 (*l*=0)**	**0.030 (*l*=0)**	-2.820 (*l*=0)*
21.01.2011-18.02.2011	21	-4.512*(***l***=1)	-	-	-	-
09.05.2011-03.06.2011	20	-4.845*(***l***=0)	-	-	-	-
13.06.2011-21.07.2011	29	-3.913*(***l***=0)	-	-	-	-

ADF test with intercept and lag *l* selected with AIC for adjacent energy markets. H0: series has a unit root* indicate rejection at 5%. Test statistics that indicate that the series contains a unit root are printed in bold.

Table 6: Unit root test for Nordpool base-load price periods

	Nordpool base		Natural gas	API2 Coal	EU ETS	NL Base	GER Base
Period	Number of days	ADF	ADF	ADF	ADF	ADF	ADF
12.12.2005-06.03.2006	61	**-0.075 (*l*=3)**	**-0.759 (*l*=0)**	No obs.	**-0.936 (*l*=0**)	-3.854 (***l***=0)*	-2.982 (***l***=0)*
13.11.2006-19.07.2007	197	-2.696 (***l***=1)*	-	-	-	-	-
31.07.2008-02.09.2008	24	**0.821 (*l*=2)**	**-0.766 (*l*=0)**	-6.377 (***l***=0)*	Near unity	**-0.969 (*l*=0)**	**-0.557 (*l*=0)**
04.02.2009-17.07.2009	118	-4.045 (***l***=0)*	-	-	-	-	-
29.10.2009-25.11.2009	20	**-1.216 (*l*=0)**	**-0.760 (*l*=0)**	-3.174 (***l***=0)*	**-0.778 (*l*=0)**	-2.808 (***l***=0)*	-0.989 (*l*=2)*
15.06.2010-26.07.2010	30	**-1.614 (*l*=0)**	**-1.614 (*l*=0)**	-1.128 (***l***=0)	**-0.777 (*l*=0)**	-3.262 (***l***=0)*	-2.584 (*l*=0)*
11.02.2013-11.03.2013	21	-3.053 (***l***=0)*	-	-	-	-	-
14.05.2013-15.10.2013	111	-2.924 (***l***=0)*	-	-	-	-	-

ADF test with intercept and lag l selected with AIC for periods of non-stationarity in Nordpool and energy markets. H0: series has a unit root. * indicate rejection at 5%. Test statistics that indicate that the series contains a unit root are printed in bold.

Table 7: Unit root test for Nordpool peak-load price periods

	Nordpool peak		Natural gas	API2 Coal	EU ETS	Ger Peak
Period	Number of days	ADF	ADF	ADF	ADF	ADF
12.12.2005-06.03.2006	61	-3.096 (***l***=0)*	-	-	-	-
08.11.2006-24.01.2007	56	**-1.966 (*l*=0)**	**-0.988 (*l*=0)**	-2.303 (***l***=1)*	**-0.220 (*l*=5)**	-3.909 (***l***=0)**
16.02.2007-18.07.2007	109	-3.268 (***l***=0)*	-	-	-	-
31.07.2008-29.08.2008	22	**0.463 (*l*=2)**	**-1.617 (*l*=0)**	**-0.685 (*l*=0)**	Near unity	**0.189 (*l*=1)**
03.02.2009-21.07.2009	121	-4.089 (***l***=0)*	-	-	-	-
16.06.2010-27.07.2010	30	**-1.858 (*l*=0)**	**-1.858 (*l*=0)**	**-0.924 (*l*=0)**	**-0.693 (*l*=0)**	-3.035 (***l***=0)*
11.05.2011-10.06.2011	23	-3.489(***l***=0)*	-	-	-	-
15.05.2013-15.10.2013	110	-3.309(***l***=0)*	-	-	-	-

ADF test with intercept and lag selected with AIC for periods of non-stationarity in Nordpool and energy markets. H0: series has a unit root* indicate rejection at 5%. Test statistics that indicate that the series contains a unit root are printed in bold.

Table 8: Unit root test for FR base-load price periods

	FR base		Natural gas	API2 Coal	EU ETS	GB	GER
Period	Number of days	ADF	ADF	ADF	ADF	ADF	
07.02.2007-11.05.2007	68	**-1.809 (*l*=5)**	**-2.052 (*l*=0)**	-4.236(***l***=0)*	-5.618 (***l***=0)*	-4.236(***l***=0)*	-5.618(***l***=0)*
16.02.2009-22.05.2009	70	**1.445 (*l*=5)**	-3.807 (***l***=0) *	-5.491 (***l***=0)*	-5.506 (***l***=0)*	-2.539 (***l***=0)*	-5.506(***l***=0)*

ADF test with intercept and lag *l* selected with AIC for non-stationary periods in France and energy markets. H0: series has a unit root* indicate rejection at 5%. Test statistics that indicate that the series contains a unit root are printed in bold.

Table 9: Unit root test for FR peak-load price periods

	FR peak		Natural gas	API2 Coal	EU ETS	GB	GER
Period	Number of days	ADF	ADF	ADF	ADF	ADF	
16.02.2009-15.04.2009	43	-3.367 (***l***=0)*	-	-	-	-	-
20.04.2009-26.05.2009	27	-4.861 (***l***=0)*	-	-	-	-	-
16.02.2011-05.04.2011	35	-3.940 (***l***=0)*	-	-	-	-	
17.06.2011-09.08.2011	38	**-1.385 (*l*=1)**	**0.031 (*l*=0)**	**-1.605 (*l*=0)**	**-2.429 (*l*=0)**	**-1.385 (*l*=1)**	**-1.417 (*l*=1)**

ADF test with intercept and lag l selected with AIC for electricity markets that neighbour France during base periods. H0: series has a unit root.* indicate rejection at 5%. Test statistics that indicate that the series contains a unit root are printed in bold.

Table 10: British base-load prices: Cointegration analysis

Period	**Variable**	λ_{trace}	λ_{eigen}
26.09.2006-08.11.2006	API2 Coal	2.930 (0.970)	2.925 (0.952)
	EU ETS	14.964 (0.060)	14.881 (0.040*)
	NL Base	8.174 (0.447)	6.940 (0.447)
28.11.2006-31.05.2007	API2 Coal	12.277 (0.144)	9.939 (0.216)
	EU ETS	18.070 (0.020*)	14.504 (0.046*)
11.03.2009-19.05.2009	Natural gas	7.485 (0.522)	0.128 (0.592)
	API2 Coal	12.404 (0.139)	9.614 (0.239)
	EU ETS	2.863 (0.973)	2.815 (0.958)
21.12.2009-14.5.2010	**Natural gas**	17.814 (0.022*)	14.048 (0.054)
	API2 Coal	26.668 (0.001*)	26.140 (0.000*)
	EU ETS	7.346 (0.538)	7.237 (0.462)

The hypothesis tested is that of *no cointegration*. Variables in bold are cointegrated and an asterisk (*) denotes 5% significance.

Table 11: British peak-load prices: Cointegration analysis

Period	**Variable**	λ_{trace}	λ_{eigen}
29.09.2006-07.11.2006	API2 Coal	2.930 (0.970)	2.925 (0.952)
	EU ETS	14.964 (0.060)	14.881 (0.040*)
	FR Peak	8.174 (0.447)	6.940 (0.447)
29.11.2006-31.05.2007	API2 Coal	12.277 (0.144)	9.939 (0.216)
	EU ETS	18.070 (0.020*)	14.504 (0.046*)
19.01.2010-14.05.2010	Natural gas	7.485 (0.522)	0.128 (0.592)
	API2 Coal	23.327 (0.003*)	23.299 (0.002*)
	EU ETS	16.141 (0.040*)	16.041 (0.026*)

The hypothesis tested is that of *no cointegration*. Variables in bold are cointegrated and an asterisk (*) denotes 5% significance.

Table 12: Nordpool base-load prices: Cointegration analysis

Period	**Variable**	λ_{trace}	λ_{eigen}
12.12.2005-06.03.2006	Natural gas	13.497 (0.098)	13.413 (0.068)
	EUETS	4.447 (0.864)	3.817 (0.878)
31.07.2008-02.09.2008	Natural gas	6.999 (0.578)	5.459 (0.683)
	NL Base	13.061 (0.113)	11.900 (0.115)
	Ger Base	18.301 (0.018*)	17.762 (0.013*)
29.10.2009-25.11.2009	Natural gas	4.460 (0.863)	4.456 (0.808)
	EUETS	4.706 (0.839)	3.666 (0.893)
15.06.2010-26.07.2010	Natural gas	6.563 (0.629)	5.503 (0.677)
	EUETS	4.128 (0.893)	4.084 (0.850)
	API 2 Coal	4.774 (0.832)	3.196 (0.933)

The hypothesis tested is that of *no cointegration*. Variables in bold are cointegrated and an asterisk (*) denotes 5% significance.

Table 13: Nordpool peak-load prices: Cointegration analysis

Period	**Variable**	λ_{trace}	λ_{eigen}
08.11.2006-24.01.2007	Natural gas	6.950 (0.584)	5.289 (0.705)
	EU ETS	10.345 (0.255)	5.534 (0.673)
31.07.2008-29.08.2008	Natural gas	5.210 (0.786)	5.202 (0.716)
	API2 Coal	9.654 (0.308)	9.222 (0.268)
	Ger Peak	18.641 (0.016*)	18.640 (0.010*)
16.06.2010-27.07.2010	Natural gas	8.700 (0.394)	8.223 (0.356)
	API2 Coal	3.332 (0.950)	2.504 (0.974)
	EU ETS	4.458 (0.863)	4.211 (0.837)

The hypothesis tested is that of *no cointegration*. Variables in bold are cointegrated and an asterisk (*) denotes 5% significance.

Table 14: EPEX-FR base-load prices: Cointegration analysis

Period	**Variable**	λ_{trace}	λ_{eigen}
07.02.2007-11.05.2007	**Natural gas**	24.907 (0.0014*)	23.129 (0.0016*)

The hypothesis tested is that of *no cointegration*. Variables in bold are cointegrated and an asterisk (*) denotes 5% significance.

Table 15: EPEX-FR peak-load prices: Cointegration analysis

Period	**Variable**	λ_{trace}	λ_{eigen}
17.06.2011- 09.08.2011	Natural Gas	11.421 (0.1869)	11.3808 (0.1361)
	API2 Coal	9.2627 (0.3417)	7.6474 (0.4157)
	EU ETS	12.561 (0.1319)	9.9515 (0.2151)
	GB peak	15.965 (0.0425*)	13.739 (0.0604)
	GER peak	16.053 (0.0412*)	14.0155 (0.0547)

The hypothesis tested is that of *no cointegration*. Variables in bold are cointegrated and an asterisk (*) denotes 5% significance.