Abstract - Regime shifts in electricity prices in USA and EU

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Abstract

The electricity market is characterized by immediate consumption of the energy supplied to the electricity grid. Consequently, prices typically varies over time according to seasonality in demand and variations in supply. Recent innovations in the European electricity market has increased interconnectivity between regional markets, increasing the ability to share regional surplus and shortfalls in supply. This study considers price volatility between 2000 and 2016 for a set of electricity price hubs in US and EU, and assess common breaks in price volatility. Moreover, we evaluate whether energy sources, like oil, gas and coal, share regime breaks with electricity prices, as they are important input for electricity generation. We identify regime breaks using the Iterated Cumulative Sum of Squares (ICSS) method (Inclan and Tiao (1994); Sansó et al. (2004)), and find that while electricity prices in the EU is reduced, electricity prices in US is increased. Further, we find no link between electricity prices and energy prices, emphasizing the importance of proper regulation of electricity markets to ensure price stability.

1 Introduction

In the past few decades, the worldwide electricity sector has gone through considerable restructuring and exchanges for trading electricity been established. The recent initiative by the EU named "Price Coupling of Regions" (PCR) to integrate the European day-ahead electricity market initiated in 2009, and finalized in June 2012 (Nordpool (2016)). When accomplished, this initiative will make the European market larger than the joint market of Midwest ISO and PJM in the USA (Biskas et al. (2014)). The PCR provides delivery of a common European price coupling solution where the basic principles are one single algorithm, decentralized operation, and decentralized governance. The integration is expected to increase liquidity, efficiency and social welfare within the market (Nordpool (2016)). This gradual market coupling process has contributed to significantly lower wholesale European energy prices, or a decrease by 35 % to 45 % in the period 2008-2012 (The European Commission (2014)). Continuing improvements in transmission and market coupling is considered key to secure energy supply in Europe. Currently 8 % (2015) of the production is interconnected, and the EU commission has set a goal at 10 % in 2020 (The European Commission (2014)). With the increasing production from renewable energy, PCR and increased interconnectivity becomes crucial. Due to the limited predictability of supply from solar and wind power, periods of regional surplus (and shortfall) of power generation depends on an interconnected market to stabilize the grid and prices (Weron (2014)).

Market decoupling and increased renewable energy supply is some of the innovations currently taking place in the global electricity market. Together with deregulation, decreased governmental control and increased competitiveness, the electricity market is changing globally and consequently risk considered with electricity supply, demand and its trading derivatives are developing. Electricity by itself is not storable and therefore has to be produced and consumed at the same time, requiring constant balance between production and consumption (Harris (2011)). In addition to input factors such as natural gas and coal prices, electricity demand varies with weather conditions and the time of day, creating both seasonality and daily variations. These variations and rapid changes in supply and demand contribute to spot prices being very sensitive to short-term uncertainties (Karakatsani and Bunn (2010)), such as demand shocks and plant outages. In the long run, transmission constraints and location of producer and consumer affect electricity availability and contribute to increased price volatility. Consequently, empirical studies show evidence that electricity prices are characterized by leptokurtosis, clustering of volatility, asymmetry and mean reversion (Weron (2009)). Deregulated electricity markets electricity is mainly traded via power pools and power exchanges (PX). Authorities commonly establish power pools where bids from generators are collected and aggregated to a supply curve. This creates the market clearing price (MCP) or system price (SYS). The power exchanges on the other hand, is based on two sided auctions, which forms a supply and demand curve (Weron (2007)). In this study, we investigate 6 series from the EU, 5 PX's and the Scandinavian based Nordpool. In USA, we study 5 price hub series.

The factors affecting volatility in commodities and other financial assets has for a long time interested academics and market participants. Volatility affects decision-making and provides information about risk and the behavior of a commodity. Price of a commodity is determined by today's equilibrium between the supply, demand and expectation about future production and consumption. If new market information show up, regarding changes in the long run equilibrium the price will shift. In a commodity market, price volatility can alter market expectations and persistent changes in volatility can change market participants' risk exposure and their willingness to invest in production and infrastructure in the industry.

Historically, oil price shocks have mainly been caused by physical disruption of supply, although the shock of 2007-08 was a consequence of abrupt changes in demand and future expectations (Hamilton (2009). Lin and Wesseh (2013) show that regime shifting is present in the natural gas market. Vivian and Wohar (2012) tested a variety of commodities for volatility breaks and found that there were limited evidence of breaks during the financial crisis. Furthermore, they suggest that commodity specific supply and demand are important determinants for volatility breaks.

In this paper, we study whether volatility regimes have shifted between 2000 and 2016, a period with several innovations in the market affecting risk and pricing in the electricity market. For this, we investigate electricity prices from the USA and Europe and compare them with other energy sources. We study whether energy commodities like oil, gas and coal, which are considered substitutes in the production of electricity, share a common trend. We apply the iterated cumulative sum of squares (ICSS) algorithm presented by Inclan and Tiao (1994), which was later revised by Aggarwal et al. (1999) and Sansó et al. (2004). Due to statistical properties of electricity prices we apply the Kappa 2 (k_2) test, advocated by Sansó et al. (2004). We consider two research questions. First, we investigate whether volatility of electricity prices have experienced regime shifts during the period. Second, we determine whether there are common volatility trends and regimes changes across electricity prices in the US, EU and among other energy commodities.

This paper is structured as followed. Section 2 introduces the data set along with some stylized facts. Chapter 3 covers the methodology, the criteria behind the test selection to support our analysis. Section 4 covers the empirical results from our study, providing dates of structural breaks and figures. Section 5 covers the conclusion of the paper.

2 Data

In this study we use average daily price data gathered from Datastream - Reuters. We investigate power exchanges and the Nordpool in Europe and power hubs in the USA. Our data set consists of 5 electricity price series from the United States, 6 series from Europe and 5 series of oil, gas and coal prices. Observation period for the data set range from January 2000 to January 2016, providing us with 2 348 - 4 249 observations per time series depending on the starting point for the series. We use weekday time series for all series except for the Nordpool series where we use the daily system price, including weekend observations.

We first apply continuously compounded daily returns of each time series by differencing

$$\log P_t - \log P_{t-1} = r_t \tag{1}$$

The data is filtered by using the residuals from an appropriate AR model[1]. As expected all the series experience a mean return close to zero. In the US, volatility ranges from 0.086-0.193 with Mid Columbia experiencing the highest volatility, while the North California hub NP experience the lowest. All series experience excessive kurtosis ranging from 7.791-47.45, with Southwest hub Palo Verde being the highest and New England pool (Nepool) being the lowest. Five of US series show positive skewness while Columbia has a slightly negative skewness. In Europe, the APX Netherlands has the highest volatily of 0.221 while the Nordpool lowest of 0.081. As expected, Nordpool price volatility is lower as it is has more continuous price observations. 4 of the series have positive skewness while the EEX and EPEX experience negative skewness. All of the series experience excessive kurtosis with the APX Amsterdam-UK connection being the lowest and Amsterdam APX being the highest.

Other commodities show more moderate volatility, ranging from 0.014-0.024. But with similar range in skewness as in electricity series. In the case of oil and gas we notice a lower kurtosis than those for electricity, with 4.466-8.389 for WTI oil and Henry hub gas, respectively. For EU and USA coal prices we notice higher kurtosis with 32.59-162.3 respectively.

Table 1: Data characteristics - From a fitted AR model

		OBS	Mean	Vol	Skewness	Kurtosis
US Electricity						
Palo Verde	Usd/MWh	3909	0.000	0.100	4.112	47.45
Nepool	Usd/MWh	3911	0.000	0.148	0.651	7.791
Mid Columbia	Usd/MWh	4069	0.000	0.193	-0.252	33.21
SP-15	Usd/MWh	3908	0.000	0.097	0.115	19.56
NP	Usd/MWh	3906	0.000	0.086	0.861	22.07
PJM	Usd/MWh	3913	0.000	0.165	0.854	11.46
EU Electricity						
BPX	Euro/MWh	2348	0.000	0.161	0.153	17.10
EEX	Euro/MWh	3910	0.000	0.199	-0.693	16.90
EPEX	Euro/MWh	3727	0.000	0.174	-0.737	12.35
APX UK	Pound/MWh	4016	0.000	0.139	0.985	5.589
APX NL	Euro/MWh	4249	0.000	0.221	0.210	21.37
Nordpool	Nok/MWh	3773	0.000	0.081	0.400	15.87
Energy						
WTI	Usd/bbl	3913	0.000	0.024	-0.187	4.466
BRENT	Usd/bbl	4032	0.000	0.022	-0.230	5.606
Coal HWWI EU	EUR/Index	3903	0.000	0.014	1.125	32.59
Coal USA	Usd/MT	4001	0.000	0.016	2.957	162.3
Henry hub gas	Usd/MMBTU	4001	0.000	0.041	0.539	8.389

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[1] Fitted in RStudio with an ar-function, according to Akaike Information Criterion.

3 Methodology

To identify regime shifts in price volatility we considered three structural breaks models. The ICSS method introduced by Inclan and Tiao (1994). The method assumes i.i.d and $N(0,1)$, which is not a common properties of commodity prices. The ICSS method was later revised by Sansó et al. (2004), which resulted in a modified statistic k_1 and k_2. Where k_1 corrects for leptokurtic data (heavy tails) and the k_2 corrects for heteroscedasticity and leptokurtosis, both properties commonly found in commodities prices. Sansó et al. (2004) demonstrated that the ICSS model resulted in spurious results when the above properties were not accounted for.

Inclan and Tiao (1994) presented the ICSS test (k^*) wich presumes stationary variance of return over time with ε_t defined as series of independent observations with zero mean and variance σ_t^2. The algorithm tests for sudden changes in variance for each interval which is specified by σ_j^2; j=0,1,...,N_t, where N_t is the number of changes in variance, in T observations where 1<K_1<K_2< ...<K_{Nt}<T are the set of change points. Therefore the variance upon the N_t intervals is defined as

$$\sigma_j^2 = \begin{cases} \sigma_0^2 & 1 < t < K_1 \\ \sigma_1^2 & K_1 < t < K_2 \\ \vdots & \\ \sigma_t^2 & K_{Nt} < t < T \end{cases} \tag{2}$$

The procedure finds statistically significant break points in the time series variance by calculating the centered sum of squares for a set of periods dependent on the model findings, where

$$C_k = \sum_{t=1}^{k} \varepsilon_i^2 \tag{3}$$

denotes the cumulative sum of squares for the first k observations of returns ε_t. Then

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, k = 1, ..., T, \tag{4}$$

which $D_0 = D_T = 0$ and $k = 1, ..., T$
and C_T is the sum of the squared residuals from the entire sample period.

Sanso et al (2004) pointed out that k^* is only free of nuisance parameters when the stochastic process is mesokurtic ($\eta_4 = 3\sigma^4$) and conditional variance is constant. Sansó et al. (2004) futher noted that when $\eta_4 > 3\sigma^4$ or when the distribution is leptokurtic, too many rejections of null of constant variance is to be expected. In addition, when $\eta_4 < 3\sigma^4$ (platykurtic) the test is too conservative.

Sansó (2004) introduced an test to deal with these problems by the following k_1 statistic proposition

$$k_1 = sup_k|\frac{1}{\sqrt{T}}B_k| \tag{5}$$

where

$$B_k = \frac{C_k - \frac{k}{T}C_T}{\sqrt{\hat{\eta}_4 - \hat{\sigma}_4}} \tag{6}$$

and

$$\hat{\eta}_4 = T^{-1}\sum_{i=1}^{T} \varepsilon_t^4 \tag{7}$$

and

$$\hat{\sigma}^2 = T^{-1}C_T. \tag{8}$$

The k_1 proposition is free of the nuisance parameters for identical and independent zero mean random variables and corrects for the 4^{th} moment of platykurtosis and leptokurtosis. But k_1 does not correct for heteroscedasticity. Heteroscedasticity refers to when the variance of the random variable in the case of time series changes over time. As Lin and Wesseh (2013) pointed out, the presence of heteroscedasticity in time series can invalidate statistical test of significance. As it makes the assumption that the modeling errors are uncorrelated, normally distributed and the variance is not changing with the effect being modeled. Sansó et al. (2004) proposed k_2 statistic that corrects for heteroscedasticity. Which is defined as

$$k_2 = sup_k | \frac{1}{\sqrt{T}} G_k | \tag{9}$$

where

$$G_k = \frac{1}{\sqrt{\hat{\omega_4}}} \left(C_k - \frac{K}{T} C_T \right) \tag{10}$$

and the non-parametric estimator ω_4 is applied as

$$\hat{\omega_4} = \frac{1}{T} \sum_{i=1}^{T} \left(\varepsilon_t^2 - \hat{\sigma_t}^2 \right) + \frac{2}{T} \sum_{t=1}^{m} w(l,m) \sum_{t=l+1}^{T} \left(\varepsilon_t^2 - \hat{\sigma}^2 \right) \left(\varepsilon_{t-1}^2 - \hat{\sigma}^2 \right) \tag{11}$$

where $w(l,m)$ is a Bartlet lag window.

We therefore determine which test to use based on the characteristics of the underlying data.

- k^* statistic: Data is i.i.d and normally distributed
- k_1 statistic: Heavily tailed and leptokurtic data.
- k_2 statistic: Data shows signs of conditional heteroskedasticity

Table 2: Test Decision

Attributes	k^*	k_1	k_2
i.i.d and Gaussian	✓	✓	✓
Leptokurtic and heavily tailed		✓	✓
Heteroskedasticity			✓

We tested the data for a unit root by applying the Augmented Dickey Fuller (ADF) test[2] and KPSS test[3] with results implying stationarity. As expected, the data shows no evidence of normality as shown by the Jarque-Bera(J-B) test. The Box-Jenkins (Q(12))[4] test was used to test for autocorrelation, where EPEX and EEX show signs of autocorrelation while other series do not. The ARCH LM[5] test shows rejection of non-ARCH effect in all series, implying ARCH effect.

According to the results in Table 3, we find that the price series experience leptokurtosis and heteroscedasticity. Consequently, we determine that the k_2 statistic test is the appropriate test for detecting regime shifts for electricity and energy prices as other tests would produce spurious results.

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[2] adf.test in the tsseries package in RStudio.

[3] kpss.test in the tsseries package in RStudio.

[4] box.test in the in RStudio.

[5] ArchTest in the FinTS package in RStudio.

Table 3: Data - Test characteristics

Energy Source US Electricity	ADF (p-value)	KPSS (p-value)	J-B (p-value)	Q(12) (p-value)	ARCH LM (p-value)
Palo Verde	-16.412	0.18971	378180	4.454	134.0
	0.00	>0.1	0.00	0.974	0.00
Nepool	-17.164	0.010	10183	1.279	382.7
	0.00	>0.1	0.00	0.999	0.00
Mid Columbia	-16.671	0.0272	52189	5.3512	451.12
	0.00	>0.1	0.00	0.9452	0.00
SP	-17.829	0.039	62361	9.55	304.25
	0.000	>0.1	0.00	0.655	0.00
NP	-17.502	0.063	79876	4.5855	336.0
	0.000	>0.1	0.00	0.970	0.00
PJM	-18.368	0.012	21930	6.443	337.5
	0.00	>0.1	0.00	0.892	0.00
EU Electricity					
BPX	-15.055	0.080576	28696	5.4516	182.99
	(0.00)	(>0.1)	(0.00)	(0.9412)	(0.00)
EEX	-19.621	0.04871	46954	23.722	257.9
	(0.00)	(>0.1)	(0.00)	(0.022*)	(0.00)
EPEX	-20.665	0.044083	80992	19.458	397.9
	(0.00)	(>0.1)	(0.00)	(0.019*)	(0.00)
APX UK	-19.455	0.060902	5886	11.971	293.87
	(0.00)	(>0.1)	(0.00)	(0.448)	(0.00)
APX NL	-20.665	0.044083	80992	19.458	397.9
	(0.00)	(>0.1)	(0.00)	(0.078)	(0.00)
Nordpool	-14.924	0.080	39792	1.8672	1221
	((0.00)	(>0.1)	(0.00)	(0.9996)	(0.00)
Energy					
WTI	-14.49	0.339	3281	0.516	460.3
	0.00	>0.1	0.00	1	0.00
BRENT	-14.422	0.23351	5322.6	16.533	258.9
	0.000	>0.1	0.00	0.168	0.00
Coal EU	-14.934	0.143	173780	6.8881	101.0
	0.000	>0.1	0.00	0.8649	0.00
Coal USA	-15.86	0.395	4400800	0.000	1.910
	0.000	0.079	0.00	1	0.9995
Henry hub gas	-16.718	0.049657	11942	1.6077	532.17
	0.000	>0.1	0.00	0.8649	0.00

4 Empirical Results

We apply the k_2 test proposed by Sansó et al. (2004) from the residuals of log-returns from an appropriate AR-model for each series. Figure 1-3 displays the regimes received from the k_2 test statistic illustrated using ±2 standard deviations.

In the US, SP-15, Nepool and the PJM hubs experience structural breaks in 06.2001, 10.2010 and 12.2010, respectively. The breaks found in Neepol and PJM in 2010 occurred within a relatively short period, and both experience an increase in price volatility. This may be explained by close geographical location of the hubs and thus similarities in production and consumption. We identify no breaks in Palo Verde, Mid Colombia and NP.

For the European market, we find that three electricity PX's experienced a reduction in price volatility in 2007/2008. APX UK in 03.2007, APX Netherlands in 09.2007 and EEX in 01.2008. All markets experience a reduction in price volatility, perhaps indicating a relationship between the markets. The additional regime shifts found for APX Netherlands in 02.2003 and 07.2005 both experience a reduced price volatility. This indicates a common trend for all series in the European market, as price volatility is reduced over time. We detect no break points in the BPX and EPEX exchanges nor for the Nordpool.

For other energy sources, we only detect break points in Brent oil, with a total of 6 shifts. The shifts are typical for Brent oil, which often experience calm periods with relatively low price volatility, interspersed with periods of high uncertainty and increased price volatility. Interestingly, WTI does not share any break points with the Brent oil, nor do other energy sources such as coal and gas.

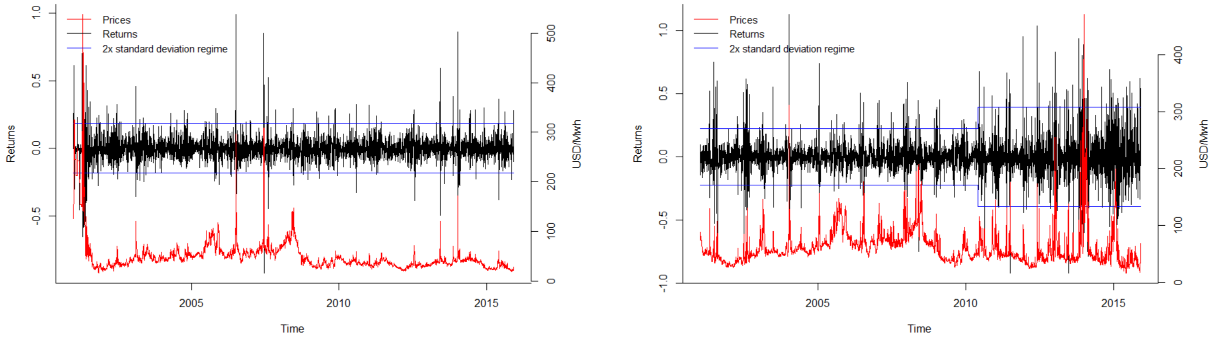
We notice that breaks occur evenly spread over the time period, indicating that there is no immediate common factor affecting the structural breaks. The results further indicate that there are no common breaks between electricity prices and other energy sources. Further, while EU electricity prices experience a reduction in volatility in 2007/2008, Brent oil experience an increase in volatility in 2008 in line with the increased global economic situation during the 2008 financial crisis. Moreover, as price volatility in the US markets increased during 2010, Brent oil experienced a reduction in volatility.

Table 4: Results from k_2 statistic test

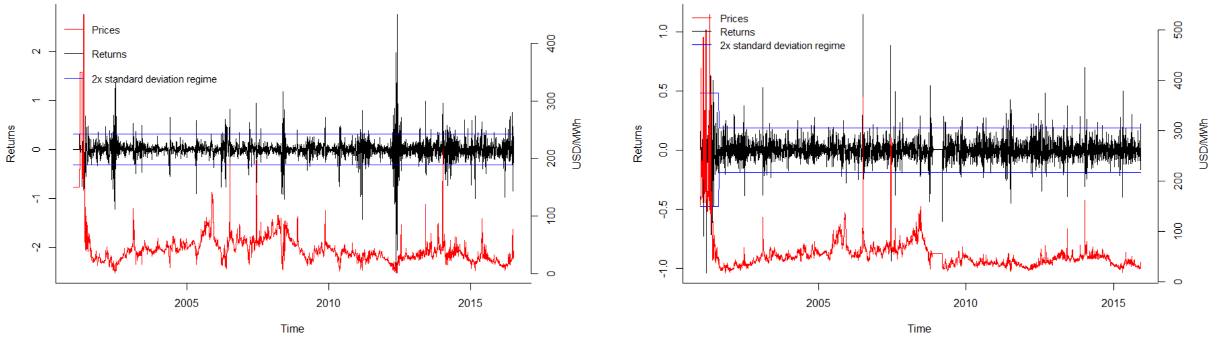
USA Electr.	Breaks #	2000-2001	2002-2003	2004-2005	2006-2007	2008-2009	2010-2011	2012-2013	2014-2015
Palo Verde	0								
Nepool	1						06.2010↑		
Mid Col	0								
Indiana	0								
SP-15	1	06.2001↓							
NP	0								
PJM	1						12.2010↑		
EU Electr.									
BPX	0								
EEX	1					01.2008↓			
EPEX	0								
APX UK	1				03.2007↓				
APX NL	1		02.2003↓	07.2005↓	09.2007↓				
Nordpool	0								
Energy									
WTI									
BRENT	6		04.2002↓			/08.2008↑ /03.2009↓	08.2010↓	07.2012↓	11.2014↑
Coal EU	0								
Coal USA	0								
Henry hub gas	0								

↓↑ indicate if volatility has increased or decreased

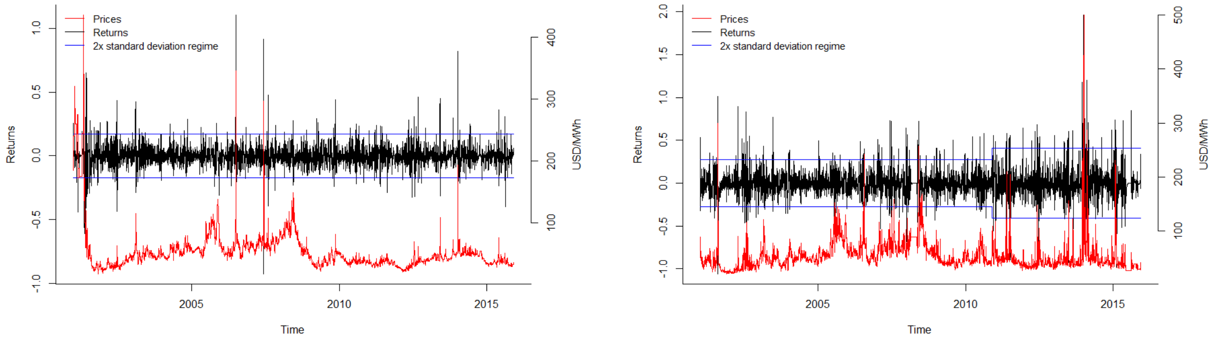
Figure 1: **USA Electricity**


(a) Pale Verde

(b) Nepool

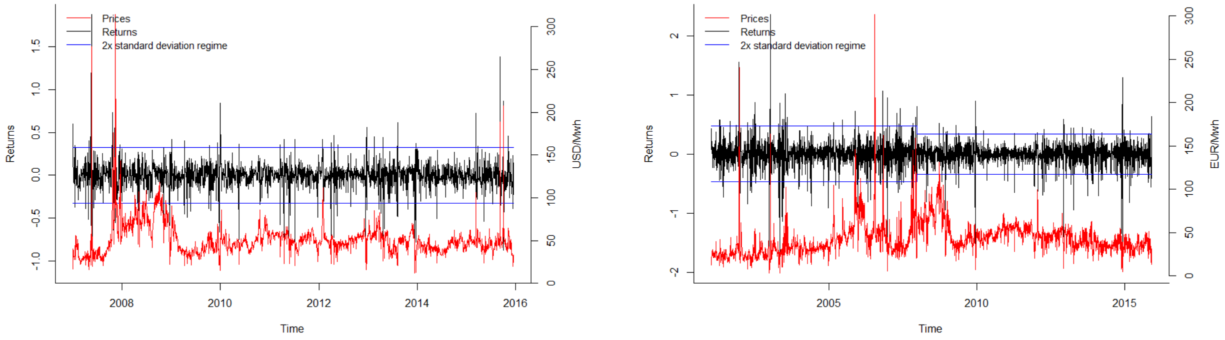

(c) Mid Columbia

(d) SP-15


(e) NP

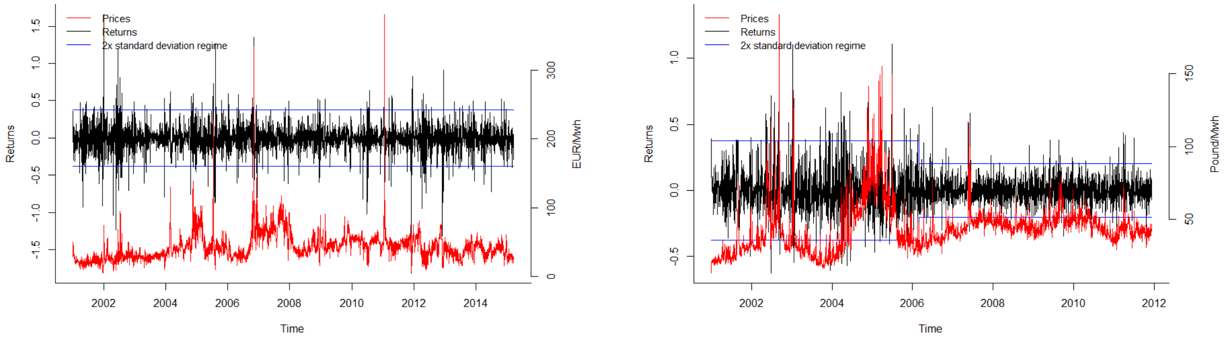
(f) PJM

Figure 2: **European Electricity**



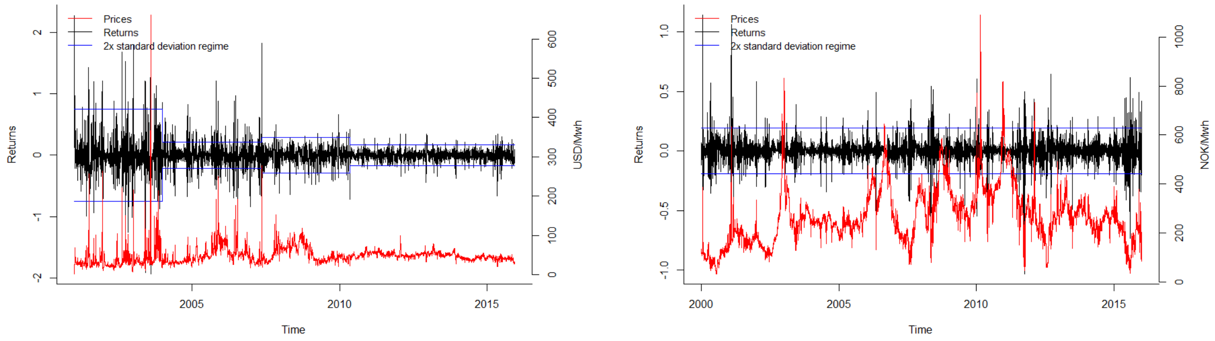
(a) BPX

(b) EEX



(c) EPEX

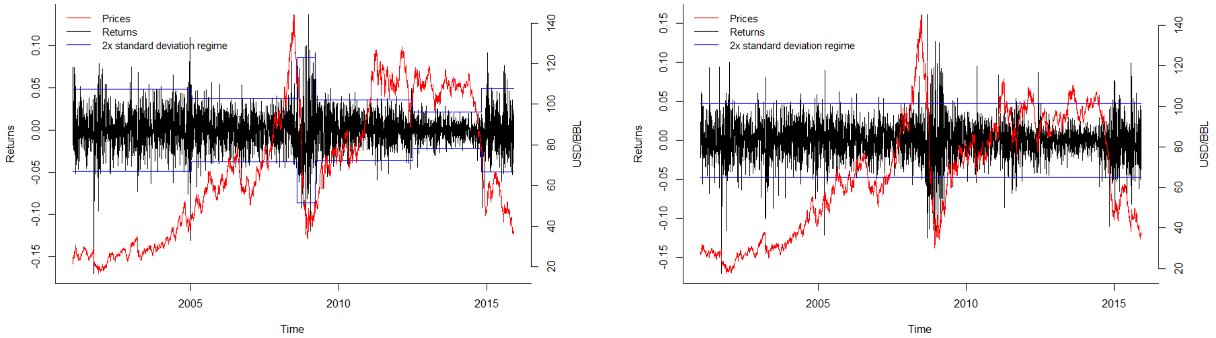
(d) APX United Kingdom



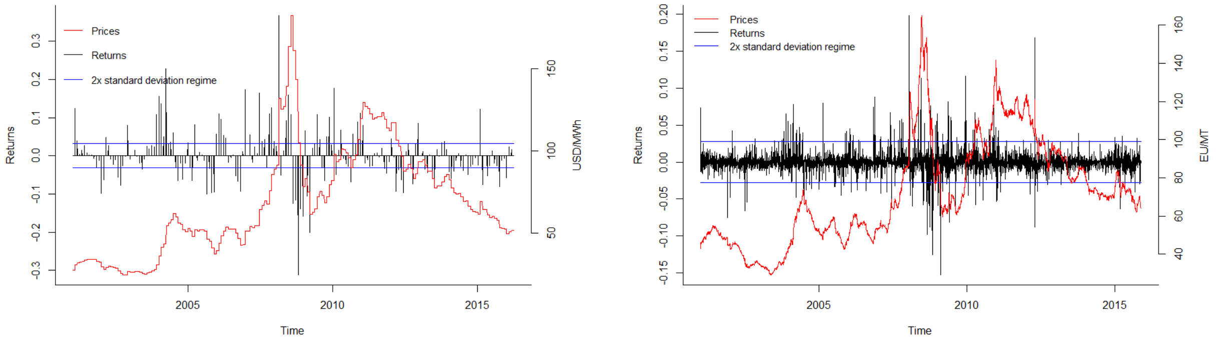
(e) APX Netherlands

(f) Nordpool

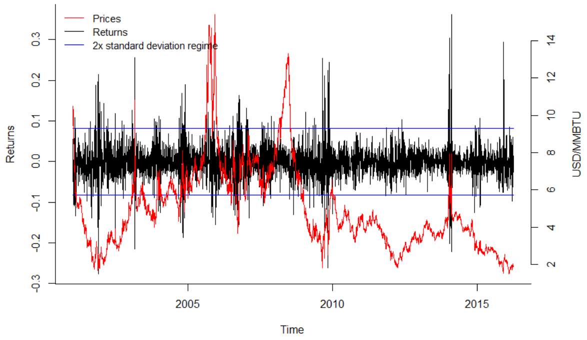
Figure 3: **Other Energy Sources**


(a) Brent Oil

(b) WTI Oil


(c) Coal USA

(d) Coal Europe


(e) Henry Hub Gass

5 Conclusions

In the observation period, we experienced regime shifts for 7 of the 18 electricity series. While the structural breaks found in the USA market have experienced an increase in volatility, the data shows that volatility in Europe has decreased in the period. In general, for the electricity and energy products considered, price volatility has varied throughout our sample period.

We find evidence of volatility regime changes in the entire period for both Europe and US. However, we cannot conclude that there is a strong link between price volatility between EU, US and other energy sources (oil, gas, coal). Contrary, we find that shifts in the price volatility for Brent oil has had the opposite direction compared to simultaneous shifts in US and EU electricity prices. Consequently, the changes in volatility found in the European and US markets may be result of other factors affecting regional market supply and demand, such as increased inter-connectivity between markets and production from renewable resources. As indicated by the literature, there are evidence from the Nee Pool and PJM to support that increased production from renewables, effects the long term volatility in electricity prices. This also might imply that increased inter-connectivity and grid transmissions in areas of decreased volatility has impacted changes in volatility regimes for electricity prices in the EU.

In all the periods that are observed there are a structural change in 1 or 2 series in the periods. However, we there are no simultaneous event between markets, indicating no direct common factors. The results then indicates that structural breaks occur do to local changes in the supply and demand equilibrium.

The results are important for the industry and regulators, as price volatility for electricity needs to be regulated by the industry itself. Electricity requires immediate consumption and as such, changes in the uncertainty of input prices from energy sources, seems to have limited affect to the daily electricity price variations. The innovations taking place in the EU market may over the last decade, increasing inter-connectivity and providing better opportunity to balance regional surplus and shortfall in supply, seems to have resulted in lower volatility and a more stable price. However, we find no effect from trading in the Nordpool-market over time, although there may be a lower intra-day price volatility due to increased trade and liquidity.

Using the k_2 statistic test to detect structural breaks, which corrects for heteroscedasticity, Sansó et al. (2004) predicts a better accuracy for the regime breaks, as our data experience fat tails and heteroscedasticity. In addition, the results found for Brent oil confirms the effects from the 2008 financial crisis, as uncertainty and volatility increased during the financial crisis, and since was reduced as global growth expectations normalized. This provides strength to our analysis for the electricity markets.

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