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Time-varying dependency in European energy markets: an analysis of Nord Pool, European Energy Exchange and Intercontinental Exchange energy commodities

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In this paper we investigate the extent to which the price of Nordic electricity derivatives correlates with European Energy Exchange (EEX) and Intercontinental Exchange (ICE) electricity contracts. We also include their price correlation with ICE gas, Brent crude oil, coal and carbon emission contracts. Using multivariate generalized autoregressive conditional heteroskedasticity models, we find significant time-varying relationships between all of the energy commodities included in the analysis, with the exception of oil. This suggests that pricing models based on constant correlation may be misleading. We also find that Nordic energy futures exhibit the strongest relationship with German electricity futures contracts traded in the EEX, and there appears to be a stronger relationship between longer maturity contracts in all markets.

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1 INTRODUCTION

This paper investigates, from the perspective of Scandinavian power companies, time-varying comovements between the returns of Nord Pool electricity futures contracts and those of other energy futures and forward[1] contracts in Europe. The other energy futures contracts investigated are European Energy Exchange (EEX) and Intercontinental Exchange (ICE) electricity, along with ICE gas, Brent crude oil, coal and carbon emission contracts.

In the late 1980s, oil gradually began to be traded internationally. From the 1990s, the European electricity and gas markets also experienced an extensive liberalization process, which has changed their structure from regulated monopolies to competitive open markets. During the last five to ten years, liberalized markets for coal and emission trading have also evolved in Europe. In general, highly volatile and “spiky” price behavior and fundamental interactions characterize these energy markets. The restructuring and deregulation of electricity and related energy markets in Europe (oil, gas, coal and carbon) has likewise facilitated trading and risk management in several energy commodities, with complex portfolios involving both long and short positions. A better understanding of the joint dynamics of these commodities is therefore crucial.

The Nordic and German electricity markets are currently directly linked (through both alternating current transmission lines and underwater direct current cables) as well as indirectly linked (via Poland). In much the same manner, the German and UK markets link via France and the powerful underwater England–France interconnector (Interconnexion France–Angleterre). In addition to being substitutes in use, several of these energy commodities also serve as input factors for producing/manufacturing other sorts of energy commodities. This is because, from the electricity producer’s point of view, electricity, gas and oil products are, to some extent, substitutes for heating. Coal, natural gas, oil, nuclear power, hydropower and other renewable energy sources are also inputs when electricity is generated (Burger *et al* (2007)). Carbon dioxide ($ICECO_2$) emission prices also relate to electricity generation costs (depending on which particular energy commodity is used as an input), and, consequently, so do electricity prices (see Bunn and Fezzi (2007, 2009) and Burger *et al* (2007) for details). This implies that electricity markets fundamentally link to related energy market commodities.

In addition to the above-mentioned dependencies between electricity and other energy markets, the liberalization of these markets has created strong competition in the energy sector. In turn, competition has created strong incentives for improv-

[1] The derivative contracts for electricity are commonly referred to as forwards and futures, although, technically speaking, they are more equal to swap contracts as their payoffs depend on the average of several daily spot prices. For simplicity, however, we refer to all derivative electricity contracts as futures contracts.

ing operational efficiency and the need for effective risk management. The growing importance of energy derivatives for asset managers and speculators has provided an opportunity for a large market of financial instruments connected to electricity and other energy commodities. In this context, a better understanding of the short- and long-term dynamics of volatility and correlation in energy commodities is of great importance.

Given that some energy commodities serve as both alternative fuels for generating electricity and substitutes for electricity use, the increasing integration of energy markets has generated an increased focus on understanding the comovements between energy markets. In fact, major participants in the electricity market, on both the supply and demand sides, employ developments and correlations in the price of oil, gas, coal and electricity in other markets, and of carbon energy commodities, as an information base for decisions on investment, production planning and risk management.[2] Moreover, in addition to enhancing the knowledge of the comovements between assets, correlation estimates are also of crucial importance in the estimation of hedge ratios, capital asset pricing model betas, portfolio value-at-risk and the prices of options and other derivatives.

Rather than only considering energy spot prices, as is the case with many previous studies, we carry out an analysis of futures prices, as these can be more readily traded and are thus of most relevance for risk management. Furthermore, if there are linkages between prices in markets, an unanticipated event in one market will influence not only the price level or returns (as in cointegration analysis) but also variances and covariances in the other markets. Accordingly, in the empirical section of this paper, we employ a multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) approach to examine the volatility and conditional correlation between energy futures markets. As this model allows for time-varying correlation, we are able to illustrate how the linear dependence between the energy commodity contracts fluctuates, and may in certain periods deviate significantly from the long-term average.

We assume that, from the perspective of a power company operating in Scandinavia, the most important energy prices are the European prices of oil, coal, gas, $ICECO_2$ emissions and electricity. As shown in the literature review to follow, several studies have already considered the dynamic comovements between two or three of these energy commodities. However, no prior work has jointly investigated the extent to which the Nordic electricity market covaries with all other mentioned energy commodities in Europe. In this paper, we correct this deficiency by analyzing and discussing the correlation in returns between Nord Pool electricity futures contracts and the returns on ICE gas, Brent crude oil, coal and carbon emission futures contracts, as well as those of the EEX and ICE electricity futures contracts.

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[2] This is based on a conversation with representatives from Norwegian energy companies.

The remainder of the paper is structured as follows. Section 2 provides a brief literature review, followed by a description of the data set and a presentation of selected descriptive statistics in Section 3. Section 4 discusses the MGARCH method used to provide estimates of the conditional correlation, with the results detailed in Section 5. The final section includes some concluding remarks, several practical implications for industry participants, and various directions for future research.

2 LITERATURE REVIEW

The interrelationships between national and international assets in conventional financial markets have been subject to analysis for decades (see, for example, Hamao *et al* (1990), Koutmos and Booth (1995) and Durai and Bhaduri (2011), among many others). A large number of alternative approaches are also available for measuring or estimating the dynamic properties of volatilities and correlation. Alexander (2008, Chapter 2.3 and 2.4) provides a review of alternative models of volatility and correlation measures and estimators. The pitfalls of unconditional correlation measures as estimators are also discussed in Alexander (2008, pp. 94–96). Examples of some recent advances in intraday range correlation estimators based on daily or less-frequent data (or non-intraday high-frequency data) include Brandt and Diebold (2006) and Harris and Yilmaz (2010). Frestad (2009) uses a random field model to analyze the empirical correlations of electricity forward returns in the Nord Pool, while Wang *et al* (2008) examine the distribution of realized energy futures correlations using intraday high-frequency data in their study of NYMEX light crude oil and natural gas futures contracts. Accordingly, in this brief review, we only discuss those studies that have utilized MGARCH to assess the interrelationships between energy markets.[3] We begin by discussing several papers that have included electricity as at least one of the commodities in their study of market interrelationships and correlation.

Byström (2003) applied constant conditional correlation bivariate GARCH and orthogonal MGARCH models to analyze the short-term hedging of Nord Pool electricity spot prices with electricity futures over the period from 1996 to 1999. Malo and Kanto (2006) tested different MGARCH model specifications used for dynamic hedging in the Nordic electricity markets using daily Nord Pool closing prices for spot and short-term futures contracts between 1996 and 2002. The results indicated that the differences in hedging performance between models was not large, implying that no particular MGARCH approach could be preferred.

In other work, Pen and Sévi (2010) used daily data from 2001 to 2005 to estimate the BEKK–MGARCH model and found evidence of return and volatility transmission

[3] Bauwens *et al* (2006), Alexander (2008, Chapter 2.4) and Silvennoinen and Teräsvirta (2009) provide useful reviews of MGARCH models.

between the German, Dutch and UK forward electricity markets. Pen and Sévi (2010) also investigated, using volatility impulse response functions, the impact of shocks on expected conditional volatility. They found connections between these markets, through either returns or volatilities, and so accounting for these dependencies should improve the accuracy of forecasts.

Solibakke (2010) analyzed corporate risk management in European energy markets using conditional and stochastic volatility/correlation models, including BEKK–MGARCH ("BEKK" comes from Baha, Engle, Kraft and Kroner, the authors of the model) models and exponentially weighted moving-average models, on spot and forward contract electricity prices from Nord Pool and Phelix. Earlier work by Solibakke (2008) also considered mean and volatility transmissions between the Phelix and Nord Pool spot energy markets, although he used a semi-nonparametric BEKK–MGARCH model on daily spot prices over the period 2000–2005. The estimates obtained suggested that the correlation between these markets varied between about 0.2 and 0.7.

Worthington *et al* (2005) also used a BEKK–MGARCH model to examine the interrelationships between wholesale prices in regional electricity markets in Australia using daily data over the period 1998–2001. Higgs (2009) later extended this work by applying constant and dynamic conditional correlation MGARCH models to the same market over the longer data period from 1999 to 2007. Higgs (2009) also concluded stronger (respectively, weaker) interdependence between well-connected (respectively, less well-interconnected) markets. However, note that both Worthington *et al* (2005) and Higgs (2009) considered only spot prices, not futures prices.

Several extant studies have also investigated the comovements between oil and gas. For example, Ewing *et al* (2002) used a BEKK–MGARCH model to investigate how the volatility in the oil and natural gas sectors had changed over time and across markets using daily Amex oil and natural gas indexes for the period 1996–99. Ewing *et al* (2002) concluded significant volatility transmission between these particular oil and natural gas markets. Similarly, Serletis and Shahmoradi (2006) specified an MGARCH model of natural gas and electricity price change, and used 1996–2004 data from Alberta's spot power and natural gas markets to test the relationships between natural gas and electricity price changes and their volatilities. Lastly, Marzo and Zagaglia (2008) analyzed the joint movements of daily returns on one-month futures for crude oil, heating oil and natural gas as traded on the New York Mercantile Exchange (NYMEX) between 1990 and 2005 using MGARCH with dynamic conditional correlations and t distributions. Marzo and Zagaglia (2008) concluded that the futures price of crude and heating oil strongly covaried. Furthermore, they found that the conditional correlation between the futures prices of natural gas and crude oil had risen during the period analyzed, but at a low level, implying that the futures markets had not priced natural gas as a function of developments in oil markets.

As this necessarily brief review suggests, most past studies in this area focus on either modeling the correlation within a particular electricity market (eg, between regional prices or contracts of different maturity) or modeling the dependency between gas and oil markets. Few, if any, studies have jointly investigated how electricity futures relate to other energy futures, such as oil, gas, coal and carbon. In this respect, our analysis fills a significant gap in the literature.

3 DATA AND DESCRIPTIVE STATISTICS

3.1 The markets

In this study, we consider selected energy contracts traded on the ICE, Nord Pool and EEX. First, founded in May 2000 with the objective of providing an electronic platform for over-the-counter (OTC) energy commodity trading, ICE expanded its business into futures trading by acquiring the International Petroleum Exchange in 2001. Derivative products currently available include those based on North Sea crude oil, UK natural gas, UK electricity, coal (deliverable in Rotterdam) and European carbon contracts with a range of different maturities (monthly, quarterly, seasonal and yearly).

Second, Nord Pool is a multinational exchange for trading electricity in Northern Europe that was founded in 1993 as a physical contract market following the deregulation of the Norwegian electricity market in 1991. It was subsequently joined by Sweden, Finland and Denmark. The financial part of the market comprises electricity futures (daily and weekly) and forward contracts (monthly, quarterly and yearly). Finally, founded in 2002, EEX is the leading energy exchange in central Europe. Products traded on the EEX currently include baseload and peakload contracts at different maturities (spot, monthly, quarterly and yearly) for German and French power, in addition to natural gas, emission rights and coal. Together, these markets form the basis for the trade of European energy commodities.

3.2 The contracts

Table 1 on the facing page describes the contracts analyzed in our study. Detailed descriptions of the contracts are also available at www.ice.com, www.nordpool.com and www.eex.com. Burger *et al* (2007) also includes a discussion of the various European energy markets.

3.3 Descriptive analysis

In this analysis, we collect daily futures prices for EEX, Nord Pool and ICE electricity as well as for ICE gas, Brent crude oil, and coal and carbon contracts. We use closing prices for our synthetic monthly, quarterly and yearly contracts. For carbon emission

TABLE 1 Contracts used in the analysis.

Contract	Strip	Period	N
Nord Pool monthly forwards, 1-pos ($NPel_M$)		09/02/2003–01/31/2011	1817
Nord Pool quarterly forwards, 1-pos ($NPel_Q$)[a]	Three-month forwards, delivery next quarter	01/05/2004–01/31/2011	1701
Nord Pool yearly forwards, 1-pos ($NPel_Y$)	Twelve-month forwards, delivery next year	04/07/2003–01/31/2011	1894
EEX monthly futures, 2-pos ($EEXel_M$)[b]		09/02/2003–01/31/2011	1862
EEX quarterly futures, 1-pos ($EEXel_Q$)	Three-month futures, delivery next quarter	04/07/2003–01/31/2011	1910
EEX yearly futures, 1-pos ($EEXel_Y$)	Twelve-month futures, delivery next year	04/07/2003–31-01-2011	1940
ICE UK monthly futures, 1-pos ($UKel_M$)		09/15/2004–01/27/2011	1520
ICE UK quarterly futures, 1-pos ($UKel_Q$)	Three-month futures, delivery next quarter	09/15/2004–01/28/2011	1561
ICE UK seasonal futures, 1-pos ($UKel_S$)	Six-month futures, delivery next season (October–March or April–September)	09/15/2004–01/28/2011	1574
ICE natural gas monthly futures, 1-pos ($ICEgas_M$)		09/01/2003–01/31/2011	1877
ICE natural gas quarterly futures, 1-pos ($ICEgas_Q$)	Three-month futures, delivery next quarter	04/07/2003–01/31/2011	1902
ICE natural gas yearly futures, 1-pos ($ICEgas_Y$)	Twelve-month futures, delivery next year	05/11/2004–01/31/2011	1635
ICE Brent crude oil monthly futures, 1-pos ($ICEoil_M$)		09/01/2003–01/31/2011	1881
ICE Brent crude oil quarterly futures, 1-pos ($ICEoil_Q$)	Three-month futures, delivery next quarter	04/07/2003–01/31/2011	1964
ICE Brent crude oil June and December next year ($ICEoil_Y$)[c]	Monthly contracts for June and December next year	02/08/2005–01/31/2011	1513
ICE coal monthly futures, 2-pos ($ICEcoal_M$)[d]		07/18/2006–01/28/2011	1101
ICE coal quarterly futures, 1-pos (2-pos) ($ICEcoal_Q$)[e]	Three-month futures, delivery next quarter	07/18/2006–01/31/2011	1128
ECX CFI phase 2, futures Z10, December 2010 and futures Z11, December 2011 ($ICEICECO_2$)[f]		04/25/2005–01/31/2011	1463

1-pos is the contract with the nearest delivery. 2-pos is the next contract for delivery. The names in parentheses are used in subsequent tables. N denotes number of observations, which vary because of the time over which the contracts have been available, while also reflecting the different trading days/holidays in the Nordic countries, Germany and the UK. [a]The first quarterly contract traded at Nord Pool was for 2006 Q1. Before this, we use the average price of the three-monthly contracts. [b]The 1-pos contract is traded during the delivery month, so the 2-pos contract is for the "next month". [c]These contracts are used because they are regularly traded and should give a good representation of the market on the long-term price of oil. [d]The 1-pos contract is traded until delivery so the contract for delivery next month is the 2-pos contract. [e]In the first month of a quarter, and until the first delivery, the contract for the current quarter is 1-pos. Here we use the 2-pos contract. [f]We use the price for December 2010 until 12/01/2010, then the price for December 2011.

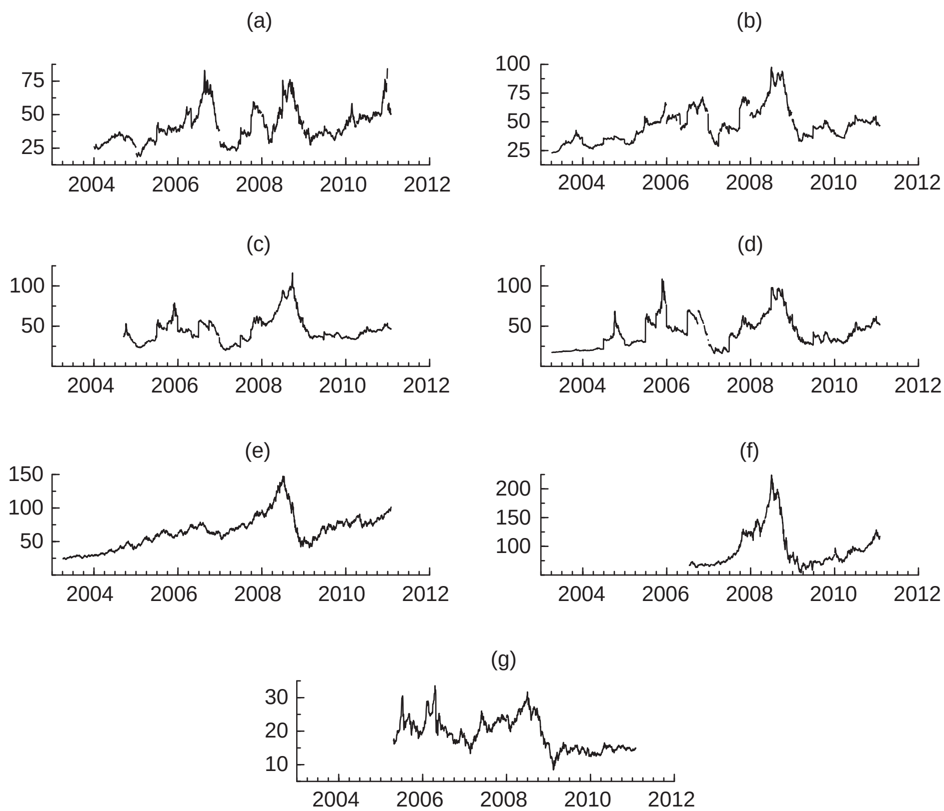
allowances we only had access to data for yearly futures contracts with delivery in 2010 and 2011, so these prices were used for all subsequent analyses. Also, we were not able to obtain data for yearly futures contracts for ICE coal and UK electricity. For these we used the quarterly contract and the seasonal contract, respectively, instead. We retrieve all data from the Reuters database Ecowin (see www.ecowin.com for details) and this forms the price times series for the underlying energy commodity delivered in the next month/quarter/year. For this time series we form the series of logarithmic returns for use in our analysis. When a contract goes to delivery and another contract takes its place as next for delivery, we remove the observed return from the data set. The prices for quarterly futures contracts for the different commodities are shown in Figure 1 on the facing page.[4] Table 2 on page 12 provides descriptive statistics for each of the series.

As shown from the plots of the price series (Figure 1 on the facing page), the electricity futures prices in the continental, Nordic and UK markets generally increased from 2003 to 2006. This period generally experienced growth in the world economy and an increasing demand for electricity. The winter of 2005–6 was also relatively cold and the gas supply less secure, and electricity prices consequently spiked. Later in 2006, gas prices fell, and because they are an important input in electricity production, electricity prices fell in 2006 and remained down in 2007. This coincided with the collapse of the carbon market and the granting of more emission rights to the market than was needed. Immediately before the 2008 financial crisis, oil, gas and coal prices rose sharply, as did electricity prices. After the financial crisis, energy prices remained at a low level, with a weakly increasing trend, on the continent and in the UK. The Nordic market, on the other hand, experienced a more significant increase in prices and price spikes in the winter. We can attribute this to the impact of cold winters and the generally low level of water in hydro reservoirs affecting the demand and supply of electricity.

The returns (log price changes) for the various series (see Table 2 on page 12) display an interesting pattern. As shown, the general level of risk for the various energy commodities is relatively high. In particular, the monthly contracts for Nord Pool electricity and UK gas exhibit the highest standard deviation of returns (2.84% and 3.36%, respectively, on a daily basis). In general, risk decreases with longer future contract maturities. Electricity contracts at the EEX have negative skewness for all maturities, while Nord Pool contracts have negative skewness for the yearly and

[4] Prices for monthly and yearly contracts have develop along similar lines, although the monthly prices have fluctuated more and the yearly contracts have fluctuated less. Charts are available from the authors upon request. EEX and Nord Pool electricity futures are quoted in €/MWh, UK electricity futures on ICE in £/MWh, ICE gas in £/British thermal unit (BTU), ICE oil in US$/barrel, ICE coal in US$/tonne, and ICE carbon in €/tonne.

FIGURE 1 Price development for EEX, Nord Pool and ICE electricity and ICE gas, oil, coal and carbon ($ICECO_2$).



(a) Prices (€/MWh) of Nord Pool quarterly futures contract for Nordic electricity. (b) Prices (€/MWh) of EEX quarterly futures contract for German electricity. (c) Prices (£/MWh) of ICE quarterly futures contract for UK electricity. (d) Prices (£/BTU) of ICE quarterly futures contract for natural gas. (e) Prices (US$/barrel) of ICE quarterly oil futures contract. (f) Prices (US$/tonne) of ICE quarterly futures contract for coal delivered in Rotterdam. (g) Prices (€/tonne) of ICE carbon futures contract for emissions in 2010 and 2011.

quarterly contracts but positive skewness for the monthly contracts. Gas has positive skewness, oil somewhat symmetric and only slightly negative, while coal and carbon contracts exhibit negative skewness. The returns for all series also exhibit high levels of kurtosis (fat tails) because of their spiky behavior. Surprisingly, all of the energy commodities (apart from oil) exhibit positive serial correlation of returns, whereas oil exhibits small (but still significant) negative serial correlation. Table 2 on the next page also reveals strong serial correlation in squared returns, as expected for most financial returns.

TABLE 2 Descriptive returns and squared statistics for EEX, Nord Pool and ICE electricity (el) and ICE gas, oil, coal and carbon. [Table continues on next page.]

(a)

	Nord Pool electricity			EEX electricity			ICE UK electricity		
Return statistics	**Month**	**Quarter**	**Year**	**Month**	**Quarter**	**Year**	**Month**	**Quarter**	**Season**
No. of observations	1728	1701	1894	1768	1910	1940	1520	1561	1574
Mean (%)	–0.12	–0.03	0.01	–0.13	–0.01	0.02	–0.11	–0.07	–0.04
Maximum (%)	12.74	10.47	9.19	12.98	8.96	8.84	23.85	17.95	7.18
Minimum (%)	–12.10	–11.83	–9.63	–14.61	–8.36	–7.05	–11.00	–11.45	–9.85
Standard deviation (%)	2.84	2.58	1.70	2.21	1.46	1.13	2.63	2.05	1.66
Skewness	0.11	–0.08	–0.47	–0.04	–0.03	–0.10	0.90	0.35	–0.22
Excess kurtosis	2.17	1.77	3.93	4.60	3.12	6.05	9.78	7.13	3.37
Jarque–Bera	338.66	220.33	1274.30	1545.60	767.10	2939.10	6197.98	3305.00	747.62
ρ_1	0.10	0.04	0.04	0.13	0.14	0.10	0.12	0.15	0.11
$Q(10)$	51.12	27.74	28.33	71.11	78.86	45.84	40.92	64.43	42.81
ρ_{1*}	0.15	0.17	0.21	0.31	0.17	0.18	0.19	0.14	0.21
$Q(10)^*$	261.34	295.24	536.11	549.51	256.17	570.41	202.40	334.15	183.14

TABLE 2 Continued.

(b)

Return statistics	ICE gas Month	ICE gas Quarter	ICE gas Year	ICE oil Month	ICE oil Quarter	ICE oil Year	ICE coal Month	ICE coal Quarter	ICE CO_2 Year
No. of observations	1779	1964	1635	1790	1964	1513	1101	1128	1463
Mean (%)	–0.21	0.04	0.03	0.04	0.04	0.04	0.06	0.05	–0.01
Maximum (%)	24.84	12.33	10.47	12.71	12.33	9.35	8.32	8.17	19.12
Minimum (%)	–15.48	–10.45	–8.33	–10.95	–10.45	–7.72	–10.82	–10.84	–27.43
Standard deviation (%)	3.36	2.10	1.77	2.25	2.10	1.78	1.93	1.94	2.66
Skewness	0.91	–0.07	0.51	–0.14	–0.07	–0.09	–0.80	–0.72	–0.87
Excess kurtosis	7.17	2.76	3.60	3.06	2.76	2.70	5.16	4.17	11.89
Jarque–Bera	4019.22	617.74	941.72	693.72	617.74	455.01	1 319.15	900.54	8707.66
ρ_1	0.14	–0.06	0.14	–0.06	–0.06	–0.04	0.17	0.16	0.09
$Q(10)$	47.08	20.25	49.49	16.72	20.25	15.05	56.18	35.12	29.48
ρ_{1*}	0.33	0.18	0.15	0.18	0.18	0.21	0.22	0.19	0.09
$Q(10)^*$	396.63	993.94	202.30	1 058.23	993.94	823.13	675.71	441.73	159.94

The asterisk denotes squared return statistics. Monthly, quarterly and yearly series. The number of observations, mean, maximum, minimum, standard deviation, skewness, kurtosis, Jarque–Bera (JB), serial correlation at lag 1 and Q-statistics with ten lags reported (the last two for returns and squared returns). Critical values at 5% are JB $= 5.99$ and $Q(10) = 18.31$.

TABLE 3 Pairwise average daily unconditional correlation between the returns on Nord Pool electricity futures returns for different energy commodity contracts over monthly, quarterly and yearly horizons. [Table continues on next page.]

(a) 07/18/2006–01/31/2011

$\mathbf{NPel_M}$		$\mathbf{NPel_Q}$		$\mathbf{NPel_Y}$	
$EEXel_M$	0.34	$EEXel_Q$	0.45	$EEXel_Y$	0.76
$UKel_M$	0.22	$UKel_Q$	0.28	$UKel_S$	0.44
$ICEgas_M$	0.18	$ICEgas_Q$	0.24	$ICEgas_Y$	0.45
$ICEoil_M$	0.14	$ICEoil_Q$	0.16	$ICEoil_Y$	0.27
$ICEcoal_M$	0.26	$ICEcoal_Q$	0.36	$ICEcoal_Q$	0.57
$ICECO_2$	0.19	$ICECO_2$	0.26	$ICECO_2$	0.43

(b) 07/18/2006–07/31/2008

$\mathbf{NPel_M}$		$\mathbf{NPel_Q}$		$\mathbf{NPel_Y}$	
$EEXel_M$	0.28	$EEXel_Q$	0.35	$EEXel_Y$	0.72
$UKel_M$	0.13	$UKel_Q$	0.18	$UKel_S$	0.33
$ICEgas_M$	0.07	$ICEgas_Q$	0.13	$ICEgas_Y$	0.36
$ICEoil_M$	0.10	$ICEoil_Q$	0.05	$ICEoil_Y$	0.12
$ICEcoal_M$	0.06	$ICEcoal_Q$	0.19	$ICEcoal_Q$	0.45
$ICECO_2$	0.16	$ICECO_2$	0.21	$ICECO_2$	0.42

(c) 08/01/2008–07/31/2009

$\mathbf{NPel_M}$		$\mathbf{NPel_Q}$		$\mathbf{NPel_Y}$	
$EEXel_M$	0.53	$EEXel_Q$	0.66	$EEXel_Y$	0.84
$UKel_M$	0.36	$UKel_Q$	0.42	$UKel_S$	0.56
$ICEgas_M$	0.30	$ICEgas_Q$	0.41	$ICEgas_Y$	0.59
$ICEoil_M$	0.28	$ICEoil_Q$	0.34	$ICEoil_Y$	0.40
$ICEcoal_M$	0.51	$ICEcoal_Q$	0.60	$ICEcoal_Q$	0.70
$ICECO_2$	0.33	$ICECO_2$	0.39	$ICECO_2$	0.51

Turning to the issue of time-varying correlation, we first show the unconditional correlation in Table 3 including observations from July 18, 2006 to January 31, 2011. Given that Nord Pool electricity futures are the focus of this study, we first consider the pairwise correlations between the Nord Pool monthly, quarterly and yearly contracts

TABLE 3 Continued.

(d) 08/01/2009–01/31/2011

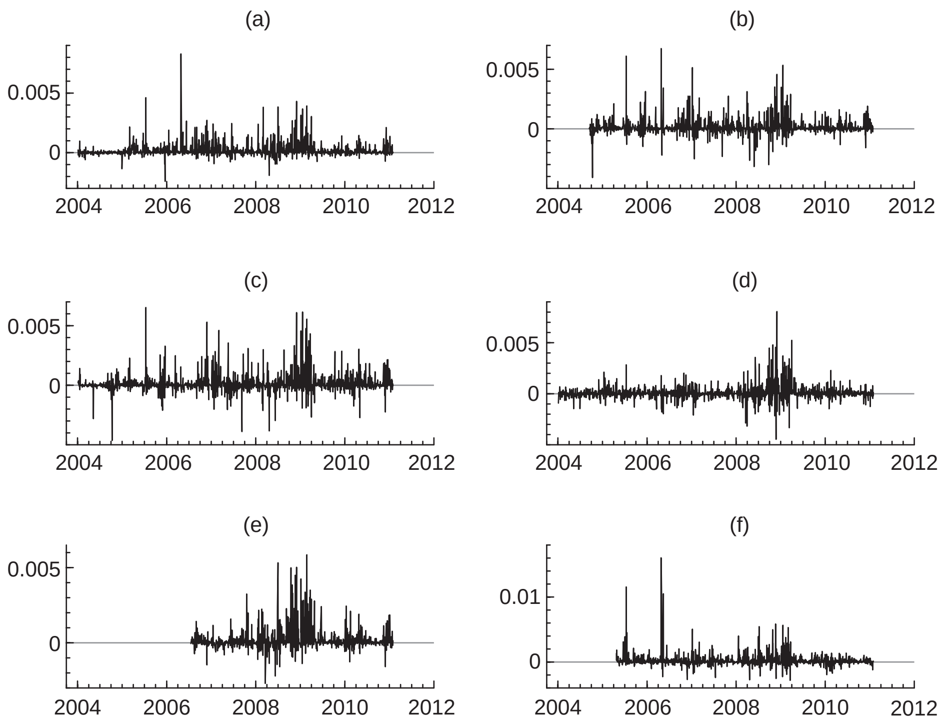
$NPel_M$		$NPel_Q$		$NPel_Y$	
$EEXel_M$	0.37	$EEXel_Q$	0.40	$EEXel_Y$	0.64
$UKel_M$	0.35	$UKel_Q$	0.31	$UKel_S$	0.40
$ICEgas_M$	0.30	$ICEgas_Q$	0.28	$ICEgas_Y$	0.39
$ICEoil_M$	0.07	$ICEoil_Q$	0.06	$ICEoil_Y$	0.14
$ICEcoal_M$	0.32	$ICEcoal_Q$	0.31	$ICEcoal_Q$	0.40
$ICECO_2$	0.11	$ICECO_2$	0.15	$ICECO_2$	0.29

To make comparison possible, we employ the same data period for all contracts from July 18, 2006 to January 31, 2011. To gain some insight into the evolution over time, we also report the average unconditional correlation over three subsamples. The first subsample is from July 18, 2006 to July 31, 2008, the second subsample is from August 1, 2008 to July 31, 2009 and the third subsample is from August 1, 2009 to January 31, 2011.

and the other energy commodities. For the complete sample, we detect a strong correlation between the Nordic and continental electricity markets, particularly for the longer contracts. As the Nord Pool and EEX market link, this is not surprising. There is also a correlation (even stronger for longer maturity contracts) with UK electricity, but not to the same extent as the EEX market. Once again, this is somewhat expected as there is no direct link between the Nordic and UK electricity markets.

As discussed, the Nord Pool contracts also link to other energy commodities, particularly coal. Yet again, we find stronger correlations for longer-term contracts. As short-term contracts (eg, monthly) can still be influenced by weather, information on power outages, etc, we expect these prices to fluctuate more randomly with each other when compared with longer contracts (eg, yearly) that are more influenced by the long-run marginal cost of electricity production. Partitioning the data into three subsamples provides a picture of the development of the dependency between the contracts. Because financial assets seem to show a higher degree of comovement during times of financial distress, the time span around the collapse of Lehman Brothers and the credit crisis is treated as a separate subperiod. Even when controlling for the credit crisis, the Nordic contracts still show a stronger relationship with most contracts in the last subperiod when compared with the first subperiod. For the monthly and quarterly contracts, oil and $ICECO_2$ emission allowances seem to be the exception, while, for the yearly contracts, we also note a small decline in the average unconditional correlation for EEX electricity and coal contracts in the last subperiod. We also note that it is the short-term contracts that exhibit the most considerable increase in unconditional correlation. Not surprisingly, all contracts show a higher average unconditional correlation with the Nordic electricity contracts during the credit crisis.

FIGURE 2 Log price changes used to illustrate pairwise dependency over time.



(a) Product of daily returns for Nordic electricity and German baseload electricity contracts. (b) Product of daily returns for Nordic electricity and ICE UK baseload electricity contracts. (c) Product of daily returns for Nordic electricity and ICE natural gas contracts. (d) Product of daily returns for Nordic electricity and ICE Brent crude oil contracts. (e) Product of daily returns for Nordic electricity and ICE coal deliverable in Rotterdam contracts. (f) Product of daily returns for Nordic electricity contracts and ICE CO_2 emission allowances contracts.

Figure 2 helps to further motivate the modeling of time-varying correlation in these energy markets. Here we depict the pairwise product of the one-day realized return for Nordic electricity contracts and those for the remaining energy commodity futures. Because of space considerations, we only provide the graphs for the quarterly contracts, but the other contract combinations display a similar pattern.[5] This forms a measure of the realized pairwise covariance on a specific trading day. If the series were independent zero-mean random processes, we would be unable to observe any trend or identify any subperiods with a large accumulation of positive or negative values. However, this is exactly what the figure confirms. Importantly, we can clearly observe periods with small fluctuations in both directions followed by longer periods

[5] These are available from the authors upon request.

with either mainly positive outcomes, much larger outcomes, or both. This gives a clear indication of a time-varying relationship between the energy commodities.

The high risk level in Nord Pool electricity futures contracts, the asymmetric fat-tailed distribution of returns, the serial correlation in returns and squared returns and the time-varying covariance all indicate that returns are not independent and identically distributed (iid). This motivates the modeling of conditional correlation and utilization of state-of-the-art MGARCH models in order to capture the dynamics of pairs of energy commodity contracts as fully as possible.

4 MULTIVARIATE GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY METHODOLOGY

To account for the time-varying nature of the variances and correlations between the various contracts, we use an MGARCH model to examine the historical correlation between the commodities. The parsimonious and intuitive family of MGARCH models, first introduced by Bollerslev (1990), employ conditional volatility and correlation to assess the conditional covariance matrices for a selection of assets. We specify the conditional covariance matrix in two stages. In the first stage, we obtain the conditional variances from a univariate GARCH process for each contract. In the second stage, we use the conditional variances to determine the conditional correlation matrix, imposing a positive definiteness for all t in the optimization process. One particular advantage of this class of MGARCH models is that the modeling of the individual volatility processes is independent and without restrictions. The models, however, do not permit the correlation response to market shocks to be asymmetric.

In this study we use the MGARCH model known as the dynamic conditional correlation (DCC) model, which is due to Engle (2002). The covariance matrix $\boldsymbol{H}$ is expressed as:

$$\boldsymbol{H} = \boldsymbol{DRD} \tag{4.1}$$

where $\boldsymbol{D}$ is a diagonal matrix of standard deviations and $\boldsymbol{R}$ is the correlation matrix. The DCC model assumes that both matrices are time varying, where the standard deviations in $\boldsymbol{D}$ follow a univariate GARCH process and $\boldsymbol{R}$ is a weighted sum of past correlations:

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t \tag{4.2}$$

Since the correlations use standardized residuals from the GARCH processes, the model has two stages.

The first stage begins with the definition of the univariate GARCH process. A basic requirement is to remove the predictable component of future prices in order to produce the price innovation ε_t, with a conditional mean of zero before a GARCH equation is specified for the variance. Denoting the price of a futures contract i at time t as $P_{i,t}$ and then taking the first difference of the natural logarithm produces the following series of returns:

$$\left.\begin{aligned} \ln(P_{i,t}) - \ln(P_{i,t-1}) &= r_{i,t} \\ E(r_{i,t}) &\approx 0 \end{aligned}\right\} \tag{4.3}$$

Given that the autocorrelation coefficients are relatively small, we proceed to a GARCH model without a mean specification:

$$r_{i,t} = \varepsilon_{i,t} \tag{4.4}$$

The conditional variance of a univariate GARCH process of order 1 and 1 is denoted as GARCH(1,1) and the random error term ε_{it} is specified as:

$$\varepsilon_{it} = \sqrt{h_{it}}\, e_{it}, \qquad e_{it} \sim \text{iid}\, d(0,1) \tag{4.5}$$

with:

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 h_{it-1} \tag{4.6}$$

and $d(M, V)$ represents the probability density function with mean M and variance V. h_{it} is the conditional variance of volatility of ε_{it} for contract i at time t, β_0 is a constant and, β_1 and β_2 are coefficients that are associated with the degree of innovation from the previous period, ε_{it-1}^2 (the ARCH term) and the previous period's volatility spillover effects, h_{it-1} (the GARCH term) for each market. A GARCH process of order 1 and 1 thus includes one ARCH term and one GARCH term.

In the second stage, the standardized innovations obtained from the univariate GARCH(1,1) process are used to estimate the conditional correlation matrix for the DCC model:

$$e_{it} = \frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}} \tag{4.7}$$

Engle's dynamic conditional correlation model defines Equation (4.2) with $\boldsymbol{R}_t$ specified as:

$$\boldsymbol{R}_t = \operatorname{diag}(q_{11t}^{-1/2} \cdots q_{KKt}^{-1/2})\boldsymbol{Q}_t \operatorname{diag}(q_{11t}^{-1/2} \cdots q_{KKt}^{-1/2}) \tag{4.8}$$

The matrix $\boldsymbol{Q}_t$ is specified as a GARCH equation and is transformed to the correlation matrix $\boldsymbol{R}_t$. This ensures that the conditional correlation matrix is positive definite for all t, where $\boldsymbol{Q}_t = (q_{ijt})$ is a $K \times K$ symmetric positive definite matrix given by:

$$\boldsymbol{Q}_t = (1 - \theta_1 - \theta_2)\bar{\boldsymbol{Q}} + \theta_1 \boldsymbol{e}_{t-1}\boldsymbol{e}_{t-1}' + \theta_2 \boldsymbol{Q}_{t-1} \tag{4.9}$$

where $\bar{\boldsymbol{Q}}$ is the $K \times K$ unconditional correlation matrix of e_t where θ_1 and θ_2 are nonnegative parameters with $\theta_1 + \theta_2 < 1$, and $\boldsymbol{e}_t$ is a vector of the standardized residuals from Equation (4.7).

Since the data return series are all nonnormally distributed, we introduce the multivariate Student t specification into the process optimizing the MGARCH parameters to take account of the fat-tailed characteristics of the futures price series. Table 4 on the next page, Table 5 on page 22 and Table 6 on page 24 show the estimated model parameters and corresponding p-values. As shown, almost all parameters are highly significant, thereby indicating good model fit.

5 RESULTS

We now present figures showing the conditional correlation estimates for the contracts with different time horizons. We then consider the dependency between the different commodities/contracts at the same time horizon.

5.1 Comparing contracts with different horizons

Figure 3 on page 26, Figure 4 on page 27 and Figure 5 on page 28 depict the conditional correlation estimates for contracts with different horizons. It is clear from the figures that the conditional correlation displays a distinct time-varying pattern. One interesting pattern appears almost immediately such that the conditional correlation between contracts with a long maturity is clearly higher than between contracts with a shorter maturity. This is a general finding for all contract correlations.

Part (a) of Figure 3 on page 26, part (a) of Figure 4 on page 27 and part (a) of Figure 5 on page 28 display a fairly stable and uniform relationship between the German and Nordic electricity contracts until 2005. From then onward, we observe a large variation in the conditional correlation. The yearly contracts also appear to interact more from 2005. One possible reason is that phase 1 of the European Union Emission Trading Scheme commenced operation in January 2005, and this may have influenced this finding. The conditional correlation between the monthly contracts also falls below zero around spring 2008. The factor causing this decrease in the conditional correlation for short-maturity contracts does not appear to have affected expected long-term prices, as the conditional correlation between the yearly contracts appears to be unaffected.

Most noticeable in part (b) of Figure 3 on page 26, part (b) of Figure 4 on page 27 and part (b) of Figure 5 on page 28 is the decrease in conditional correlation for all contract maturities in September 2007. Putting this aside, we can observe quite similar conditional correlations between monthly (Figure 3) and quarterly contracts (Figure 4) for Nordic and UK electricity.

Part (c) of Figure 3 on page 26, part (c) of Figure 4 on page 27 and part (c) of Figure 5 on page 28 indicate a moderately time-varying conditional correlation between Nord Pool electricity futures and ICE natural gas futures, taking a negative

TABLE 4 Estimated model parameters for monthly contracts. [Table continues on next page.]

(a) Monthly contracts

	$\mathbf{NPel_M}$		$\mathbf{NPel_M}$		$\mathbf{NPel_M}$		$\mathbf{NPel_M}$		$\mathbf{NPel_M}$		$\mathbf{NPel_M}$	
	Coeff.	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**
Cst $(\beta_0) \times 10^4$	0.247	0.0003	0.255	0.003	0.245	0.007	0.204	0.005	0.195	0.019	0.281	0.005
ARCH (β_1)	0.121	0	0.130	0	0.126	0	0.112	0	0.135	0	0.144	0
GARCH (β_2)	0.854	0	0.859	0	0.857	0	0.864	0	0.858	0	0.843	0

(b) Monthly contracts (continued)

	$\mathbf{EEXel_M}$		$\mathbf{UKel_M}$		$\mathbf{ICEgas_M}$		$\mathbf{ICEoil_M}$		$\mathbf{ICEcoal_M}$		$\mathbf{ICECO_2}$	
	Coeff.	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**
Cst $(\beta_0) \times 10^4$	0.084	0.001	0.162	0.0009	0.242	0.011	0.056	0.041	0.049	0.0077	0.304	0.0002
ARCH (β_1)	0.167	0	0.220	0	0.242	0	0.048	0.0001	0.148	0	0.148	0
GARCH (β_2)	0.830	0	0.776	0	0.771	0	0.940	0	0.846	0	0.811	0

TABLE 4 Continued.

(c) Correlation

	Coeff.	*t* prob.	Coeff.	*t* prob.	Coeff.	*t* prob.	Coeff.	*t* prob.	Coeff.	*t* prob.	Coeff.	*t* prob.
Unconditional correlation	0.365	0	0.264	0	0.173	0	0.093	0.0002	0.236	0.0001	0.229	0
θ_1	0.022	0.002	0.013	0.109	0.023	0.006	—	—	0.020	0.046	0.011	0.193
θ_2	0.957	0	0.945	0	0.940	0	—	—	0.961	0	0.954	0
Student t freedom	6.759	0	5.310	0	5.447	0	11.265	0	7.446	0	5.777	0
No. of observations	1672		1394		1617		1634		1026		1335	
No. of series	2		2		2		2		2		2	
No. of parameters	10		10		10		8		10		10	
Log-likelihood	8183.5		6576.9		7208.7		7744.3		5094.5		6114.9	

Estimated parameters used to produce Figure 3 on page 26, Figure 4 on page 27 and Figure 5 on page 28 and their corresponding p-values. The unconditional correlation may vary from that presented in the descriptive statistics, since we use the longest sample possible for the bivariate analysis here, while, in the descriptive statistics, we specified equal samples for all contracts of the same maturity. The values for β and θ are, respectively, the univariate GARCH and conditional correlation processes described in the methodology. Student t degrees of freedom is a measure of leptokurtosis in the bivariate distribution assumed when optimizing the log-likelihood. The Student t distribution approaches the normal distribution as the degrees of freedom increase toward infinity.

TABLE 5 Estimated model parameters for quarterly contracts. [Table continues on next page.]

(a) Quarterly contracts

	$\mathbf{NPel_Q}$		$\mathbf{NPel_Q}$		$\mathbf{NPel_Q}$		$\mathbf{NPel_Q}$		$\mathbf{NPel_Q}$		$\mathbf{NPel_Q}$	
	Coeff.	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**
Cst $(\beta_0) \times 10^4$	0.183	0.0003	0.225	0.002	0.182	0.007	0.176	0.006	0.166	0.023	0.222	0.003
ARCH (β_1)	0.096	0	0.118	0	0.112	0	0.107	0	0.099	0	0.123	0
GARCH (β_2)	0.879	0	0.864	0	0.870	0	0.867	0	0.885	0	0.858	0

(b) Quarterly contracts (continued)

	$\mathbf{EEXel_Q}$		$\mathbf{UKel_Q}$		$\mathbf{ICEgas_Q}$		$\mathbf{ICEoil_Q}$		$\mathbf{ICEcoal_Q}$		$\mathbf{ICECO_2}$	
	Coeff.	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**
Cst $(\beta_0) \times 10^4$	0.045	0.0016	0.128	0.002	0.113	0.002	0.059	0.046	0.048	0.018	0.279	0.0001
ARCH (β_1)	0.148	0	0.167	0	0.185	0	0.054	0.0002	0.123	0	0.140	0
GARCH (β_2)	0.840	0	0.808	0	0.814	0	0.932	0	0.867	0	0.820	0

TABLE 5 Continued.

(c) Correlation

	Coeff.	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**
Unconditional correlation	0.425	0	0.273	0	0.210	0	0.1130	0	0.310	0.0032	0.305	0
θ_1	0.038	0.029	0.010	0.197	0.020	0.0033	—	—	0.022	0.0001	0.018	0.034
θ_2	0.923	0	0.947	0	0.958	0	—	—	0.972	0	0.947	0
Student t freedom	7.233	0	6.118	0	6.298	0	14.184	0	8.618	0	6.470	0
No. of observations	1666		1481		1633		1666		1069		1376	
No. of series	2		2		2		2		2		2	
No. of parameters	10		10		10		8		10		10	
Log-likelihood	8976.0		7361.9		7876.8		8125.4		5381.1		6462.6	

This table displays the estimated parameters used to produce Figure 3 on page 26, Figure 4 on page 27 and Figure 5 on page 28 and their corresponding p-values. The unconditional correlation may vary from that presented in the descriptive statistics as we here use the longest sample possible for the bivariate analysis, while, in the descriptive statistics, we specified equal samples for all contracts of the same maturity. The values for β and θ are, respectively, the univariate GARCH and conditional correlation processes described in the methodology. Student t degrees of freedom is a measure of leptokurtosis in the bivariate distribution assumed when optimizing the log-likelihood. The Student t distribution approaches the normal distribution as the degrees of freedom increase toward infinity.

TABLE 6 Estimated model parameters for yearly contracts. [Table continues on next page.]

(a) Yearly contracts

	$NPel_Y$		$NPel_Y$		$NPel_Y$		$NPel_Y$		$NPel_Y$		$NPel_Y$	
	Coeff.	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**
Cst $(\beta_0) \times 10^4$	0.056	0.0013	0.118	0.0009	0.099	0.0029	0.109	0.006	0.056	0.032	0.093	0.002
ARCH (β_1)	0.095	0	0.120	0	0.111	0	0.105	0	0.093	0	0.125	0
GARCH (β_2)	0.883	0	0.849	0	0.860	0	0.859	0	0.892	0	0.857	0

(b) Yearly contracts (continued)

	$EEXel_Y$		$UKel_Q$		$ICEgas_Y$		$ICEoil_Y$		$ICEcoal_Q$		$ICECO_2$	
	Coeff.	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**	**Coeff.**	***t* prob.**
Cst $(\beta_0) \times 10^4$	0.023	0.0001	0.100	0.0112	0.087	0.0032	0.062	0.043	0.050	0.011	0.254	0.0002
ARCH (β_1)	0.138	0	0.085	0	0.118	0	0.074	0.0003	0.114	0	0.143	0
GARCH (β_2)	0.844	0	0.876	0	0.858	0	0.906	0	0.870	0	0.823	0

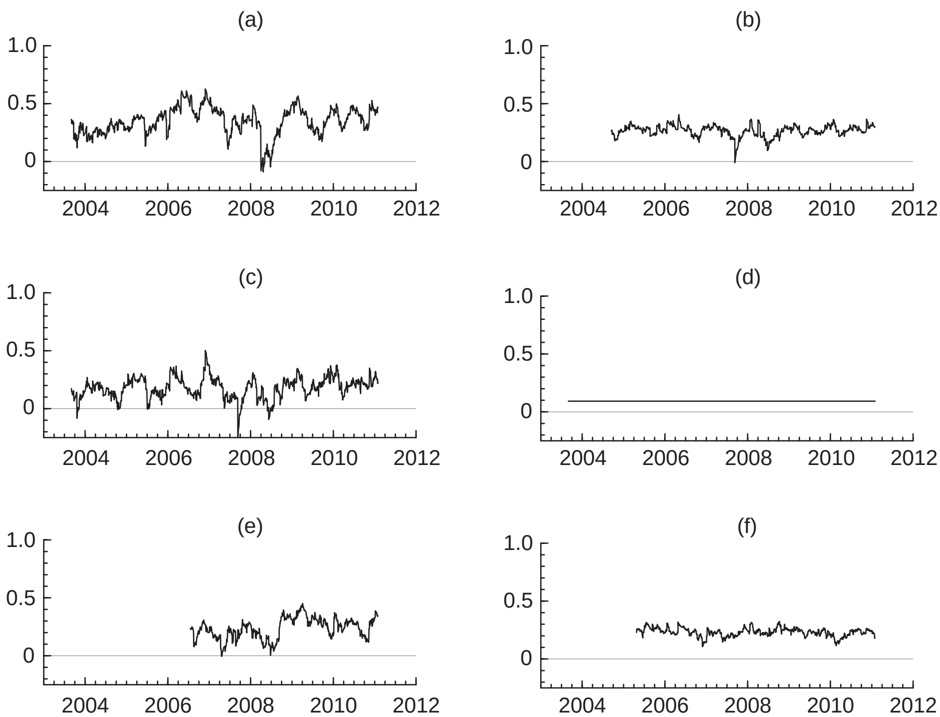
TABLE 6 Continued.

(c) Correlation

	Coeff.	t prob.	Coeff.	t prob.	Coeff.	t prob.	Coeff.	t prob.	Coeff.	t prob.	Coeff.	t prob.
Unconditional correlation	0.577	0	0.360	0	0.324	0	0.218	0	0.403	0.0019	0.460	0
θ_1	0.034	0	0.014	0.019	0.028	0.0004	—	—	0.019	0.0001	0.024	0.0005
θ_2	0.957	0	0.971	0	0.955	0	—	—	0.975	0	0.955	0
Student t freedom	9.597	0	6.456	0	7.495	0	11.149	0	9.901	0	6.506	0
No. of observations	1884		1504		1563		1438		1074		1390	
No. of series	2		2		2		2		2		2	
No. of parameters	10		10		10		8		10		10	
Log-likelihood	1990.3		8362.9		8642.8		7804.6		5965.1		7213.3	

This table displays the estimated parameters used to produce Figure 3 on the next page, Figure 4 on page 27 and Figure 5 on page 28 and their corresponding p-values. The unconditional correlation may vary from that presented in the descriptive statistics as we here use the longest sample possible for the bivariate analysis, while, in the descriptive statistics, we specified equal samples for all contracts of the same maturity. The values for β and θ are, respectively, the univariate GARCH and conditional correlation processes described in the methodology. Student t degrees of freedom is a measure of leptokurtosis in the bivariate distribution assumed when optimizing the log-likelihood. The Student t distribution approaches the normal distribution as the degrees of freedom increase toward infinity. Where data for yearly contracts was not available, we used the longest maturity available (seasonal contracts for UK electricity and quarterly contracts for ICE coal).

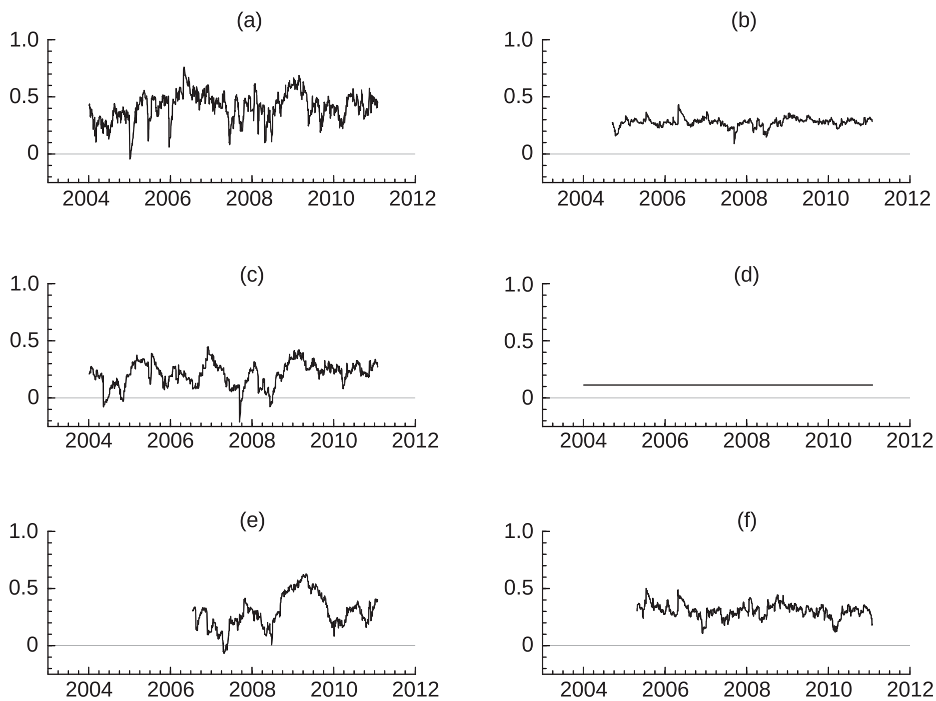
FIGURE 3 Conditional correlation between monthly contracts.



(a) Nord Pool base electricity futures and EEX German base electricity futures. (b) Nord Pool electricity forwards and ICE UK base electricity futures. (c) Nord Pool electricity futures and ICE natural gas futures. (d) Nord Pool electricity forwards and ICE Brent crude oil futures. (e) Nord Pool electricity futures and ICE coal futures. (f) Nord Pool electricity futures and ICE CO_2 emission allowance futures.

value for the monthly (Figure 3) and quarter contracts (Figure 4) in fall 2007 and summer 2008. We also have evidence of a uniform decrease for all maturities in conditional correlation in October and November 2004. We observe the lowest value for all contracts in September 2007, and this also coincides with the lowest value observed for the conditional correlation between UK and Nordic electricity contracts. Examining our data set, we find nothing extraordinary in this period, and, going back to Figure 1 on page 11, we see that the general trend in both Nordic and UK energy prices is increasing in this period. However, four price increments of opposite sign cause the conditional correlation to plunge due to the construction of the DCC model. Furthermore, we may see that the decrease in conditional correlation for monthly and quarterly contracts in June 2008 does not appear to affect the yearly contracts.

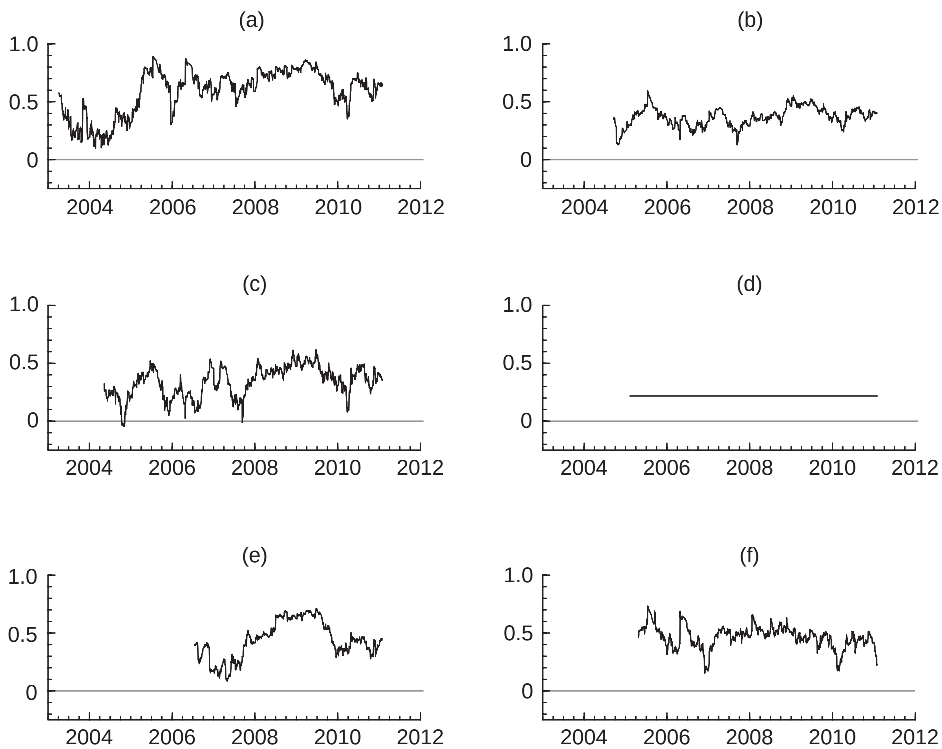
FIGURE 4 Conditional correlation between quarterly contracts.



(a) Nord Pool base electricity futures and EEX German base electricity futures. (b) Nord Pool electricity forwards and ICE UK base electricity futures. (c) Nord Pool electricity futures and ICE natural gas futures. (d) Nord Pool electricity forwards and ICE Brent crude oil futures. (e) Nord Pool electricity futures and ICE coal futures. (f) Nord Pool electricity futures and ICE CO_2 emission allowance futures.

We were unable to model any dynamics in the conditional correlations between the Nord Pool contracts and those for Brent crude oil. The reason for this is that the DCC model depends on some kind of persistence in the covariance between returns (eg, a period of high dependence is likely to be followed by another period of high dependence), so if there is little dependence and/or the evolvement of the dependence is highly random, these estimates will not make much sense. A historical average correlation might therefore be just as good an estimate as what is produced by a more advanced model with highly uncertain coefficients. As suggested by the plot of the estimated constant correlation in part (d) of Figure 3 on the facing page, part (d) of Figure 4 and part (d) of Figure 5 on the next page, we can observe a rather low correlation between the short (Figure 3) and medium maturity (Figure 4) contracts, and, as for all other commodities, a somewhat stronger relationship for the yearly

FIGURE 5 Conditional correlation between yearly contracts.



(a) Nord Pool base electricity futures and EEX German base electricity futures. (b) Nord Pool electricity forwards and ICE UK base electricity futures. (c) Nord Pool electricity futures and ICE natural gas futures. (d) Nord Pool electricity forwards and ICE Brent crude oil futures. (e) Nord Pool electricity futures and ICE coal futures. (f) Nord Pool electricity futures and ICE CO_2 emission allowance futures. Where data for yearly contracts was not available, we used the longest maturity available (seasonal contracts for UK electricity and quarterly contracts for ICE coal).

contracts (Figure 5). Going back to Table 3 we can see that, apart from the period around the credit crisis, the correlation with Brent crude oil is very close to zero. This is to some extent unexpected, since oil is such an important source of energy. A possible reason for this observation is that oil may serve as a long-term marginal fuel, with little effect on contracts with maturity of one year or less.

The relationship between Nord Pool contracts and coal delivered in Rotterdam shown in part (e) of Figure 3 on page 26, part (e) of Figure 4 on the preceding page and part (e) of Figure 5 is the most stable for the monthly contracts (Figure 3). From summer 2008 until summer 2009, we observe a high conditional correlation between the yearly contracts (Figure 5) and, to a certain degree, the quarterly contracts (Figure 4). When we consider the other commodity pairs, we also detect a similarly high correlation with Nord Pool contracts throughout this period for the natural gas, EEX and UK electricity contracts. The fact that this coincides with the bankruptcy of Lehman Brothers and the ensuing global financial crisis indicates a reaction to macroeconomic events that could form a possible extension of the work in this paper.

Part (f) of Figure 3 on page 26, part (f) of Figure 4 on page 27 and part (f) of Figure 5 on the facing page indicate a somewhat stable conditional correlation between the three contracts for Nordic electricity and ICECO_2 allowances. There are, however, three discernible drops in the conditional correlation: early winter 2006–7, winter 2009–10 and, most recently, winter 2010–11. In terms of explanation, December 2009 and January, November and December 2010 were significantly colder in the Nordic countries than normal. When combined with problems with Swedish nuclear power in the winter of 2009–10 and low water levels in Norwegian hydro reservoirs in late 2010, this brought about fears of an electricity shortage.

5.2 Comparing contracts with the same horizon

When comparing contracts with the same horizon, the main findings from the perspective of a power producer in Scandinavia are the very high correlations between the Nord Pool base electricity forwards and EEX German base electricity futures. In contrast, Nord Pool base electricity forwards appear to have quite a low conditional correlation with ICE gas and oil. This is consistent with the simple descriptive analysis presented earlier. As described, the Nordic electricity market connects directly with the German market, and therefore this is to be expected.

Furthermore, as already mentioned, the conditional correlation between long-maturity contracts generally tends to be higher (Figure 5 on the facing page) than between contracts with a shorter maturity (Figure 3 on page 26 and Figure 4 on page 27). Once again, we expect this, since, for long-term contracts, the long-run marginal cost of producing electricity is the main determinant, whereas, for short-term contracts, meteorological and hydrological conditions and supply interruptions have a more significant influence on the market price.

6 CONCLUSION

We have analyzed and discussed the conditional correlation between the returns of Nord Pool electricity futures contracts and the returns for ICE gas, Brent crude oil, coal and carbon emission futures contracts, as well as for EEX and ICE electricity futures contracts. An improved understanding of the volatility dynamics and correlation for these energy-related commodities is of great importance, as major participants in the electricity market use correlations in the price of oil, gas, coal, electricity in other markets, and carbon emissions as information for, among other things, decisions on investment and production planning. In addition, accurate correlation estimates are also of crucial importance as parameter inputs in risk management and hedging.

The analysis of contracts with different maturities allows us to confirm the expected higher correlation between longer maturity contracts. Additionally, it provides several reference points that allow the reader to interpret a conditional correlation at, say, 0.2 for a short-term contract, in the light of conditional correlation for the longer-term contracts and contracts for different energy commodities.

Throughout the period analyzed, we found that Nord Pool base electricity futures have the highest correlation with EEX German base electricity futures, and the lowest conditional correlation with Brent crude oil. Furthermore, for the commodities investigated in this study, we find a general increase in the correlation with UK electricity, natural gas and coal, particularly for short-term contracts. This, and a general high correlation with German electricity contracts, implies a movement toward more highly integrated and efficient energy markets in Europe.

Importantly, the significant GARCH effect in the conditional correlation could complicate risk management for portfolios comprising a number of energy commodities and the pricing of derivatives with several energy commodities specified as the underlying asset. Practitioners in statistical analysis should also give special attention to these effects. In particular, our analysis shows that models based on constant correlation, such as naive mean variance optimization, are inappropriate for these markets.

By using the traditional unconditional measure of correlation in addition to conditional correlation estimates produced by an MGARCH model, we have showed how the Nordic electricity market has related to other European energy commodities throughout the last decade. Besides the fact that we find very little evidence of dependency between Brent crude oil and Nordic electricity contracts, our findings conform to the existing economic literature. However, one should not take such conclusions for granted, as history shows that economic theory does not always go hand in hand with empirical findings. Since, to the best of our knowledge, a scientific work stating the empirical evidence for these effects in all the analyzed markets does not exist, our paper provides an additional argument and a reference point for taking time-varying dependencies into consideration when working with energy commodities.

For participants in energy markets, a good subjective knowledge of the market has, and will no doubt remain, of great importance. Regardless of this, frequent updates of "objective" correlation estimates/predictions between relevant energy commodities, as in this study, may be useful for additional decision support.

Considering future research directions, the correlation presented here is a linear measure of dependency. There are certainly reasons to believe that there are nonlinear relations between energy commodities. For this reason, assessing the tail dependency in energy commodities, assessed using, say, copulas and other nonlinear measures, would be an interesting extension. Moreover, if high-frequency data were available for the same energy commodities, we would have tested other correlation estimate techniques, such as realized correlation and intraday range-based estimators. Finally, we note that the investigation of comovements between energy prices and macroeconomic variables could also be another fruitful direction for future research.

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