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Article

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Volatility Spillovers in Electricity Markets: Evidence from the United States

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ABSTRACT

This paper examines the degree of market integration, as observed by measuring volatility spillovers, in selected wholesale electricity spot markets from United States. We choose markets located at interconnected and non-interconnected areas. We use a Multivariate GARCH framework, which allows us to model time varying correlations and to conclude whether the markets show evidence of interdependency. We estimate the variance-covariance and correlation structure, in order to observe the evolution of interactions among markets, accounting for asymmetric effects. We find evidence of significant correlations between interconnected markets, which are mainly due to electricity transmission, since the observed correlations are above 0.5, but our results show that the desired level of integration has not been accomplished yet. Nevertheless, full integration is not an objective target, unless new technologies offer a boost towards that direction. Our results suggest that we should move towards a more integrated market, through legislation reforms and investment in infrastructure, which could increase competition and could lead to capital savings through lower electricity prices. The unique selection of the markets under examination and the 4-variate BEKK model for electricity markets are special characteristics of this paper.

Keywords: Energy Markets, Electricity Markets, Market Integration, BEKK, Asymmetric Dynamic Conditional Correlation
JEL Claasifications: Q43, Q48, O21, C44

1. INTRODUCTION

Electricity prices variate on a daily or even an hourly basis, similarly to financial markets. However, electricity prices exhibit greater volatility which is triggered by supply and demand mismatches. Additionally, derivatives markets are closely related to spot markets, through no arbitrage conditions, and hence hedging (thus accounting for volatility) is an important part of doing business. Volatility in energy markets is also affected by other factors, such as political decisions, oil and gas production, nuclear power reduction protocols and increasing use of renewable resources for electricity generation. In this context, the key issue is not only measuring price volatility but also modelling volatility spillovers. To avoid spillovers, the policy makers and regulatory authorities work together to achieve a higher degree of market integration. It is this important to be able to measure market integration using pre-set benchmarks, in order to limit uncertainty.

In this study, we investigate the correlations and inter-dependencies of four main wholesale USA markets. We propose a market integration model, which would enable authorities to track the effect of integration policies, deciding between different alternative policies and offering targeted incentives in the direction of more integrated markets. We choose to examine two pairs of markets, located at the Western and Eastern Interconnects of continental United States (US). There can be no electricity transmission between distant market areas, due to physical borders, but there exists a significant relationship between neighbouring markets. However, there are additional forces that drive markets towards integration, which are not directly observable, such energy commodities different than electricity and shifts of capital. We aim to reveal the effect of those latent factors through correlations. We employ multivariate covariance and correlation models to measure the degree of market integration.

As discussed above, price volatility is an important parameter for market participants and energy regulators. It has a significant effect on trading activity, risk management decisions, hedging and pricing of assets and derivatives. Moreover, policymakers and market participants are moving towards an integrated market, based on similar market structure and through an interconnected transmission network that allows transmission of electricity through countries and region borders. This trend is obvious in Europe and North America and allows the examination of the way a positive or negative shock in one price series affects others. Hence, volatility interactions are crucial for all participants in energy markets.

The contribution of this study is focused around five points. First, it investigates volatility persistence, volatility spillovers and correlation in markets that are located in different geographical regions, purposely selected so as to examine the degree and the causes of correlation. Assuming similar market structure, as implied by government regulations, markets that are located in neighbouring areas are expected to be highly correlated, due to power interchanges and similar weather conditions. Second, we attempt to answer questions concerning the degree of correlation and the persistent and asymmetric effects between markets that are located in distant areas. This correlation should be a result of fuel prices movements, trading activity and other intangible factors. Third, we contribute to the extension of the literature of MGARCH concerning electricity market prices, which is limited, especially in studies using BEKK and asymmetric dynamic conditional correlation (ADCC) models. To the best of our knowledge, there is no other attempt to use a 4-variate BEKK model for electricity prices. Four, we use relatively recent data to measure the degree of market integration improvement. Five, we provide conclusions which could be useful to power producers, power consumers and policy makers in shaping their bid-ask strategies, improving market interconnections. This is of great importance since integration has significant impacts on environmental, social and economic dimensions.

The rest of this paper is organised as follows: In Section 2, we present a literature review of empirical applications concerning energy markets, especially with MGARCH models. In Section 3, we describe our selected markets and the datasets, including descriptive statistics, tests for normality and tests for heteroscedasticity. Section 4 presents a brief literature review of MGARCH models and the selected methodologies and in Section 5 we present the empirical results. Section 6 concludes this study and includes a discussion of policy implications which could facilitate the goal of an integrated market.

2. LITERATURE REVIEW

There are numerous studies testing for the interconnections between different electricity markets. De Vany and Walls (1999) examine the Western U.S.A. area and test for cointegration and the degree at which markets are integrated. Hadsell et al. (2004) use a TARCH model to examine the volatility of wholesale electricity prices for five US markets and find persistent and asymmetric properties. For the Australian electricity network, Higgs (2009) tests for spillovers between different markets and concludes that there is presence of inter-relationships for the well interconnected markets.

Researchers have also attempted to relate integration to other commodities markets and their structure. Mjelde and Bessler (2009) examine the degree of market integration and how several fuel factors affect electricity prices while Park et al. (2006) conclude that similar regulatory arrangements lead to better market integration. In Europe, Bosco et al. (2010) examine six major European markets and indicate that there is strong evidence of market integration and interdependence between natural gas and oil markets. Another interesting research on European market integration is Castagneto-Gissey (2014), who investigates the interaction between electricity and carbon prices. Related studies are also presented in Balaguer (2011) and Amundsen and Bergman (2007). Koenig (2011) examines the interdependence between electricity prices, carbon emissions and natural gas, but from the perspective of the power plant operator. More recently, Efimova and Serletis (2014) used multivariate correlation models to examine the electricity markets in the United States. Their results indicate a high degree of market integration and suggest a close relationship with natural gas markets and a looser relationship with the oil market. Bunn et al. (2010) conclude that market integration decreases market power.

Many research articles attempt to model the wholesale electricity prices and make inferences regarding energy options pricing and hedging. To mention a few, we refer to Lucia and Schwartz (2002) and Cartea and Figueroa (2005) who propose models that account for the special features of electricity spot prices. Also, Huisman (2008), Samitas and Armenatzoglou (2014) and Weron and Misiorek (2008) use regime switching models to account for spiky behaviour and mean reversion. In these articles, the authors demonstrate the dependencies between markets and show how energy commodity prices volatility and correlation of returns are of great concern to oil, natural gas and electricity market participants. However, fuel price series in particular are used as exogenous factors, that influence electricity price formation (Pirrong and Jermakyan, 2008; Geman and Roncoroni, 2006). In this framework, volatility modelling and the interdependencies between energy prices are of great concern. Also, electricity price will be formulated after considering changes in oil and natural gas prices, since electricity prices are highly correlated with natural gas and oil prices.

3. MARKETS AND DATA

In this section, we present some basic characteristics of electricity markets. We briefly mention the basic market agents and we present what integration has to offer to electricity market participants, to consumers and to the environment. Moreover, we describe the selected markets and their geographical and regional characteristics. Finally, we present the selected data, with descriptive statistics which indicate the special characteristics of electricity, such as mean reversion and price spikes.

3.1. Industry and Benefits of Market Integration

The largest part of US population, more than three quarters, is served by Investor-Owned Utilities, while the rest is served by Consumer-Owned Utilities, which are public utilities in most cases. Among them, vertically integrated utilities are responsible for generation, transmission and distribution of electricity to customers.

In the United States, the Federal Energy Regulatory Commission (FERC) is responsible for regulating interstate transmission of electricity and other energy resources with some activities being under the regulatory authority of the Environmental Protection Agency. FERC has the authority to set the rates and standards for most bulk power transmission in 47 states, which have interconnected transmission networks. Overall, the US energy industry consists of more than 3000 utilities of all kinds which are regulated by several regulatory authorities.

Integration could provide benefits in many aspects and in different dimensions, since interstate electricity transmission and regional electricity cooperation have the potential to reduce the consumption of non-renewable primary energy sources. Additionally, the development of renewable electricity technology could mitigate Green House Gas emissions and avoid deforestation. Moreover, integration allows for extra demand for electricity in a specific region or state to be covered through transmission, thus eliminating the need for new infrastructure in power plants, which would constitute extra environmental burden.

From an economic point of view, electricity integration will result in reduced production costs, which, when combined with more efficient generating technologies, like the combined cycle gas turbine, will result in reduced electricity prices, leading to deflating prices, where electricity is a significant part of the production cost. Additionally, similarly to financial markets integration which leads to the development of related markets, integrated electricity markets could force further development of carbon emissions markets. It is important to note, however, that economic gains are not linked solely to the carbon emissions market, since there is correlation between energy markets and most internal country markets. New investments in power generation, transmission and distribution require motivation and market stability, which comes naturally through the channel of market integration. At the same time, interdependence in energy markets helps improve geopolitical integration, as energy transmission and common infrastructure have a direct impact on economic relations and help strengthen interstate relationships.

3.2. Markets

In North America, including Canada, there are five distinct market areas. More specifically, these are the Western Interconnection, the Eastern Interconnection, the Texas Interconnection, the Alaska Interconnection and the Quebec Interconnection. Especially the first two interconnections are broken down into smaller areas, which we put under investigation. In these smaller areas, which are also trading areas, independent system operators (ISOs) and regional transmission operators (RTOs) are responsible for operating the system and managing power transmission. These agents and their business strategies are of great importance vis-à-vis market integration. Legislation obligates them to offer transparency so as to be in compliance with a very specific regulatory framework. According to FERC-issued regulations, RTOs are obligated to exchange data and to harmonise their model assumptions. Full market integration does not mean that there is a single electricity wholesale price for the entire integrated market at all times. This is not possible because electricity is a special, "flow" commodity and thus the target is a single price over several states which could handle transmission constraints in an optimal manner.

Instruments have been put in place, such as the Market Monitoring Units (MMUs), which analyse measures of market structure, and demonstrate results regarding market performance, including prices and volumes. These units assist regulatory authorities by offering information for the market structure on supply, demand, market concentration, generation fuel mix and price caps. As for the market performance, they analyse prices, mark-ups (KPI for market competitiveness) and price convergence. In general, MMUs help make recommendations and cooperate with regulatory authorities to ensure a functional and global market structure.

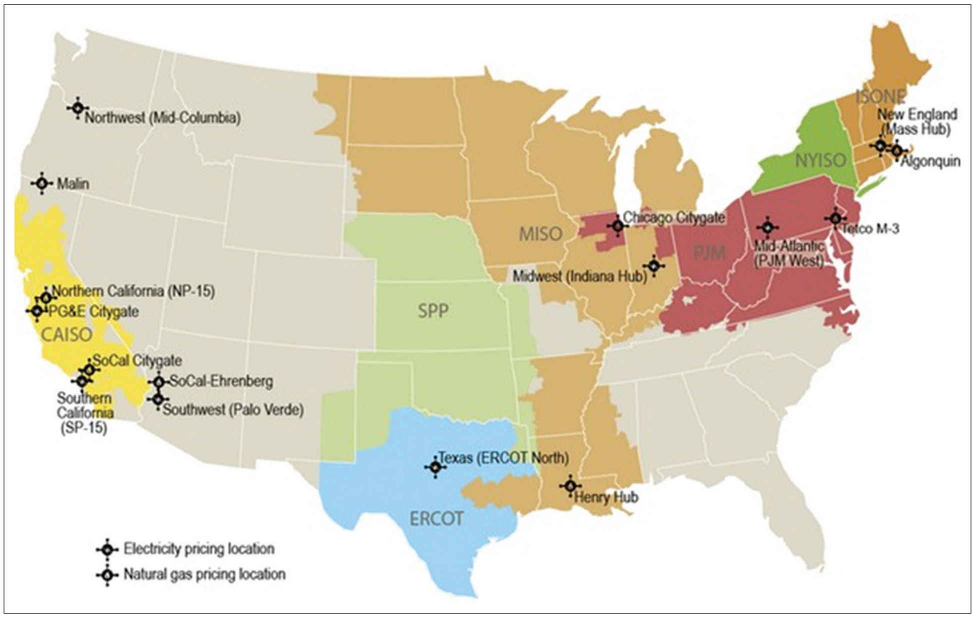
3.3. Data

In our work, we use daily electricity prices from four main USA markets. These are Mid Hub from Columbia (MID), NePool from New England (NE), PJM from Pennsylvania (PJM) and Palo Verde (PV) in California. The data covers a period of 6 years, from 1 January 2008 to 31 December 2013 and was obtained from the U.S. Energy Information Administration (EIA). This time period is important since it is relatively clean of external structural shocks that occurred in 2015 and onwards. Geographically, we concentrate our attention in two large regions for electricity separated by the Rocky Mountains. In the east, our set of zones expands between the Canadian border and the southern border (Florida) and in the west, our selected regions extend from Columbia to California. In Figure 1, we can observe the geographical distribution of the markets used. NEpool and PJM are located in neighbouring areas with similar weather conditions and generation fuel mix and together they serve a population of around 75 million. Mid-Columbia and Palo Verde also have a lot of common features.

We should note here that, in the last year of our study (2013), the generation fuel mix for the continental United States was dominated by coal as a first-generation fuel, followed by natural gas, nuclear power while renewables were last. Projections indicate that by the end of 2040, coal will remain the key fuel but with a decreasing trend, while the use of natural gas and renewables will move upwards (Figure 2).

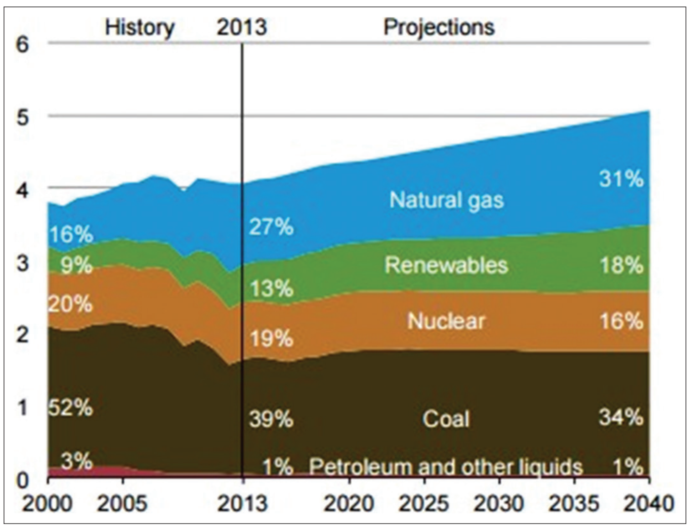
The two couples also exhibit a close price relationship, which can be observed graphically, by calculating the descriptive statistics of the four time series. In Figure 3, we plot the original price series for a period of 1500 days, where we can see the symmetrical fluctuations in the electricity price series of the two couples. Since the four markets are located in distant geographical areas with varying weather conditions and in order to account for the different seasonal parts, we de-seasonalise the data by removing the annual seasonal component. We plot the price series without the seasonal component in Figure 4. We use a Daubechies wavelet

Figure 1: Geographical location of the USA markets



Source: Energy Information Administration

Figure 2: Generation fuel mix and future projections



Source: Federal energy regulatory commission

decomposition to estimate the long run seasonal component which we subtract from the original price series. Wavelets are able to represent both smooth and locally spiky functions because they offer both frequency and time localisation. Electricity price series are characterised by smooth price changes with sudden spikes and this can be better represented by wavelets. The use of de-seasonalised prices series isolates the price process from weather, weekday, season and intra-day effects, leaving a pure price process which is suitable for investigation of volatility spillovers.

3.4. Data Descriptive Statistics

As a first step to account for differences in trading dates of the price series, we use linear interpolation for the missing values in each price series and this results in a series with common trading dates. In Table 1, we present the descriptive statistics of our data. The lower price is observed for the MID Columbia market and is close to zero (sometimes electricity prices could be turn negative). Minimum prices for the other three markets do not differ significant. Maximum prices are extremely high for NE and PJM and correspond to spikes due to congestion or electricity outage. The highest prices are close to 250$/MWh. The mean price for each market is in all cases greater than the median, indicating that prices do not display a normal distribution.

Table 1: Descriptive statistics for electricity prices series

Statistic	Mid	NE	PJM	PV
Min.	0.49	23.93	28.14	19.55
Max.	120.03	255.25	255.99	146.96
Mean	37.6	58.76	53.32	41.44
Median	33.83	48.23	45.08	35.94
Std. Dev.	17.64	29.58	23.59	17.92
Range	119.54	231.32	227.85	127.41
Skewness	1.2828	2.4446	2.7415	2.3643
kurtosis	4.9041	11.5104	15.0290	9.5003
Jarque-Bera test	638.0028	6020.68	10922.41	4038.33
JB P-value	0.000	0.000	0.000	0.000

P-values indicate the rejection of normality

The descriptive statistics also shows the relationship between the pairs of the markets. MID and PV have close range values for all the statistics except the kurtosis. Similarly, NE and PJM have familiar characteristics. The market with the greater volatility is NE with a standard deviation close to 30% while MID exhibits greater stability. The higher values in skewness and kurtosis are observed in the PJM market. In general, the skewness values are greater than zero for all the data series and this we have right asymmetry. This means that large positive returns are more common than large negative returns. This suggests the existence of inverse leverage effects[1]. Kurtosis values are also greater than 3, which would be the value if there was normal distribution of

1 An inverse leverage effect occurs when volatility rises more due to positive shocks than due to negative shocks.

Figure 3: Price series

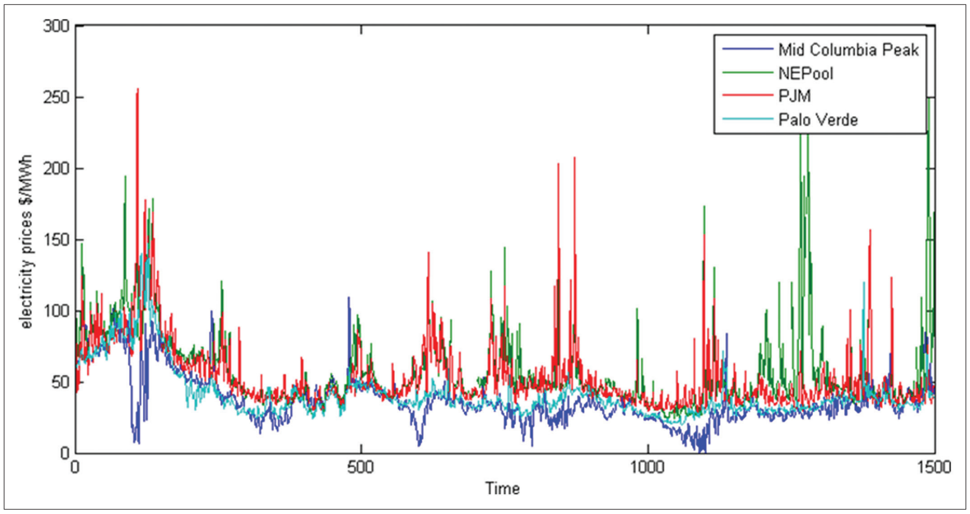
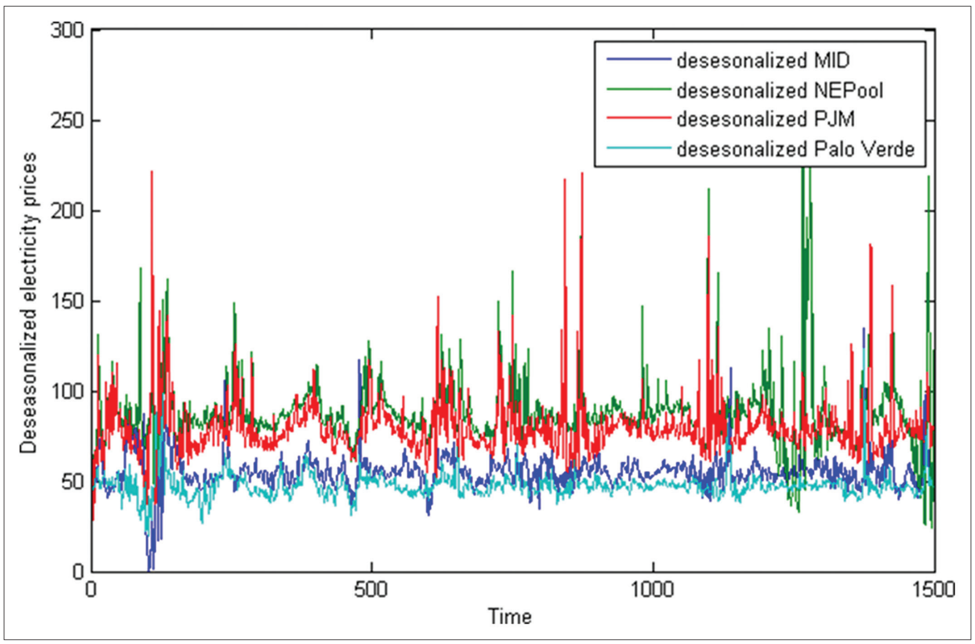


Figure 4: Price series after removing the long-term seasonal component



the observed values, and standard deviation is higher than other commodities like gas or oil.

In Figure 5, we plot the time series returns scaled by 100. The bulges in the return plots below are graphical evidence of time-varying volatility. We test the null hypothesis that each price series comes from a normal distribution, using the Jarque-Bera test at the 0.01 significance level. The results in all series lead us to reject the null hypothesis. Moreover, we test for dynamic correlation of the residuals by using the Engle and Sheppard test (Engle and Sheppard, 2001) and we reject the null hypothesis of no dynamic correlation with a p value of 0.19213 and X^2 (2 d.f.) statistic value of 3.3. We apply Engle's test for residual heteroscedasticity and we found that there are significant ARCH effects in the return series. More precisely, the rejection of the null hypothesis of no conditional heteroscedasticity is strong. These results are presented in the Table 2 and Figure 5, where heteroscedasticity in the returns series is obvious.

Table 2: Engle's ARCH test for residuals heteroscedasticity

Statistic	Mid	NE	PJM	PV
LR test	161.4680	142.1730	184.3166	180.7730
P-value	0.000	0.000	0.000	0.000

P-values indicate the rejection of homoscedasticity

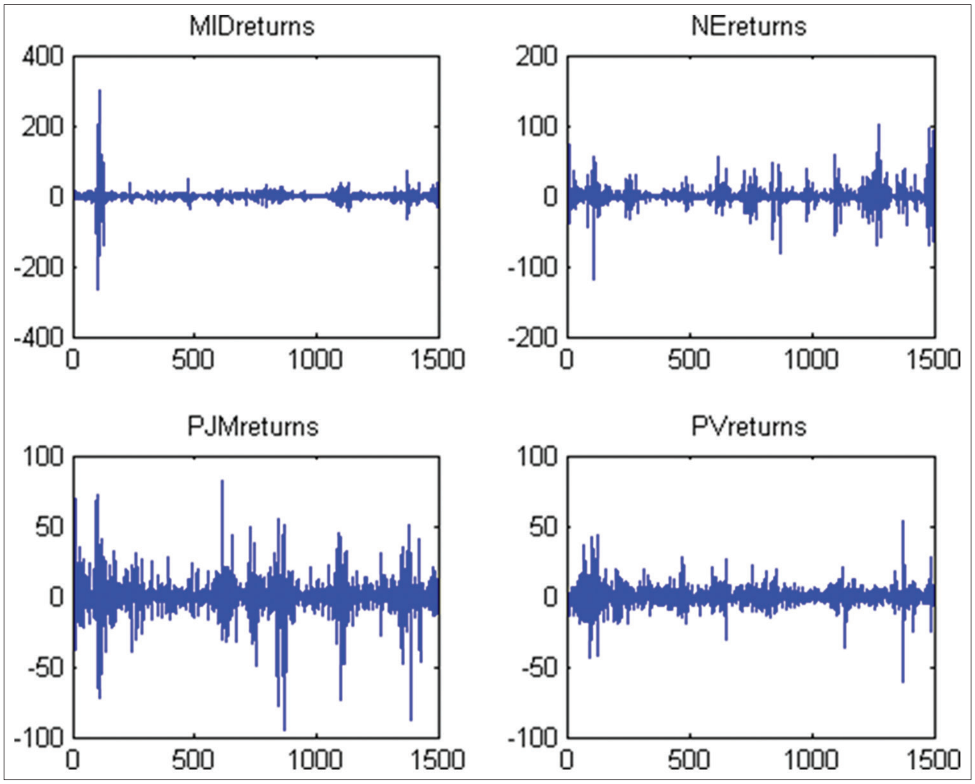
4. METHODS

4.1. Literature Review of MGARCH Models

The above analysis indicates that the proper ethodology is to build a MGARCH[2] model. In this section, we will give a brief literature review of MGARCH models explaining how this is linked to our choice of methodology. In this type of modelling, the main prerequisite is varying volatility in combination with the

2 MGARCH: Multivariate Generalised Autoregressive Conditional Heteroscedasticity.

Figure 5: Returns series multiplied by 100



inclusion of time-varying correlations. The class of MGARCH models for volatility and correlation is mainly used to examine the co-movements of wholesale electricity prices and offers the advantage of accounting for both interdependencies and asymmetric movements.

As it is well known from the beginning of the 90's (Nelson, 1991; Engle and Ng, 1993), that asymmetric effects occur when there is greater dependence between returns during market downturns. Also, unexpected downward movements in the price of an asset raise the conditional volatility of returns more than when there are unexpected upward movements. Asymmetries can be classified in two broad categories: Those between individual returns and those concerning dependence between returns.

If we build a matrix containing correlation covariance parameters associated with lagged values, then the diagonal elements measure the effect of own past values while the off-diagonal elements capture the relation across different price series, also known as spillovers. As a consequence, many MGARCH models have been developed in the recent years in order to model the conditional second moments which describe the interdependences between those prices.

Based on the seminal work of Engle (2002) and Tse and Tsui (2002), a variety of extensions for ARCH models have been proposed and tested in empirical studies. In this context, it is of considerable importance to understand the co-movements of asset returns. Starting with univariate GARCH models for energy commodities, which offer simplicity and quick convergence, the trend nowadays is towards multivariate GARCH, first proposed by Bollerslev (1986). The usage of ARCH and GARCH models for energy commodity prices volatility has received an extensive amount of research in the last two decades. Those models have the disadvantage that they are not able to incorporate the dependencies between conditional volatilities.

To accommodate for asymmetric effects, in the framework of univariate models, the asymmetric GARCH approach is typically modelled by using the GJR-GARCH model of Glosten et al. (1993), whereby positive and negative shocks of equal magnitude have different effects on conditional volatility. The GJR model uses a threshold indicator function to describe the asymmetric effects by adding an extra parameter in case of negative returns. Kroner and Ng (1998) and Ang and Chen (2002) make these points clear by modelling the asymmetric co-movements, with MGARCH models. In many commodities this effect is reverted. Here, an inverse leverage effect can be observed, which is a common occurrence in electricity prices (Knittel and Roberts, 2005).

4.2. Methodology

In the following we present the models we use to examine the degree of market integration. We describe issues concerning the validity of the models together with their applications and constraints. The following methodologies are used in a variety of business applications and academic research, including financial and commodities markets, macroeconomic modelling and natural sciences. They have been used and tested for a long period of time and their main advantage is the modelling of both constant and dynamic correlations.

4.2.1. BEKK(1, 1, K) Model

The BEKK(1, 1, K) model, as defined in Engle and Kroner (1995) is given by the following equation:

$$H_t = C^{*'}C^{*} + \sum_{k=1}^{K} A_k^{*'}\varepsilon_{t-1}{}'\varepsilon_{t-1}A_k^{*} + \sum_{k=1}^{K} B_k^{*'}H_{t-1}B_k^{*} \qquad (1)$$

Where C^*, A_k^*, B_k^* are NxN matrices but C^* is upper triangular to ensure positive definiteness of H_t. The summation limit K determines the generality of the process.

The diagonal elements of matrix A measure the impact of shocks on the series' own volatility. On the other hand, the off-diagonal elements of matrix A capture the effect of shocks in the price series on the volatility of other price series, thus modelling the interdependence in volatility.

Matrix B is associated with the impact of past volatility, as it is multiplied with the lagged matrix H_{t-1}. In a similar manner, like the shocks effect, the diagonal elements of B, measure the impact of past volatility of a series on its conditional variance, while the off-diagonal elements show the volatility spillovers. To reduce the number of parameters and consequently to reduce the generality, one can impose a diagonal BEKK model, i.e., A_k^* and B_k^* in 4.1 are diagonal matrices.

However, the above described models are not able to allow for asymmetric effects. The asymmetric BEKK model proposed by Kroner and Ng (1998) accounts for asymmetry and is given by the following equation.

$$H_t = C^{*'}C^* + \sum_{k=1}^{K} A_k^{*'}\varepsilon_{t-1}{}'\varepsilon_{t-1}A_k^* + \sum_{k=1}^{K} B_k^{*'}H_{t-1}B_k^* + \sum_{k=1}^{K} G_k^{*'}\xi_{t-1}{}'\xi_{t-1}G_k^* \quad (2)$$

Where G is the matrix of coefficients for the asymmetric effects. Again, the diagonal elements of matrix G measure the impact of bad news (negative shocks) on the price series and the off-diagonal elements demonstrate the volatility spillovers. In our model, it is the latter elements that will show us if there exist volatility spillover between the electricity markets.

The plainest BEKK model is the scalar BEKK, where matrixes A and B are restricted to be scalar and is defined by the following equation.

$$H_t = C' C + a^2\varepsilon_{t-1}\varepsilon_{t-1}{}' + \beta^2 H_{t-1} \quad (3)$$

In this way variances and covariances have the same speed of mean reversion and they just differentiate by the intercept term. Scalar BEKK models can be modified to account and for asymmetric effects.

4.2.2. Constant conditional correlation (CCC) model

The main benchmark is the CCC model of Bollerslev (1990), which is specified as follows:

$$H_t = D_t R D_t \quad (4)$$

Where D_t is a diagonal matrix with the square root of the estimated univariate GARCH variances on the diagonal, and R is the sample correlation matrix of returns y_t.

CCC decomposes the conditional covariance into κ time-varying conditional variances and the conditional correlation, which is assumed to be constant. It is also possible to model the conditional variances as different models for each asset, which is an advantage. Although the model is useful, the assumption of CCCs can be too restrictive, as it is the case here since we rejected the null hypothesis of constant correlation, as stated section 3.4.

4.2.3. DCC model

As we mentioned earlier, Engle, 2002 generalised the CCC model to the DCC model. This model is:

$$H_t = D_t R_t D_t = \rho_{ijt}\sqrt{h_{iit}h_{jjt}} \quad (5)$$

$$H_t = diag(Q_t)^{-1/2}\, Q_t diag(Q_t)^{-1/2} \quad (6)$$

$$Q_t = (1-a-\beta)\bar{Q} + a\varepsilon_{t-1}\varepsilon_{t-1}{}' + \beta Q_{t-1} \quad (7)$$

Where α and β are non-negative parameters, $\bar{Q}$ is the unconditional co-variance of $\varepsilon_t = D_t^{-1}y_t$, and it is, in fact, the sample correlation matrix of ε_t, which are the standardised correlated residuals. The conditional variances of the components of ε_t are equal to 1, but the conditional correlations are given by $R_t = E[\eta_{t-1}\eta'_{t-1}]$. The term diag($Q_t$) is a diagonal matrix with the same diagonal elements as Q_t. If $\alpha = \beta = 0$, the model is simply the CCC.

In a DCC model, the ij-th equation contains the parameters to be estimated and is specified as follows:

$$q_{ij,t} = \bar{\rho}_{ij} + a\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \bar{\rho}_{ij}\right) + \beta\left(q_{ij,t-1} - \bar{\rho}_{ij}\right) \quad (8)$$

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \quad (9)$$

Where $\bar{\rho}_{ij}$ in 4.8 are the unconditional correlations. The typical estimated set of parameters have slow decay ($\beta > 0.9$) and a small news parameter ($\alpha < 0.01$). Conditional correlation models defined through 4.7, require positive definiteness of R_t and the $h_{i,t}$ to be well defined. The DCC model focuses on the dynamic evolution of R_t, through the standardised residuals. This multivariate GARCH model estimates the covariance matrix of returns H_t by a decomposition into conditional standard deviations and correlations. To do that, we fit each conditional variance, namely the marginal density of the returns, with a univariate GARCH(1, 1) model and, in the next step, we evaluate the dynamic conditional correlations, given the conditional volatility estimated in the first step. However, the main disadvantage of this model is that it cannot account for asymmetries[3] in conditional variances, covariances and correlations. Also, one extra point which could be though as restrictive weakness is that correlations are only affected by their own past values and not on shocks.

4.2.4. ADCC model

To overcome the previous mismatch, (Cappiello et al., 2006) employ a revised version of the DCC model, which addresses asymmetries in conditional variances, covariances and correlations of two assets named ADCC. In that case Q_t is given by the following equation.

$$Q_t = (1-a-\beta)\bar{Q} - q\bar{N} + az_{t-1}z_{t-1}{}' + bQ_{t-1} + g\eta_{t-1}\eta_{t-1}{}' \quad (10)$$

3 Asymmetries occur when negative returns imply larger increases in volatility than equal size positive returns

Where α and β are scalar parameters, g is the asymmetry term, $\bar{Q}$ is the unconditional covariance of the standardized residuals, $\bar{N}$ is the covariance matrix of z_t and η_t is a function indicator that takes the value 1 if the residuals are negative and 0 otherwise.

5. EMPIRICAL RESULTS

As we mentioned earlier, a robust way to assess market integration is to analyse volatility transmission across markets. In this section, we apply the econometric model described above and estimating their parameters, in order to analyse volatilities and the manner in which they are correlated. For each time series of returns we use an ARMA(1, 1) model, to estimate the residuals. The parameters of the model are given in Table 3. The θ vector stands for the intercept, the autoregressive parameter and moving average parameters. σ_i is the estimated variance of the residuals and y_i are the unconditional ARMA model means. All parameters presented in this table are significant at the 0.05 level.

5.1. BEKK Models

We estimate the parameters of several BEKK models in order to describe the variance-covariance dynamics of our data. In Table 4, we present the parameters of the full BEKK model and full Asymmetric BEKK model. We observe that the parameter values of the diagonal elements are significant, which implies volatility persistence, through the effect of past shocks and past volatilities. The parameters that account for volatility spillovers (i.e., the off-diagonal elements) are not significant, which means that we can reject a major effect from shocks and past volatility between the markets.

The same conclusion holds if we include asymmetric terms in the model. An asymmetric effect is present in each price series of returns, but not between different markets. This result indicates that it is better to model the variance-covariance structure with a diagonal BEKK model. In this way, we can reduce the number of estimated parameters.

In Table 5, the parameters of interest are A_{ii}, B_{ii} and G_{ii}. All these diagonal parameters suggest volatility persistence and asymmetric effects. The parameter values for the intercept matrix C for all BEKK models are omitted since they are not of interest. However, for scalar and asymmetric scalar BEKK models, variances and covariances are only differentiated due to the intercept term CCj.

The scalar BEKK model parameters are calculated to be $\alpha = 0.4022$ and $\beta = 0.9148$, which indicates a high degree of volatility persistence. Similar results can be found for the scalar BEKK model, with an extra asymmetric term G_{11}. The first two models confirm volatility persistence through high GARCH estimates

Table 3: ARMA (1, 1) estimated parameters

Market	θ_i	σ_i	y_i
MID	(0.0067; 0.7898; −0.9985)	273.3	0.063
NE	(−0.007; −0.5565; 0.7082)	193.6	1.8632
PJM	(−0.0019; 0.7233; −0.9824)	159.91	−1.1702
PV	(0; −0.5601; 0.6574)	55.61	0.1723

All parameters are significant at 0.05 level

and high impact of short-term variations. The next two models, namely diagonal and AD BEKK, are used to estimate the volatility persistence for each market. The obtained parameter values indicate that the PV market has the highest value of volatility persistence, followed by PJM, MID and NE. The effect of each series' own past shocks on conditional variance is stronger in NE, followed by MID, PJM and PV. For the AD model, the highest effect of asymmetric shocks is presented in MID series, while NE has the lowest asymmetric effects.

We observe high values of ARCH parameters, indicating short term spillover effects, which however do not decline significantly from the DCC results and are in line with electricity price process dynamics. In the scalar BEKK model, all the correlation equations have the same parameters with the GARCH parameter with values above 0.9, indicating persistent volatility. This is also the case when we include an asymmetric term to the previous model. This is normal for electricity markets since extreme positive shocks in the returns series stem from prices spikes due to network congestion. In the case of the Diagonal BEKK model, all GARCH parameters are high, with NE having the lowest price of 0.8816 and PV with the higher price of 0.9606. Similar results are presented in the column of AD BEKK, where the asymmetric term is stronger for MID Columbia electricity.

5.2. Correlation Models

Since the class of BEKK models model the covariances and not the correlation, we use the class of Conditional Correlation models to examine the correlations between the markets. In this class of models, the estimation is performed in a two-step process. The first step is the estimation of the univariate GARCH model. Then, in the second step, the estimation results are used as input to estimate the correlation parameters. A comparison of the Akaike information criterion of each estimation indicates that a GARCH (1, 1) model is the best fit for our data. The correlation matrix R is the following:

$$R = \begin{bmatrix} 1 & 0.1219 & 0.1066 & 0.4299 \\ 0.1219 & 1 & 0.6231 & 0.1296 \\ 0.1066 & 0.6231 & 1 & 0.0953 \\ 0.4299 & 0.1296 & 0.0953 & 1 \end{bmatrix}$$

From the above correlation matrix, we observe that there is a positive correlation between the markets, with a high correlation value between Mid-Columbia and Palo Verde, with a correlation value of 0.4299 as it was expected. The correlation between New England and Pennsylvania is the greatest in the sample and has a value of 0.6231. As stated earlier, the selected markets exhibit (in couples) strong similarities. Hence, the empirical results are in line with what we would intuitively expect. The correlations between Palo Verde, on the one side, and New England and Pennsylvania, on the other, are 0.1296 and 0.0953 respectively, suggesting a low interdependence. This is evidence that, even though the aim is towards market integration, there is a lot to be done since electricity markets are still heavily localised.

In the next step, we use fat-tailed GARCH models to estimate the variance equations, in cases where the standardised errors are

Table 4: Full BEKK and full asymmetric BEKK parameter estimation

Parameter	Full BEKK			Full asymmetric BEKK		
	Parameter value	Std. error	T-test	Parameter value	Std. error	T-test
A_11	0.27815*	0.08599	3.2348	0.30954*	(0.08544)	3.6231
A_21	−0.01736	0.12469	−0.13919	−0.02746	(0.13102)	−0.20961
A_31	−0.01882	0.07312	−0.2574	−0.00535	(0.02728)	−0.19612
A_41	0.03966	0.26111	0.1519	0.02558	(0.11522)	0.22198
A_12	0.02047	0.04286	0.47765	0.00793	(0.01823)	0.43525
A_22	0.2407*	0.0501	4.80479	0.24183*	(0.08494)	2.84706
A_32	0.02525	0.17127	0.14744	0.03335	(0.05574)	0.59841
A_42	0.02805	0.09895	0.28346	−0.01878	(0.05232)	−0.35898
A_13	0.02046	0.05001	0.40916	−0.00939	(0.05804)	−0.16181
A_23	−0.03531	0.10564	−0.3342	−0.00382	(0.04098)	−0.09315
A_33	0.27634*	0.0424	6.51821	0.23981*	(0.09929)	2.41526
A_43	−0.03004	0.18818	−0.15965	−0.01201	(0.13625)	−0.08817
A_14	0.00557	0.03539	0.15731	−0.01596	(0.0382)	−0.41788
A_24	−0.00684	0.01925	−0.35518	−0.04397	(0.05226)	−0.84142
A_34	−0.026	0.06569	−0.39575	−0.01394	(0.03309)	−0.42116
A_44	0.22981*	0.09845	2.33427	0.22862*	(0.08114)	2.81776
B_11	0.89587*	0.05047	17.74975	0.18726	(0.31355)	0.59722
B_21	−0.01315	0.12507	−0.10513	−0.02587	(0.23578)	−0.10972
B_31	−0.00846	0.07539	−0.1122	0.00858	(0.06704)	0.12796
B_41	0.01083	0.11751	0.09215	0.00539	(0.02959)	0.18221
B_12	0.00872	0.04003	0.21785	0.01599	(0.07356)	0.2174
B_22	0.90803*	0.03108	29.21451	0.16842	(0.10791)	1.56071
B_32	−0.04023	0.03326	−1.2095	0.01147	(0.0748)	0.15337
B_42	0.00952	0.03604	0.26405	−0.02891	(0.06808)	−0.42463
B_13	−0.01787	0.04852	−0.36826	0.01547	(0.0454)	0.34085
B_23	0.0281	0.0841	0.33419	−0.02902	(0.1274)	−0.22776
B_33	0.90985*	0.03206	28.3797	0.15777*	(0.06467)	2.43968
B_43	0.01728	0.08806	0.19628	0.02242	(0.08605)	0.26059
B_14	−0.02476	0.01804	−1.3727	−0.01586	(0.14977)	−0.10589
B_24	−0.00192	0.01537	−0.12501	0.02833	(0.02876)	0.98485
B_34	0.01469	0.02948	0.49823	0.0151	(0.09287)	0.16256
B_44	0.91176*	0.02705	33.70088	0.16809	(0.10096)	1.66489
G_11				0.89361*	(0.07974)	11.20632
G_21				0.01606	(0.03995)	0.40188
G_31				−0.00733	(0.01309)	−0.55987
G_41				−0.00616	(0.05357)	−0.11491
G_12				0.00505	(0.01957)	0.25817
G_22				0.91655*	(0.02301)	39.83269
G_32				−0.02289	(0.02781)	−0.82309
G_42				0.01745	(0.06204)	0.28136
G_13				0.02022	(0.07313)	0.27643
G_23				0.01827	(0.04759)	0.38381
G_33				0.90743*	(0.0578)	15.69943
G_43				0.01469	(0.07027)	0.20904
G_14				−0.00183	(0.00709)	−0.25756
G_24				0.00244	(0.01058)	0.2305
G_34				−0.00915	(0.0217)	−0.42167
G_44				0.9071*	(0.07893)	11.49198
	Full BEKK			Full asymmetric BEKK		
Loglikelihood	−21936.70			−21342.67		

multivariate Gaussian distributed with joint distribution of the form $f\left(z_t\right)=\prod_{t=1}^{T}\frac{1}{\left(2\pi\right)^{n/2}}exp\left(-\frac{1}{2}z_t^T z_t\right)$. Figure 5 indicates the existence of volatility clustering, i.e., periods with high volatility and periods with low volatility, which leads to the conclusion that a GARCH model can be used to fit the data. The parameters of the GARCH(1, 1) models are given in Table 6.

The value of a indicates short run persistence of shocks while β indicates the contribution of shocks to the long run persistence ($\alpha+\beta$). We observe that the parameter estimates are very similar, while the biggest volatility persistence is observed in the PV market. This is something that is expected since the selected markets have similar characteristics, like mean reversion and spiky behaviour, and thus the impact of shocks should be similar.

Next, we estimate the parameters of the DCC model. The GARCH(1, 1) parameters are the same like in the CCC model given in Table 6 and the estimated DCC parameters are $\alpha=0.01691$ and $\beta = 0.94444$. A high value in the β parameters suggests that conditional variance is persistent, while a high a value signifies

Table 5: Variance-covariance structure for diagonal parameters in the class of BEKK models

Parameters	(S) BEKK	(A) BEKK	(D) BEKK	(AD) BEKK
A_11	0.4022* (0.0223)	0.3829* (0.0218)	0.4311* (0.1552)	0.3095* (0.0804)
A_22			0.4719* (0.0693)	0.4739* (0.0614)
A_33			0.3433* (0.0347)	0.3196* (0.0353)
A_44			0.2368 (0.1099)	0.3093* (0.0997)
B_11	0.9148* (0.0081)	0.9126* (0.0522)*	0.9023* (0.0619)	0.9138* (0.0836)
B_22			0.8816* (0.0401)	0.8802* (0.0432)
B_33			0.9255* (0.0132)	0.9201* (0.052)
B_44			0.9606* (0.0251)	0.9372* (0.0658)
G_11		−0.2023* (0.0073)		0.3718* (0.0357)
G_22				0.0356 (0.0345)
G_33				0.2516* (0.0131)
G_44				−0.1148 (0.0323)
Loglikelihood	−20907.19	−20899.67	−20871.25	−20814.32

S: Scalar, D: Diagonal, A: Asymmetric, AD: Asymmetric diagonal values in parentheses are the standard errors. All parameters are significant in 0.05 level

spiky volatility. In our case, conditional variances seem to be more persistent.

We now focus on the ADCC Results. Once again, we use a GARCH(1, 1) model to estimate the conditional volatilities. In order to handle the fat tailed returns of the electricity price series, we normalise the values by dividing the residuals with the time-varying variances $\tilde{\varepsilon}_t = \frac{\varepsilon_t}{\sqrt{h_t}}$. A classic feature of GARCH models is that it evaluates the next period variance by squaring the past time innovation. Thus, big shocks may dramatically increase the estimated variance and for this reason it is necessary to include an asymmetric term in the model. The variance equations are the following as follows:

$$\sigma_{it} = \omega_{it} + a_i\varepsilon^2_{i(t-1)} + \beta_i\sigma_{i(t-1)} \qquad (11)$$

We use the standardised residuals as input data and we estimate the variance-covariance matrix H_t. The diagonal elements in a matrix containing correlation covariance parameters associated with lagged returns measure the effect of own past returns while the off-diagonal elements capture the relation in terms of returns across markets, also known as return spillover. Kroner and Ng (1998) and Ang and Chen (2002) illustrate these points by modelling the asymmetric co-movements. Table 7 includes the parameter estimations for the ADCC model.

To interpret the results in Table 7, we examine the persistence coefficient which is defined as the sum of α and β. Both dynamic models have this sum <1, which implies that volatility spillovers and asymmetric effects do exist. We showed earlier that one of the characteristics of electricity spot prices is that is demonstrates volatility clusters, since large changes in spot prices are often followed by other large changes and, similarly, small changes in daily spot prices are often followed by yet more small changes. The implication of volatility clustering is that any volatility shocks today will influence the volatility expectations in the future. DCC and ADCC models have a formation like ARMA processes where α is the AR parameter and β is the MA parameter. Low AR parameters indicate quicker convergence to the long run mean, which is our case here, since α_{DCC}= 0.01691 and α_{ACC}= 0.00154. These values are expected since they are in line with the quick reversion of electricity prices to the long run mean after a jump occurs. Moreover, the asymmetric term *g* is relative low, indicating that an inverse leverage effect in electricity returns is possible.

Table 6: GARCH (1, 1) estimated parameters for CCC and DCC models

Market	ω_i	α_i	β_i	$\alpha_i + \beta_i$
MID	3.5841	0.3061	0.6938	0.9999
NE	3.8956	0.2937	0.7063	0.9946
PJM	5.9531	0.2856	0.7009	0.9865
PV	1.7308	0.2621	0.7352	0.9973

Table 7: ADCC model parameters and estimated log likelihood

Parameter	CCC	DCC	ADCC
α		0.01691	0.00154
β		0.94444	0.87166
α + β		0.96131	0.8732
g			0.12678
Loglikelihood	−20584.65	−20564.49	20706.41

ADCC: Asymmetric dynamic conditional correlation

By observing Figures 6 and 7, where we plot correlations between the four markets for DCC and ADCC models, we can reach some conclusions regarding the interdependencies of the markets under examination. Correlations between MID and the distant markets NE and PJM are low and they seem to be fluctuating in values close zero. This means that correlations between these markets have very low persistence. As it was expected, the correlations between neighbouring markets, namely the pairs MID-PV and NE-PJM, are higher and above 0.5. This is evidence of volatility spillovers and indicates the close connection of these two sets of markets.

6. POLICY IMPLICATIONS

In this study, we examine the interdependencies between four United States electricity markets. We examine the degree of market integration and, at the same time, we offer useful inferences for market participants and policy makers by measuring the degree of correlation. For this reason, the selected markets are located

Figure 6: Correlation graphs for dynamic conditional correlation model

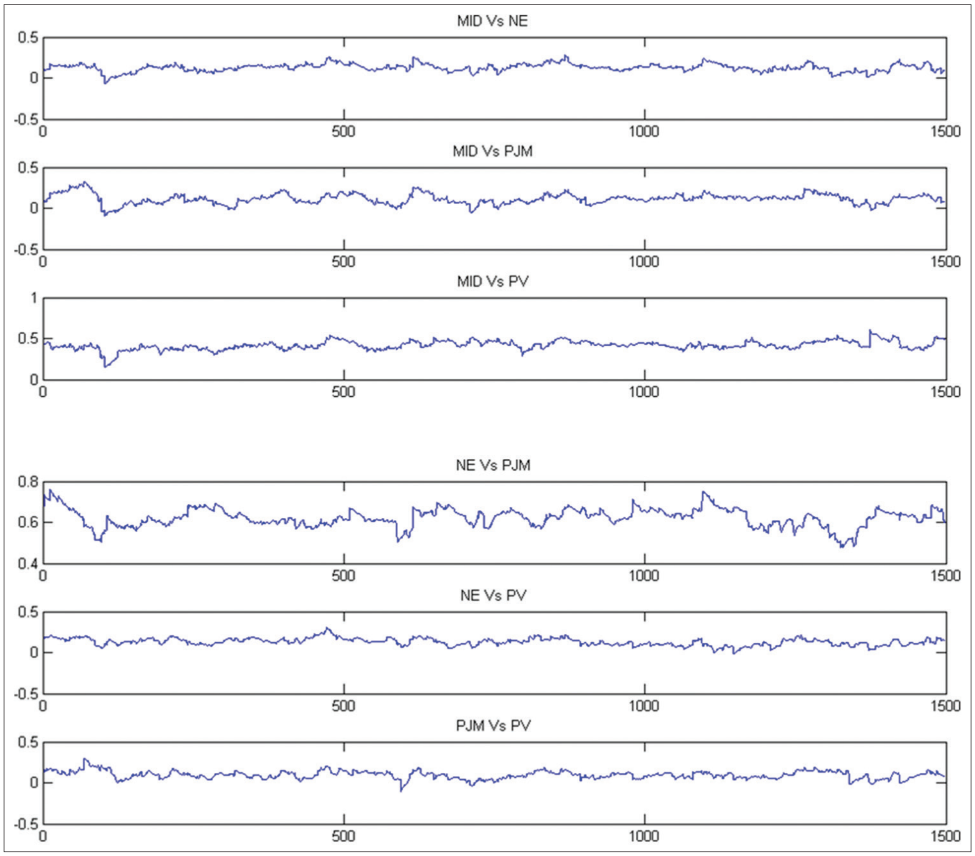
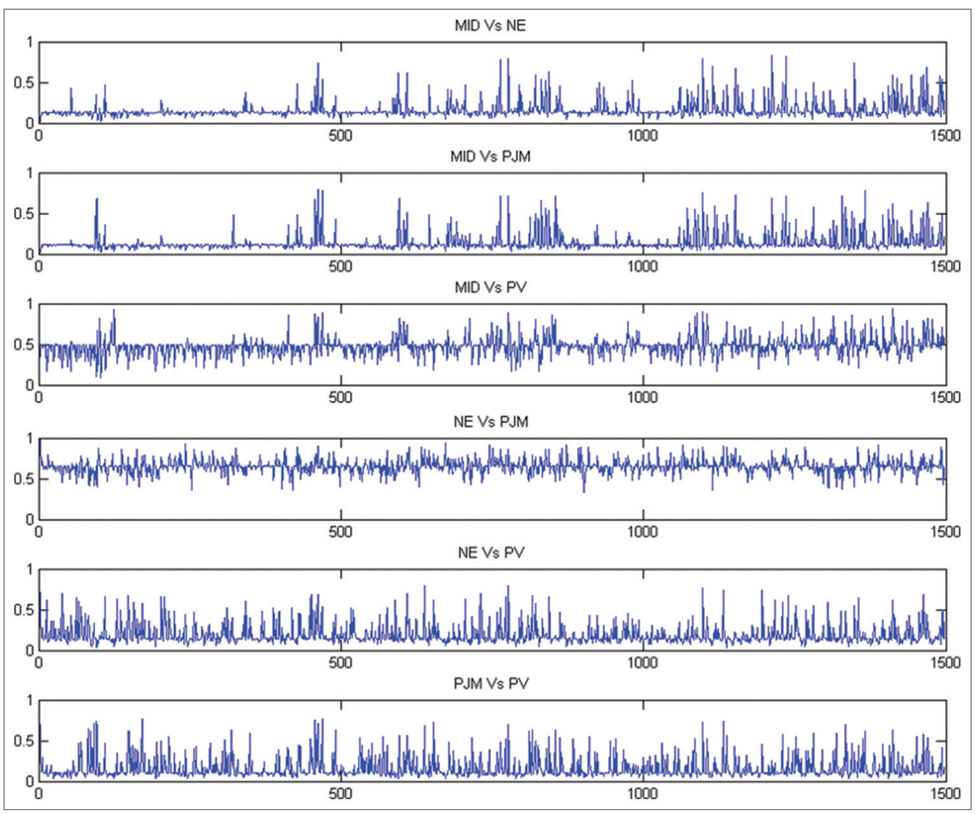


Figure 7: Correlation graphs for the asymmetric dynamic conditional correlation model



both in close and distant geographical regions. In this manner, we examine market interconnections through higher correlations in neighbouring markets. Similarly, we examine market structure, trading activities and fuels prices through the study of correlations for distant markets. We use a class of multivariate GARCH models to examine long and short-term persistence of volatility and correlations and we experiment with several alternative BEKK, CCC, DCC and ADCC models. We evaluate the implied correlations and examine the existence of volatility spillovers taking into account asymmetric effects.

We find evidence of significant correlations between interconnected markets, mainly due to electricity transmission, in the framework of a developed transmission network, since the observed correlations are above 0.5. With these results in hand, ISOs and regulatory authorities should take action towards higher integration in electricity markets, which should lead to capital savings through lower electricity prices. For example, legislation could be designed in the context of emissions allowances, since their cost affects electricity generation and prices.

Moreover, possible investment in new infrastructure, like high voltage transmission networks, will boost this effort. ISOs would be faced with increased competition in a more integrated market and will need to decrease local markets prices, since integration allows for new competitors. Other parameters that contribute to the observed correlations are the prices of factor goods like fuels. This seems to affect primarily the distant markets. However, fuel prices influence close markets correlations as well since electricity prices are highly related to the marginal cost of production. Policy makers and market participants should account for this complexity of such special markets. In non-interconnected markets in particular, correlations in electricity spot prices are mainly influenced by correlations in fuel prices and only partly by similarities in the market structure.

Convergence to an integrated electricity market is essential to ensure the supply/demand matching in a secure way without congestion and extreme price differences. At the same time, environmental issues put pressure towards that direction and motivate electricity companies to invest in new infrastructure, in order to increase competition and the usage of renewable sources for power production. Even though regulators should aim towards an economically and physically integrated electricity market, the desired level has not been accomplished yet for both interconnected and non-interconnected markets. Nevertheless, the physical transfer limitations of electricity may never allow for full or even satisfactory market integration, unless new technologies offer a boost to that direction.

REFERENCES

Amundsen, E.S., Bergman, L. (2007), Integration of multiple national markets for electricity: The case of Norway and Sweden. Energy Policy, 35(6), 3383-3394.

Ang, A., Chen, J. (2002), Asymmetric correlations of equity portfolios. Journal of Financial Economics, 63(3), 443-494.

Balaguer, J. (2011), Cross-border integration in the European electricity market. Evidence from the pricing behavior of Norwegian and Swiss exporters. Energy Policy, 39(9), 4703-4712.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327.

Bollerslev, T. (1990), Modelling the coherence in short-run nominal exchange rates: A multivariate generalized arch model. The Review of Economics and Statistics, 72(3), 498-505.

Bosco, B., Parisio, L., Pelagatti, M., Baldi, F. (2010), Long-run relations in European electricity prices. Journal of Applied Econometrics, 25(5), 805-832.

Bunn, D.W., Martoccia, M., Ochoa, P., Kim, H., Ahn, N.S., Yoon, Y.B. (2010), Vertical integration and market power: A model-based analysis of restructuring in the Korean electricity market. Energy Policy, 38(7), 3710-3716.

Cappiello, L., Engle, R.F., Sheppard, K. (2006), Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial Econometrics, 4(4), 537-572.

Cartea, A., Figueroa, M. (2005), Pricing in electricity markets: A mean reverting jump diffusion model with seasonality. Applied Mathematical Finance, 12, 313-335.

Castagneto-Gissey, G. (2014), How competitive are EU electricity markets? An assessment of ETS Phase II. Energy Policy, 73, 278-297.

De Vany, A.S., Walls, W.D. (1999), Cointegration analysis of spot electricity prices: Insights on transmission efficiency in the western us. Energy Economics, 21(5), 435-448.

Efimova, O., Serletis, A. (2014), Energy markets volatility modelling using GARCH. Energy Economics, 43(C), 264-273.

Engle, R. (2002), Dynamic conditional correlation. Journal of Business and Economic Statistics, 20(3), 339-350.

Engle, R.F., Kroner, F. (1995), Multivariate simultaneous generalized ARCH. Econometric Theory, 11, 122-150.

Engle, R.F., Ng, V.K. (1993), Measuring and testing the impact of news on volatility. The Journal of Finance, 48(5), 1749-1778.

Engle, R.F., Sheppard, K. (2001), Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH. Working Paper No. 8554. Cambridge: National Bureau of Economic Research.

Engle, R.F., Sokalska, M.E. (2012), Forecasting intraday volatility in the US equity market. Multiplicative component GARCH. Journal of Financial Econometrics, 10(1), 54-83.

Geman, H., Roncoroni, A. (2006), Understanding the fine structure of electricity prices. Journal of Business, 79, 1225-1261.

Glosten, L.R., Jagannathan, R., Runkle, D.E. (1993), On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 48(5), 1779-1801.

Hadsell, L., Marathe, A., Shawky, H.A. (2004), Estimating the volatility of wholesale electricity spot prices in the US. The Energy Journal, 25(4), 23-40.

Higgs, H. (2009), Modelling price and volatility inter-relationships in the Australian wholesale spot electricity markets. Energy Economics, 31, 748-756.

Huisman, R. (2008), The influence of temperature on spike probability in day ahead power prices. Energy Economics, 30, 2697-2704.

Knittel, C.R., Roberts, M.R. (2005), An empirical examination of restructured electricity prices. Energy Economics, 27(5), 791-817.

Koenig, P. (2011), Modelling Correlation in Carbon and Energy Markets. Cambridge Working Papers, Faculty of Economics. Cambridge: University of Cambridge.

Kroner, K.F., Ng, V.K. (1998), Modeling asymmetric co-movements of asset returns. Review of Financial Studies, 11(4), 817-844.

Lucia, J.J., Schwartz, E.S. (2002), Electricity prices and power derivatives: Evidence from the Nordic power exchange. Review of Derivatives Research, 5, 5-50.

Mjelde, J.W., Bessler, D.A. (2009), Market integration among electricity markets and their major fuel source markets. Energy Economics, 31(3), 482-491.

Nelson, D.B. (1991), Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59(2), 347-370.

Park, H., Mjelde, J.W., Bessler, D.A. (2006), Price dynamics among U.S.

electricity spot markets. Energy Economics, 28(1), 81-101.
Pirrong, C., Jermakyan, M. (2008), The price of power: The valuation of power and weather derivatives. Journal of Banking and Finance, 32(12), 2520-2529.
Samitas, A., Armenatzoglou, A. (2014), Regression tree model versus Markov regime switching: A comparison for electricity spot price modelling and forecasting. Operational Research, 14(3), 319-340.
Tse, Y.K., Tsui, A.K.C. (2002), A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. Journal of Business and Economic Statistics, 20(3), 351-362.
Weron, R., Misiorek, A. (2008), Forecasting spot electricity prices: A comparison of parametric and semiparametric time series models. International Journal of Forecasting, 24, 744-763.