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Hedging spark spread risk with futures*

Beatriz Martínez and Hipòlit Torró **

Abstract

This is the first paper to discuss the spark spread risk management using electricity and natural gas futures. We focus on three European markets in which the natural gas share in the fuel mix varies considerably: Germany, the United Kingdom, and the Netherlands. We find that spark spread returns are partially predictable, and consequently, the Ederington and Salas (2008) minimum variance hedging approach should be applied. Hedging the spark spread is more difficult than hedging electricity and natural gas price risks with individual futures contracts. Whereas spark spread risk reduction for monthly periods produces values of between 20.05 and 48.90 per cent, electricity and natural gas individual hedges attain reductions ranging from 31.22 to 69.06 per cent. Results should be of interest for agents in those markets in which natural gas is part of the fuel mix in the power generation system.

Keywords: natural gas market, electricity market, futures contracts, forward contracts, spark spread, hedging ratio, seasonal effects.
JEL Classification: G11, G13, L94, L95.

Resumen

En este documento se aborda por primera vez en la doctrina la gestión del riesgo del *spark spread* utilizando futuros sobre la electricidad y el gas natural. Se ha focalizado la atención en tres mercados europeos en los que la participación del gas natural en el mix de generación es muy diferente: Alemania, Reino Unido y Holanda. Un primer resultado es que las rentabilidades del *spark spread* son parcialmente predecibles y, en consecuencia, el enfoque de cobertura mínima varianza propuesto en Ederington y Salas (2008) debe ser aplicado. La cobertura del riesgo del *spark spread* resulta ser mucho más difícil que la cobertura individualizada del riesgo de precio de la electricidad y el gas natural con sus respectivos contratos de futuros. Mientras que la reducción del riesgo alcanzada para el *spark spread* para coberturas mensuales obtiene reducciones de riesgo de entre el 21,22% y el 48,90%, las coberturas individualizadas de ambas commodities alcanzan reducciones de entre el 31,22% y el 69,06%. Estos resultados son de interés para aquellos agentes en cuyos mercados en el gas natural forma parte del mix de generación eléctrico.

Palabras clave: mercado del gas natural, mercado de la electricidad, contratos de futuro, contratos *forward*, *spark spread*, ratio de cobertura, efectos estacionales.
Clasificación JEL: G11, G13, L94, L95.

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1. Introduction

The deregulation of energy markets initiated in the 1990s has led to competition and price uncertainty in many countries. In the case of a gas power plant this uncertainty is double because it sells electricity produced with the burning of gas. The spark spread can be defined as the gross profit margin earned by buying and burning natural gas to produce electricity. The size of this profit depends on energy prices and generator efficiency. The clean spark spread reduces the spark spread with the cost of emitting CO2 to the atmosphere. Further to the spark and clean spark spreads, the range of the energy and commodities spreads family is quite wide: quark (nuclear to electricity); dark (coal to electricity); clean dark (coal to electricity and CO2); crack (oil to gasoline and heating oil); and crunch (soy bean to soy oil and soy meal). In many cases, these spreads can be traded in a closed combination of futures contracts bought and sold in the market. Following Emery and Liu (2002), the spark spread became available when the NYMEX initiated trading in electricity futures in March 1996 and remained possible until 2002. However, in May 2002 electricity contracts on Nymex became over-the-counter (OTC), and so spark spreads had to also become OTC on NYMEX. Spark spreads have also started OTC trading in Europe. The spark spread forward curve is very important to energy industry planners as it provides a method for electricity producers to lock in generation profits. The forward curve of the spark spread and its average values can indicate to gas-fired generation companies how to maximise profits in their forward trading by choosing maturities with higher spreads. The spark spread can also help regulators monitor if electricity forward prices are directly influenced by gas prices, and in case of remarkable divergences, help reveal if a market anomaly has occurred (Capitan and Rodriguez, 2013).

As Borovkova and Geman (2006) remarked, in the energy industry, inter-commodity spreads are as important as prices. In this paper, we deal with several important issues related to the joint risk management of electricity and natural gas prices. This is the first-time that spark spread risk hedge is discussed in the doctrine using financial futures. There are several papers on electricity and natural gas price risk management, but no paper has attempted to simultaneously determine the optimal position in futures on electricity and natural gas to hedge spark spread risk (see for example Torró, 2011, and Martinez and Torró, 2016). We show that clean spark spread risk and spark spread risk are two indistinguishable variables for futures hedging purposes. Therefore, this paper looks for the simultaneous optimal futures hedging positions on electricity and natural gas that minimise the profit risk that CCGT plant managers face. Before this decision is made, a manager must be sure that the clean spark spread ensures a profit for the company. Hedging negative spark spreads with futures makes no sense. In fact, the spot price in the electricity market is determined by the intersection of the supply and demand curves at an auction in which the price for the 24 hours of the following day is settled. Power producers make their electricity offers according to their short-term marginal costs, principally fuel costs and CO2–costs. Offers are then sorted from lowest to highest, obtaining the merit order curve, that is, the electricity offer curve. As power producers from renewable sources offer electricity at nearly zero marginal costs, they are the first to enter the merit order, followed by nuclear energy, coal or gas (depending on the country, coal before gas for UK and Germany and gas for the Netherlands) and fuel oil plants.[1] When electricity demand is low, the price setting units are coal power plants and in hours of high demand the price is set by gas units. CCGT plants would only make an offer and enter the merit order curve if the clean spark spread is positive and consequently profitable, otherwise they will remain mothballed. The CCGT plant profit would then depend on the days entering the merit order and the volume of electricity allocated in the auction.

A common feature of natural gas and electricity prices is that spot price changes are partially predictable due to weather, demand, and storage level seasonalities.[2] Our paper is also innovative in uncovering and considering the seasonal effects detected in the spark spread that makes its changes partially predictable. Ederington and Salas (2008) showed that in these cases the linear regression

[1] See Sensfuß et al. (2008) and Cludius et al. (2014).

[2] See, for example, Koopman et al. (2007) and Martínez and Torró (2015) for electricity and natural gas prices, respectively.

hedging ratio estimate is inefficient, the riskiness of the spot position is overestimated, and the achievable risk reduction underestimated. We apply to the spark spread the methodology proposed by Ederington and Salas (2008) that overcomes these problems. In the Ederington and Salas (2008) framework the expected spot price changes are approximated using the information contained in the basis (futures price minus spot price). If futures prices are unbiased predictors of futures spot price, the basis will be a measure of the expected change in the spot price until maturity (Fama and French, 1987).

In the last few decades the demand for natural gas in Europe has continuously increased, reducing the use of coal and oil products in the space heating and industrial sectors. From the 1990s onwards, the proliferation of combined-cycle gas turbine (CCGT) plants in Europe has reinforced the importance of gas as an energy source, especially in power generation. Nevertheless, the demand for natural gas in Europe has stopped growing since 2008 because of several simultaneous factors: (i) stagnant power demand after the economic crisis of 2008; (ii) the rising share of renewables in the energy mix as part of the transition to a low carbon economy; (iii) the arrival of cheap coal after the US shale gas production boom in 2009 put gas-fired plants at a disadvantage in the merit order; and (iv) the fall of CO2 allowance prices that exacerbated competition between natural gas and coal. Because of all these factors, CCGT plants have been operating mostly in peak periods (except in the UK and Italy where gas plants still run on base load). The future of natural gas in the long-run European power generation mix will improve as it provides backup for the intermittency of renewables, and the effects of emissions legislation, and the retirement of coal and nuclear capacity in the coming decades (see Honoré, 2014, for more details). In the International Energy Outlook for 2016, an average increase of the 3.6% per year in natural gas consumption for power generation for the period 2020-2040 is projected for OECD Europe – this being the largest increase in the sector for any energy source (EIA, 2016).

Our empirical application has been applied to three European markets: the UK, the Netherlands, and Germany. These three markets have several important differences, especially notable because of the fuel mix in the power generation system and the shares of natural gas. Electricity generation in Germany had the following fuel mix in 2014: 10% natural gas; 45% coal; 15% nuclear; 21% renewables; 7% biofuels; and 2% other fuels (see IEA, 2014). The sharp increase in renewable capacity in Germany has lowered electricity prices and gas-fired plants must face negative spark spread. Furthermore, backup for the intermittency of renewables is mostly provided by flexible lignite plants. This situation has prompted several gas-fired plants to apply for closure. Electricity generation in UK had the following fuel mix in 2015: 30% natural gas; 22% coal; 21% nuclear; 25% renewables; and 2% other fuels. Coal and gas-fired shares change each year, with some of the switching between the two reflecting fuel prices (see UK Government, 2016a). Gas power plants have a long-term role in the UK energy system by providing both flexibility and critical capacity, although utilisation is reducing over time (UK Government, 2016b). Electricity generation in the Netherlands had the following fuel mix in 2014: 50% natural gas; 31% coal; 4% nuclear; 10% renewables; and 5% other fuels (see IEA, 2014). The Dutch gas transfer facility has grown enormously in the past years, and is now the biggest on mainland Europe. The Title Transfer Facility is its virtual hub and whose price has become an important benchmark for gas transactions across continental Europe (see Honoré (2014)). Recently, an induced earthquake caused by the extraction of natural gas from the Groningen field has forced the Dutch government to reduce extraction volumes (since 2014) to avoid more severe quakes. Nevertheless, Dutch market prices continue to be the most important reference across continental Europe.

The most insightful results obtained in the empirical experiment with the above three markets are: (i) the spark basis has an important predictive power explaining spot price changes (between 19.83% and 54.14% for the base load spark spread and between 3.67% and 44.43% for the peak load spark spread).; (ii) we analyse five possible futures hedging strategies and find that no hedging strategy clearly dominates the remaining strategies in all cases; (iii) results for Germany and the Netherlands are much better than results for the UK; (iv) the best performing monthly hedging strategies can produce risk reductions of between 20.05 and 48.90 for the spark spread; (v) individual monthly hedges of natural gas and electricity (base and peak load) produce higher risk reductions with values of between 31.22 and 69.06 per cent.

Hedging the spark spread with futures implies a simultaneous hedge on electricity and natural gas prices using futures contracts in both assets. The existing literature on hedging natural gas price risk with futures shows that risk reductions above 80% are possible for hedging periods equal or longer than a month (see Ederington and Salas (2008) and Martínez and Torró (2015)). Nevertheless, hedging electricity price risk using futures is more difficult because it is a non-storable commodity. The lack of a cash-and-carry arbitrage mechanism produces a looser relationship between spot and futures prices, especially as futures maturity becomes more distant. In addition, electricity spot price behaviour has some well-known characteristics: jumps, positive skewness, very high volatility, mean-reversion, seasonalities, and heteroscedasticity (see, for example, Koopman et al. (2007) for daily frequency data in European markets). Both effects combined produce a lower than usual correlation between spot and futures prices, and might generate a poor performance when hedging spot price risk with futures contracts.[3] Alexander et al. (2013) obtain a 70% of risk reduction when hedging the crack spread using NYMEX futures contracts on crude oil, gasoline and heating oil. Achieving such a high risk reduction seems much more difficult with the spark spread because it is much more unstable due to the lower correlation existing between natural gas and electricity compared to the correlations between oil, gasoline and heating oil.

[3] For the California-Oregon-Border and Palo Verde futures traded at NYMEX Moulton (2005) obtains a risk reduction varying between -2% and 20% for daily hedges using monthly electricity futures. At the Nord Pool, Bystrom (2003) obtains risk reductions that range between 7% and 29% for weekly hedges. In Torró (2011), weekly spot price risk is hedged with weekly futures in the Nord Pool electricity market. It is shown that increasing the hedging period and closing futures positions near to its maturity may produce risk reductions over to 80%.

We structure the remainder of this article as follows. In Section 2, we present the minimum variance framework. In Section 3, we describe our data and some preliminary descriptive statistics. In Section 4 we carry out an empirical exercise. We offer conclusions in Section 5.

2. The minimum variance hedge ratio

Alexander et al. (2013) argue that the minimum variance (MV henceforth) framework has several advantages over optimal hedging (OH henceforth). OH is based on normality or mean-variance utility functions. These are unrealistic hypotheses. Furthermore, assuming futures prices are martingale, the high volatility in energy prices points to MV as the essential problem (see Alexander et al. 2013, page 699). Furthermore, Cotter and Hanly (2013) conclude that in the oil market the OH approach is not sufficiently different to warrant using a more complicated utility-based approach as compared with the simpler MV. Cotter and Hanly (2010) estimate the time-varying coefficient of relative risk aversion in energy markets by obtaining values between 0 and 1.25 (quite low values compared to financial markets). Ex-ante and using a mean variance utility function with the average value of lambda (risk aversion parameter) makes MV the best performing strategy for weekly and monthly hedges and for long and short hedgers. Similarly, for the oil market and its refined products, Wang and Wu (2012) compare the effectiveness of several hedge ratio computation methodologies using the variance reduction and the utility obtained in a mean-variance utility function (using a degree of risk aversion of four). In both cases, the performance ranking of the hedge ratio computation methodologies is the same. Based on this evidence from the energy markets we use the MV framework. Below we describe the MV framework and the extension proposed in Ederington and Salas (2008).[4]

[4] For an excellent revision on futures hedging see Lien and Tse (2002).

Let's suppose a company buying natural gas and selling electricity produced in a CCGT plant. The spark spread, S_t, of this company is defined as:

$$S_t = S_t^e - aS_t^g$$

where S_t^e is the spot price of the electricity, S_t^g, the spot price of the natural gas, and a the conversion factor, considering the efficiency factor of the plant and homogenising energy and monetary units. This company is long in natural gas and short in electricity and will probably need to take short positions in natural gas futures/forward contracts and long positions in electricity futures/forward contracts to hedge the position in futures markets. The spark spread in the futures/forward markets is defined as:

$$F_t = F_t^e - aF_t^g$$

The spark spread in the futures/forwards markets can be explicitly traded as an individual contract or a specific position to take in each individual contract. In the most general case, let's suppose that this company is committed to a given position in the spot market and wishes to reduce its price risk exposure taking at the same time '*t*' positions in both forward/futures markets. The hedged company result per unit of spot at the end of the period, say, '*t*+1', is calculated as follows:

$$x_{t+1} = \Delta S_t - (\beta_t^e \Delta F_t^e - a\beta_t^g \Delta F_t^g) \tag{1}$$

where x_{t+1} is the value variation between t and t+1, $\Delta S_t = S_{t+1} - S_t$ is the spark spread value variation; $\Delta F_t^e = F_{t+1}^e - F_t^e$ and $\Delta F_t^g = F_{t+1}^g - F_t^g$ are the futures value variations for electricity and natural gas, respectively; and β_t^e and β_t^g are the corresponding hedging ratios. If β_t^e is positive (negative), short (long) positions are taken in electricity futures market. If β_t^g is positive (negative), long (short) positions are taken in natural gas futures markets. The hedger will choose β_t^e and β_t^g to minimise the risk associated with the random result x_{t+1}. We use realized returns instead log returns because we agree with the Alexander et al. (2013) methodology on several points. These authors argue that "...for assets with prices that can jump, log returns can be highly inaccurate proxies for percentage returns even when measured at the daily frequency. Additionally, since the hedged portfolio can have zero value, even its percentage return may be undefined. Thus, our hedging analysis is based on profit and loss (P&L) rather than on log or percentage returns". A standard way to measure risk in economics is by the variance conditional on the available information, ψ_t. The risk of a hedge strategy is calculated as the variance of x_{t+1},

$$VAR[x_{t+1}|\psi_t] = VAR\left[\Delta S_t - (\beta_t^e \Delta F_t^e - a\beta_t^g \Delta F_t^g)|\psi_t\right] \tag{2}$$

A direct mathematical solution of this problem will lead us to minimize the function with respect to β_t^e and β_t^g. The measure of obtained risk reduction will finish the experiment. Nevertheless, we will contemplate various options to obtain β_t^e and β_t^g and we will compare the risk reduction obtained in each case and obtain optimal option.

To estimate these hedge ratios, a realistic methodology is to consider a conditional estimation using several econometric specifications modelling conditional second moments. The number of published papers modelling conditional covariance in energy markets has increased significantly in the last few years.[5] The most widely used models are: (1) the VECH model proposed by Bollerslev et al. (1988); (2) the constant correlation model, CCORR, proposed by Bollerslev (1990); (3) the BEKK model of Engle and Kroner (1995) and (4) the dynamic conditional correlation or DCC of Engle (2002). Each model imposes different restrictions on the conditional covariance and can lead to substantially different conclusions in any application that involves forecasting conditional

[5] See Behmiri et al. (2016), Efimova and Serletis (2014), Chang et al. (2011), Ji and Fan (2011), Wang and Wu (2012) and Alexander et al. (2013)

covariance matrices. Many studies introduce asymmetries in the second moments using the Glosten et al. (1993) approach. These specifications have also been used in multivariate variance modelling in energy prices. Chang et al. (2011) found that the diagonal version of the BEKK model beats the DCC model and other specifications in hedging effectiveness. Ji and Fan (2011) found that the DCC specification beats the remaining hedging alternatives. Wang and Wu (2012) obtain that simplified versions of the BEKK model (diagonal and scalar) had a better performance than the full BEKK, DCC, and CCORR. We have tested the above mentioned conditional variance models and many of its variants, but we decided to skip these results as the conclusions of the paper will remain unchanged. Estimated hedging ratios based on bivariate and tri-variate conditional covariance specifications obtained worse risk reductions to those hedging ratios estimated using simple linear regressions. These results agree with Alexander et al. (2013), Martinez and Torró (2015), and Torró (2011) for energy markets.

Therefore, the methodology we propose to estimate the hedging ratios will be based on unconditional second moments based on the methodology proposed by Ederington (1979) and extended in Ederington and Salas (2008) to the case where spot price changes are partially predictable and futures prices are unbiased estimators of future spot prices. In this context, it is shown that the riskiness of the spot position is overestimated and the achievable risk reduction underestimated. Furthermore, as two commodities with respective futures contracts are considered there are several possibilities for estimating the hedging ratios in this framework. Specifically, the following cases are contemplated:

1. β_t^e and β_t^g are jointly obtained.
2. β_t^e and β_t^g are separately obtained in each market as independent problems.
3. $\beta_t^e = \beta_t^g = \beta_t$, jointly obtained but restricted to be equal.
4. $\beta_t^e = \beta_t^g = 1$, the naïve framework.
5. $\beta_t^e = \beta_t^g = 0$, the natural hedge.

Case 1. β_t^e and β_t^g are jointly obtained.

The hedge ratios that minimise the variance in equation (2) can be obtained by solving the first order conditions. When an unconditional probability distribution is used, the hedging ratios in equation (2) can be estimated by ordinary least squares (OLS henceforth) from a linear relationship between spot and futures returns

$$\Delta S_t = \alpha - \beta^e \Delta F_t^e + a\beta^g \Delta F_t^g + e_t \tag{3}$$

This is the extension to the one future contract framework originally proposed in Ederington (1979). Correlation between natural gas and electricity may produce collinearity and hedge estimates with biased standard errors.

Here, we present the Ederington and Salas (2008) framework adapted to this case by reformulating equations (1) and (2) to introduce the partial predictability of the spark spread return. Under this new approach, the unexpected result of the hedge in equation (1) can be reformulated as

$$x_{t+1} = (\Delta S_t - E[\Delta S_t|\psi_t]) - (\beta_t^{e\prime} \Delta F_t^e - a\beta_t^{g\prime} \Delta F_t^g) \tag{4}$$

The risk of the hedge strategy in equation (2) is reformulated as

$$VAR[x_{t+1}|\psi_t] = VAR\left[(\Delta S_t - E[\Delta S_t|\psi_t]) - (\beta_t^{e\prime} \Delta F_t^e - a\beta_t^{g\prime} \Delta F_t^g)|\psi_t\right] \tag{5}$$

Ederington and Salas (2008) propose using the basis (futures price minus spot price) at the beginning of the hedge as the information variable to approximate the expected spot price change. If futures prices are unbiased predictors of futures spot price, the basis will be a measure of the expected change in the spot price until maturity (Fama and French, 1987). An unconditional estimate of the hedge ratio in equation (5) can be obtained by estimating the following linear regression using OLS

$$\Delta S_t = \alpha - \beta^{e\prime} \Delta F_t^e + a\beta^{g\prime} \Delta F_t^g + \lambda(F_t - S_t) + e_t \tag{6}$$

where $\lambda(F_t - S_t)$ is used to estimate $E[\Delta S_{t+1}|\psi_t]$. Ederington and Salas (2008) show that OLS estimation of equation (6) produces an unbiased and more efficient estimation of the unconditional minimum variance hedge ratio than that obtained by using equation (3). This is true providing the expected change in the spot price is perfectly approximated with the product between the basis at the beginning of the hedge and its estimated coefficient (namely $\hat{\lambda}(F_t - S_t) = E[\Delta S_{t+1}|\psi_t]$).

Case 2. β_t^e and β_t^g are separately obtained.

It is interesting to investigate four more cases in which the above framework is simplified or restricted. A second possibility is to view the hedging problem as a double and independent hedging problem. That is, managing the two spot price risk separately, while measuring the hedging effectiveness jointly in the same performance measure. In this way, the unconditional hedging ratio estimation in the conventional framework will be obtained after separately estimating the following two linear regressions,

$$\Delta S_t^e = \alpha_1 + \beta^e \Delta F_t^e + e_{1,t}; \qquad \Delta S_t^g = \alpha_2 + a\beta^g \Delta F_t^g + e_{2,t} \tag{7}$$

and in the Ederington and Salas (2008) framework, we will use the following specification to obtain the unconditional hedging ratio estimation

$$\Delta S_t^e = \alpha_1 + \beta^e \Delta F_t^e + \lambda(F_t^e - S_t^e) + e_{1,t}; \quad \Delta S_t^g = \alpha_2 + a\beta^g \Delta F_t^g + \lambda(F_t^g - S_t^g) + e_{1,t} \tag{8}$$

Case 3. $\beta_t^e = \beta_t^g = \beta_t$*, jointly obtained but restricted to be equal*

A third option consists in reducing the dimensionality of the problem by using the same hedging ratio in both futures markets, or equivalently, trading on a futures/forward contract on the spark spread. That is, imposing the restriction $\beta^e = \beta^g = \beta$ in the unconditional estimation. This imposition will increase the estimation error. In this case, the conventional and the Ederington and Salas (2008) frameworks using unconditional estimation will be obtained, respectively, with the following expressions:

$$\Delta S_t = \alpha + \beta \Delta F_t + e_t \tag{9}$$

$$\Delta S_t = \alpha + \beta \Delta F_t + \lambda (F_t - S_t) + e_t \tag{10}$$

Case 4. $\beta_t^e = \beta_t^g = 1$*, the naïve framework.*

Hedging analysis is completed with the 'naïve' hedging ratios, that is, a hedge where futures positions have the same size but the opposite sign to the position held in the spot market. It is interesting to note that a perfect hedge is possible when futures positions are held until maturity and a naive hedge is adopted. Explicitly, if the maturity of the futures contracts matches with the final time of the hedge and $\beta_t^e = \beta_t^g = 1$, then the basis will be equal to zero in $t + 1$, $F_{t+1} - S_{t+1} = 0$, with $S_t = S_t^e - aS_t^g$ and $F_t = F_t^e - aF_t^g$. In this very specific case, the variance of the result in Equation (2) will be zero. Naïve hedges in the Ederington and Salas (2008) approach will also eliminate the risk if in Equation (5) the expected changes in spot returns are substituted by $\lambda(F_t - S_t)$ and $\lambda = 1$, as the basis convergence on futures maturity requires. Nevertheless, when futures positions are closed before maturity, the naïve framework may perform poorly. Following the results of Torró (2011) for electricity and Martínez and Torró (2015) for natural gas, the naive strategy can produce a good performance, and even represent the best hedging strategy in some cases (for long period hedges especially when futures positions are closed near to the futures maturity). That is, when the premises of this approach are close to being true.

Case 5. $\beta_t^e = \beta_t^g = 0$*, the natural hedge*

If the electricity market is not very competitive and there is no a diversified energy source generation mix, it is possible that main fuel price shocks would be transferred to the electricity prices. That is, the unhedged position may be optimal in some energy markets in which natural gas has a significant share in the power source energy mix, and there is no fully competitive behaviour by electricity producers and marketers. This is known as the natural hedge ($\beta_t^e = \beta_t^g = \beta^e = \beta^g = 0$). When electricity and natural gas prices are highly and positively correlated, gas-fired plants are said to enjoy a 'natural hedge'. Guo et al. (2016) found that a typical gas-fired power plant enjoyed a natural hedge in the UK in the period 2006 to 2011 using its daily aggregated dispatch decisions. That is, it was better off facing uncertain spot prices rather than locking in its generating costs. However, these authors argue that the natural hedge is not a perfect hedge, i.e., even modest risk aversion makes using some further hedging strategy optimal.

Measuring hedging effectiveness

In the empirical application in Section 4, the effectiveness of the hedging strategies are compared. The hedging ratios obtained following the conventional framework are labelled 'without basis' – and those hedging ratios estimated by following the Ederington and Salas (2008) framework are labelled 'with basis'. The hedging effectiveness of each strategy is obtained by using Equations (2) and (5) to compute the risk in each framework and then comparisons are made with respect to the spot position: that is $VAR[\Delta S_t|\psi_t]$ and $VAR[\Delta S_t - E[\Delta S_t|\psi_t]|\psi_t]$, respectively. Furthermore, *ex post* and *ex-ante* results are distinguished by splitting the data sample into two parts. In the first part, the hedging strategies are compared *ex post,* whereas in the second part, an *ex-ante* approach is used. That is, in the *ex-ante* study, strategies are compared using forecasted hedge ratios, and models are estimated when a new observation is considered.[6]

To test if the difference in hedging reductions are statistically significant we performed White's reality check as described in Lee and Yoder (2007) – but using equation (5) as a risk measure instead equation (2) because we were applying the Ederington and Salas (2008) approach. For technical details, we referred to Lee and Yoder (2007a), Lee and Yoder (2007b), and White (2000). Specifically, the variance of the estimated optimal hedged portfolio in the *ex-ante* study under the Ederington and Salas (2008) approach was computed as:

$$VAR\left[(\Delta S_t - \hat{\lambda}_t(F_t - S_t)) - (\hat{\beta}_t^{e\prime}\Delta F_t^e - a\hat{\beta}_t^{g\prime}\Delta F_t^g)\right] \tag{11}$$

where $\hat{\lambda}_t$, $\hat{\beta}_t^{e\prime}$ and $\hat{\beta}_t^{g\prime}$ are predicted parameter estimations conditioned for the information available on *t* as previously described. For each pair of hedging strategies, and for each observation included in the *out of sample* period, the following performance measure is computed:

$$\begin{aligned}\hat{f}_{k,t+1} = &-\left[\left(\Delta S_t - \hat{\lambda}_t(F_t - S_t)\right) - \left(\hat{\beta}_{k,t}^{e\prime}\Delta F_t^e - a\hat{\beta}_{k,t}^{g\prime}\Delta F_t^g\right)\right]^2 \\ &+\left[\left(\Delta S_t - \hat{\lambda}_t(F_t - S_t)\right) - \left(\hat{\beta}_{BM,t}^{e\prime}\Delta F_t^e - a\hat{\beta}_{BM,t}^{g\prime}\Delta F_t^g\right)\right]^2\end{aligned} \tag{12}$$

where $\hat{\beta}_{BM,t}^{e\prime}$ and $\hat{\beta}_{BM,t}^{g\prime}$ are the hedging ratios estimate of the strategy used as a benchmark; that is, the hedging strategy with the lowest risk reduction in each pair of strategies compared. And each pair $\hat{\beta}_{k,t}^{e\prime}$ and $\hat{\beta}_{k,t}^{g\prime}\,\hat{b}_{k,t}^{\prime}$ correspond to the set of all possible hedging strategies with better risk

[6] In the Ederington and Salas (2008) framework, the λ coefficient in equations (6), (8) and (10) is estimated each time a new observation is introduced in the *ex-ante* study. To enable a comparison between the obtained risk reductions across the five studied cases, we have measured the unexpected shocks in the spot position using the λ value estimated from equation (10). The results are almost identical when equation (5) is used instead.

reductions than the compared benchmark strategy. White's reality check is based on the following performance statistic:

$$\bar{f} = \frac{1}{n}\sum_{t=R}^{T} \bar{f}_{t+1} \tag{13}$$

where n is the number of observations in the *out of sample* experiment, that is $n = T - R$. The null hypothesis that the best performing hedging strategy from each pair of possible strategies considered has no predictive superiority over the worst performing in each pair is given by:

$$H_0: E[f_k^*] \leq 0 \tag{14}$$

where f_k^* is the true performance value for each model applied to the data. Following White (2000), White's reality check is implemented with the stationary bootstrap resampling method of Politis and Romano (1994) in which pseudo-time series are generated by resampling blocks of random length drawn from a geometric distribution. This procedure is repeated to generate an approximate sampling distribution of the $\bar{f}$ performance measure. To apply the stationary bootstrap method of Politis and Romano (1994), the smoothing parameter q and the resamplings are set to 0.5 and 10000, respectively.

3. Data and preliminary analysis

We examine three representative European markets: the United Kingdom, the Netherlands, and Germany. Table 1 summarises data sources used for the three markets. For both electricity and gas, we use futures prices (except for UK electricity where we employ forward prices because of the lack of liquidity in futures negotiation in this market). The electricity market has a different demand pattern depending on the hours. Hours in which demand is high and capacity is tight are known as *peak load* hours. Contracts supplying electricity 24 hours a day are known as *base load*. We analyse short time hedges of weekly and monthly frequency with the front futures contract for the UK and the Netherlands and with weekly and monthly electricity futures for Germany. Weekly time series are built by taking the closing prices on Wednesday (or the day before if non-tradable) and monthly time series are constructed by picking the last negotiated Wednesday of the month (or to avoid the instabilities of the last trading day we take the previous day if the last Wednesday is the last negotiated day).

In the winter of 2014, the British electricity market switched from trading based in the EFA (electricity forward agreement) calendar to Gregorian calendar months, to match the NBP gas market and the main power and gas markets in Europe. The EFA calendar runs on a rolling 4/4/5 week, that is, under the EFA system the months of March, June, September, and December have five weeks, the rest of the months are four weeks and the year begins on 1 April (week 14 of the calendar year). Despite the ending of the EFA agreement there are still many products traded on an EFA basis. We switch the series on September 2014, a little before the end of the system because of liquidity issues concerning the forward price series. The spot price is the average price of the volume-weighted reference price for each half hour settlement period, from 07:00 until 19:00 Monday to Friday if peak hours and from 23:00 until 23:00 of the next day for every single day of the week if base hours. The base and peak forward prices are a composite of Reuters broker contributors. It is assessed by considering the Latest Trade/Tick of the Thomson Reuters Power Composite (TRPC) instruments received from different brokers. All end of day values received from the different brokers are manually checked, validated, and then compared against benchmark sources such as Argus, Platts, and McCloskey. Monthly contracts expire at the end of the month prior to delivery month.[7] Regarding natural gas markets we take the *national balancing point* as the benchmark for the British natural gas market. We use as a spot price, the *system average price* (SAP) provided by the National Grid (the average price of all gas traded via the on-the-day

[7] Thomson-Reuters power TRPC methodology guide.

commodity market (OCM) mechanism for the gas day). The future prices are from Intercontinental Exchange (ICE) and we take the front month contract as the most liquid of all futures contracts.

The electricity data for the Netherlands is from APX (spot prices) and Reuters (futures prices). The day ahead market is based on a two-sided auction model comparing demands and supplies for every hour for next day delivery. Based on these results, APX publishes the APX Index, for base load (average of hourly prices all hours) and for peak load (average of hourly prices from 8:00 until 20:00), on a daily basis. The APX Index can be used as a reference price for spot electricity. The electricity futures are negotiated in ICE ENDEX, the futures contracts are for physical delivery of power to the Dutch high voltage grid. Delivery is made equally each hour throughout the delivery period from 00:00 (CET) on the first day of the month until 24:00 (CET) on the last day of the month if futures base contracts; or from 08:00 (CET) until 20:00 (CET) if peak contracts. Delivery takes place in kilowatt per quarter hour. The end of the day settlement price (EDSP) at which the electricity is delivered will be the end of day Reference Price on the day the contract expires, that is, the last settlement price of the contract period on the expiration day. The reference natural gas market for the Netherlands is the Title Transfer Facility (TTF) hub. As spot price, we take the day ahead price from Platts, since ICE only has data for the day ahead market from 2015. The TTF futures prices are from ICE, and we take the front month contract as the most liquid of all futures contracts.

The electricity data for Germany is from EEX. We use the Phelix Day Base and Phelix Day Peak Indexes as spot references. The index is calculated as the mean value of all auction prices of the hourly contracts traded from 00:00 until 24:00 for all days of the week, if Phelix Day Base Index; and from 08:00 until 20:00, Monday through Friday, for the Phelix Day Peak Index. For futures prices, we take the Phelix month and week future (available also for base and peak load). The Phelix Future is a financial derivative contract whose underlying is the above index, fulfilment is by cash settlement based on the final settlement price on the European commodity clearing business day following the last trading day. Trading participants have the option of arranging the physical delivery of power on the spot market, a constant output of 1 MW into the maximum voltage grid. The natural gas market used as a benchmark for Germany is the TTF because even although Germany has its own natural gas hubs, they are insufficiently liquid to be significant.

Summarising, we have three markets: the UK, the Netherlands, and Germany; with two electricity futures prices, base and peak and one spot price for each, and two natural gas markets (NBP for UK and TTF for the Netherlands and Germany) with one futures and spot price.

Table 1. Data description

Market	Variable	Unit	Source (Spot/Futures)	Period
UK	Electricity base load	GBP/MWh	Reuters/APX	November 2007-February 2016
	Electricity peak load	GBP/MWh	Reuters/APX	November 2004-February 2016
	Gas	pence/therm	Platts/Intercontinental Exchange (ICE)	November 2004-February 2016
	Exchange rate	EUR/GBP	Bank of England	November 2004-February 2016
Netherlands	Electricity base load	EUR/MWh	Datastream/APX	January 2004-April 2016
	Electricity peak load	EUR/MWh	Datastream/APX	May 2009-April 2016
	Gas	EUR/MWh	Platts/Intercontinental Exchange (ICE)	January 2004-April 2016
Germany	Electricity	EUR/MWh	EEX	January 2004-December 2015 (monthly electricity futures) March 2010-December 2015 (weekly electricity futures)
	CO_2-EUAs	EUR/ tonne	EEX/Intercontinental Exchange (ICE)	March 2008-December 2015

The spark spread is computed as electricity prices minus natural gas corrected with some technical adjustments. Following Borovkova (2004) and Borovkova and Geman (2006) the spark spread in the UK (£/MWh) can be computed as the difference between the electricity price (£/MWh) and 0.68 times natural gas futures price (pence/therm).[8] In the Dutch and German markets, the natural gas

[8] The factor 0.68 is obtained by transforming therms to MWh dividing by 0.0293071 (MWh per therm), then dividing by 0.5 (assumed generator efficiency ratio) and transforming pence to pounds by dividing by 100. The full number is 0.6824284. Note that with a contract unit in the NBP natural gas futures represents 1000 therms per day or its equivalent 29,3071 MW per day. For each MWh sold in the electricity market, it is necessary to burn $(1/e)\times(1/0.0293071)$ therms of gas – that is 68.24285 therms using $e = 0.5$ as efficiency ratio. For base load 24 hour electricity contracts it is necessary to burn 25,000 therms to obtain 15 MW each hour if an efficiency ratio of 0.4913 is

price is measured in €/MWh. The underlying asset in the futures contracts correspond to 1 MWh for each hour contained in the delivery period of the contract. In these markets the spark spread is obtained as the electricity price minus two times the natural gas price, supposing an efficiency ratio of 0.5. The efficiency ratio measures how many units of electricity are produced with 1 unit of natural gas in a CCGT plant. When clean spark spread is computed, the spark spread is reduced with the CO2 allowance price corrected with a gas emissions intensity factor. In the three markets, we use the value of 0.38 for the gas emissions intensity factor.[9] Additionally, for the case of the UK, the EU emissions allowance prices are transformed from euros to pounds using the exchange rate obtained from the Bank of England. Furthermore, in the UK the carbon price support is added to the EU emissions allowance price expressed in pounds sterling to obtain the clean spark spread.[10]

Figure 1 shows that spark spreads have become negative in many cases after 2009 because rising renewables, reduced coal and CO2 prices, and low power demand forced down electricity prices and left little room for gas-fired generation in Europe. In this context, it is important to optimise the hedging performance not to incur losses. Charalampous and Madlener (2015) state that natural gas-fired plants are suffering from severe losses since wholesale peak-load electricity prices have plummeted while renewable electricity generation has surged, making hedging in today's energy markets essential for power plant operators (given that many energy companies experience large problems in maintaining profitability).

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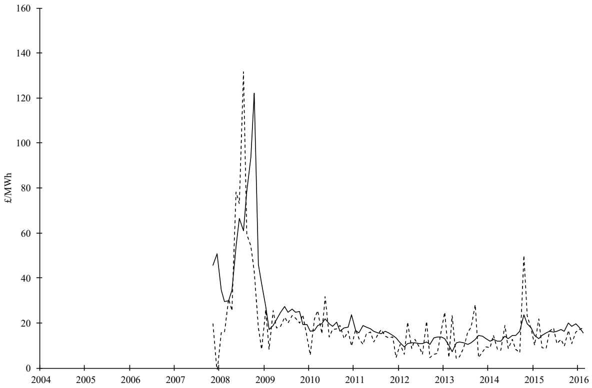
used (25,000/(24×(1/*e*)×(1/0.0293071)) = 15.031). This calculation enables trading the spark spread for contracts containing the same underlying period by taking three positions in electricity contracts for each pack of five natural gas contracts. In the UK, this computation is the way in which agents trade the spark spread in the market. For peak load electricity contracts, the number of contracts must be taken in the proportion of peak hours contained in the whole delivery period – but the spark spread computation procedure will not change.

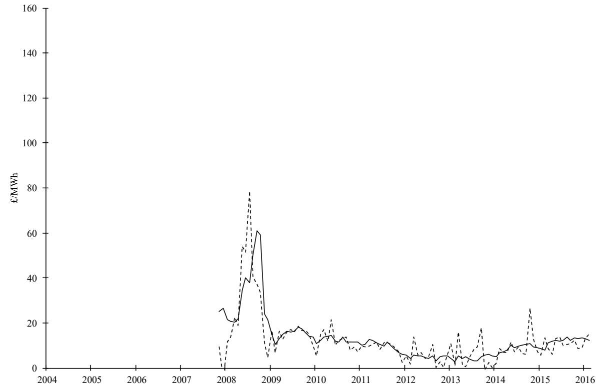
[9] In Abadie and Chamorro (2008) the efficiency ratio for CCGT plants is approximated with values ranging between 50% and 60%. Capitán and Rodríguez (2013) use an efficiency ratio 0.55 and a gas emissions intensity factor of 0.37. We use the same values as Reuters for the efficiency ratio (0.5) and the gas emissions intensity factor (0.38).

[10] The Carbon Price Support (CPS) is a tax that businesses using fossil fuels to generate electricity must pay on those fuels. The cost of the British Government CPS levy in GBP per mega tone of CO2 is 9.55 from 1 April 2014 to 31 March 2015, 18.08 from 1 April 2015 to 31 March 2016 and 18.00 from 1 April 2016 to 31 March 2017.

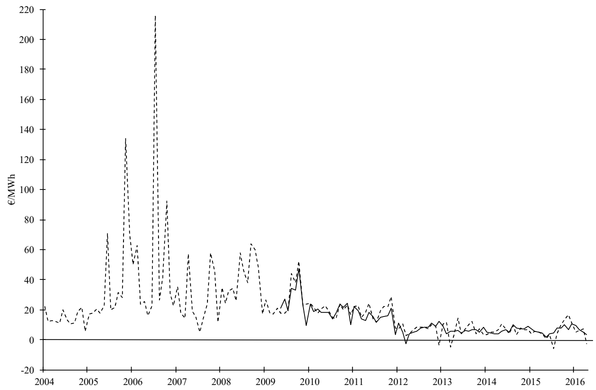
Figure 1. Futures (—) and spot (----) spark spreads.



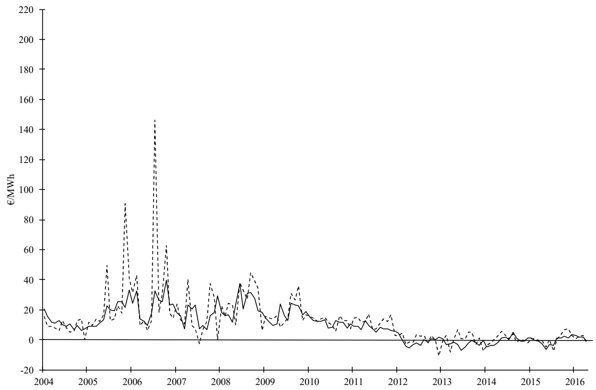
a) UK peak spark spread



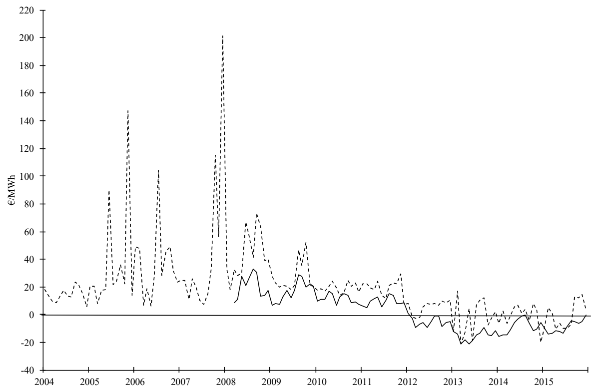
b) UK base spark spread



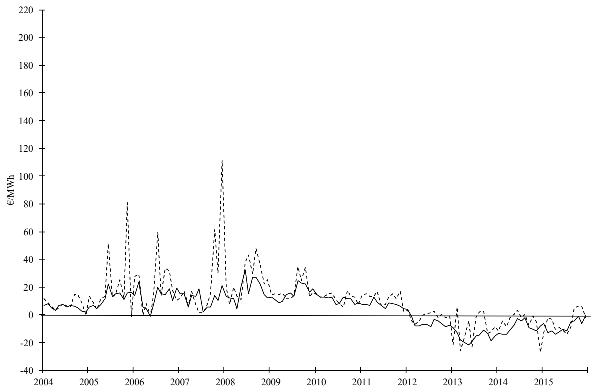
c) Netherlands peak spark spread



d) Netherlands base spark spread



e) Germany peak spark spread



f) Germany base spark spread

Table 2. Standard deviation of the bases

The variables appearing in the heading of each row correspond, respectively, to the basis, that is the futures price minus the spot price, of the following variables: electricity base load; electricity peak load; natural gas; CO2; clean spark spread for the base load; clean spark spread for the peak load; spark spread for the base load and spark spread of the peak load. Data is taken at weekly frequency for the period March 2008 to December 2015.

Basis	UK	Netherlands	Germany
$F_t^{e,base} - S_t^{e,base}$	8.49	5.82	6.67
$F_t^{e,peak} - S_t^{e,peak}$	15.28	4.56	7.93
$F_t^{g} - S_t^{g}$	3.38	1.33	1.19
$F_t^{co2} - S_t^{co2}$	0.19	0.19	0.19
$F_t^{cs,base} - S_t^{cs,base}$	7.51	5.46	6.91
$F_t^{cs,peak} - S_t^{cs,peak}$	14.14	4.67	10.48
$F_t^{s,base} - S_t^{s,base}$	7.51	5.47	6.91
$F_t^{s,peak} - S_t^{s,peak}$	14.14	4.66	10.46

Table 3. Summary statistics of price returns and basis returns of the CO2

Variables appearing in the heading of each column correspond, respectively, to the realised returns of the spot, futures, and basis for CO2. Note that basis is defined as futures price minus spot price. The heading of the last rows symbolises the correlation coefficient between futures and spot returns. Futures returns are obtained considering that rollover in the next front annual contract is done at the end of the year. Data is taken at weekly frequency for the period March 2008 to December 2015.

	ΔS_t^{co2}	ΔF_t^{co2}	$(F_t^{co2} - S_t^{co2}) - (F_{t-1}^{co2} - S_{t-1}^{co2})$
Mean	-0.18	-0.15	-0.01
S.D.	1.50	1.47	0.21
Skewness	-1.30	-1.24	0.04
Excess Kurtosis	0.28	0.29	-1.03
$\rho(\Delta F_t^{co2}, \Delta S_t^{co2})$	0.99		

Is common in the literature to read that when a futures contracts hedge is taken, the spot price risk is exchanged for the basis risk.[11] In Table 2, the basis risk of each commodity is reported. The most important comment on this table comes when volatilities of the bases of the spark spread and clean spark spread are compared. Both variables have almost the same basis risk since up to the second decimal place, volatility values are equal. This is because the introduction of CO2 prices has no effect on the spark spread bases because CO2 futures and spot prices are virtually indistinguishable variables. We also observe in Table 3 that correlation between CO2 spot and futures returns is 0.99 as in Trück and Weron (2016), and that both variables have almost the same statistical properties. From Tables 2 and 3, it can be concluded that the spark basis and the clean spark basis have

[11] The result of a simple naïve hedge can be seen as the subtraction of futures returns to spot returns, $(S_{t+1} - S_t) - (F_{t+1} - F_t)$, or equivalently, as the basis return, $(F_{t+1} - S_{t+1}) - (F_t - S_t) = \Delta Basis_t$. The uncertainty of the hedge result then depends on the uncertainty of the basis at the end of the hedge. That is, the basis risk. See Hull (1997) pages 32 to 35.

virtually the same risk properties. Therefore, the dimensionality of the problem of hedging risk under the minimum variance framework for the clean spark spread can be reduced to hedging the risk of the spark spread. Nevertheless, it must be said that in the minimum variance framework, the return of a hedged strategy is not considered. Consequently, before engaging in a hedging risk strategy, the electricity producer must decide if burning fuel in a CCGT plant is profitable or not. This decision depends on the level of the clean spark spread, and consequently the plant manager needs to buy CO2 futures or spot contracts to ensure the profitability of turning on the plant. A subsequent decision is to reduce the spark spread risk for a specific period by taking positions in the electricity and natural gas futures markets.

Summary statistics for electricity, natural gas, and sparks spreads are reported in Table 4. One common result of all the return time series is the positive excess kurtosis. The skewness sign varies across time series and markets, consequently, no conclusive feature is observed. It is interesting to note that electricity and the spark returns have a similar volatility. This result may imply that the main source of uncertainty in the spark spread seems to come from electricity price spikes. Finally, from the comparison between each pair of spot and futures return volatility, it can be observed that in 28 out of 30 cases, spot return volatility is larger than futures return volatility.

Correlations are reported in Table 5. The highest values of the correlation between spot and futures pairs correspond to natural gas, with correlation values ranging between 0.55 and 0.62. For electricity and spark spreads spot-futures pairs, we have lower values: between 0.10 and 0.30 for weekly frequency and between 0.26 and 0.55 for monthly frequency. It is then crucial for hedging purposes to increase the hedging period, especially for electricity and spark spread risk management. Another interesting result comes when correlations between futures returns of natural gas and electricity base load are observed. In monthly frequency (Panels E, F, and G) this correlation has values of between 0.57 and 0.78; and in weekly frequency (Panels A, B, and C) it

Table 4. Summary statistics of price returns

The ten variables appearing in the heading of each column correspond, respectively, to the realised returns of the following prices: electricity peak load spot; electricity peak load futures; electricity base load spot; electricity base load futures; natural gas spot; natural gas futures; spot peak load spark spread; futures peak load spark spread; spot base load spark spread and futures base load spark spread.

Panel A. One week variations. UK.

	Electricity				Natural Gas		Spark Spread			
	$\Delta S_t^{e,peak}$	$\Delta F_t^{e,peak}$	$\Delta S_t^{e,base}$	$\Delta F_t^{e,base}$	ΔS_t^{g}	ΔF_t^{g}	$\Delta S_t^{s,peak}$	$\Delta F_t^{s,peak}$	$\Delta S_t^{s,base}$	$\Delta F_t^{s,base}$
Mean	-0.0820	-0.1773	-0.0434	-0.2004	-0.0600	-0.4446	-0.0412	0.1250	-0.0026	0.1019
S.D.	8.4190	4.2775	5.7225	2.8098	4.5461	2.3161	8.3674	4.1064	5.8468	2.5858
Skewness	-0.7086	-2.7216	-0.7326	-2.1702	-0.5316	-0.3422	-0.3386	-0.9092	-0.1354	0.3972
Excess Kurtosis	8.6899	42.9220	10.4136	29.1232	8.2866	2.6373	6.2070	42.9726	5.6145	36.8345
Panel B. One week variations. Netherlands.										
Mean	-0.0329	-0.4253	-0.0152	-0.3264	0.0043	-0.1588	-0.0483	-0.2573	-0.0238	-0.0089
S.D.	5.0101	3.0810	9.3041	2.5254	1.9548	0.9382	5.2070	2.8538	9.3158	2.3000
Skewness	1.0351	-0.5919	0.6853	0.1451	-0.3385	-0.2941	0.7815	-1.0190	0.6732	0.9433
Excess Kurtosis	14.4183	14.2115	13.0742	4.9142	25.8294	2.6949	11.4026	16.916	10.9578	6.8641
Panel C. One week variations. Germany.										
Mean	-0.0517	-0.2258	-0.0428	-0.3177	0.0065	-0.0728	-0.0630	-0.0806	-0.0558	-0.1722
S.D.	6.1352	4.8144	5.9784	3.6037	1.0827	0.7120	6.4357	4.3023	6.2325	3.1490
Skewness	-0.1823	-0.0534	-1.3282	-0.6636	0.0639	0.1324	-0.1185	-0.1093	-1.0178	-0.8061
Excess Kurtosis	4.6578	3.4092	11.4195	4.6611	5.5599	1.9377	4.6963	3.4761	8.7927	4.9237
Panel D. One month variations. UK.										
Mean	-0.3048	-0.6911	-0.1641	-0.8849	-0.1806	-1.7869	-0.1820	0.5240	-0.0413	0.3301
S.D.	7.0149	7.6105	5.4680	5.0392	6.0925	4.9154	5.7031	6.5098	4.3768	3.6865
Skewness	0.0601	-2.8583	0.3746	-2.3622	-0.4388	-0.5398	0.3232	-1.6235	0.5855	-0.5912
Excess Kurtosis	3.3801	21.9359	3.8945	16.543	7.0572	1.6742	3.3137	17.8530	2.9788	14.7833
Panel E. One month variations. Netherlands.										
Mean	-0.1062	-1.9034	0.8798	-2.1526	0.2321	-0.7288	-0.1434	-1.1351	-0.0601	-0.0393
S.D.	5.8143	5.5026	12.0543	8.3805	3.0897	2.5794	6.2940	4.7429	9.2318	5.0642
Skewness	0.1646	-0.7869	-0.1496	-0.0379	-0.4187	-0.7642	0.5746	-0.3462	0.0725	0.4477
Excess Kurtosis	1.2588	3.3061	0.2204	0.0684	0.6843	0.9798	2.9214	3.8289	3.4044	3.0555
Panel F. One month variations. Germany.										
Mean	0.011	-1.8905	0.004	-1.0206	0.0178	-0.7052	-0.0246	-0.4801	-0.0317	0.3899
S.D.	10.2835	8.4325	7.6476	5.1254	2.9268	2.2479	10.7682	7.4066	8.7126	4.6006
Skewness	0.6787	-0.1181	0.4249	-0.0846	-0.513	-1.1008	0.2441	0.2506	0.1339	0.0522
Excess Kurtosis	2.3577	2.6059	1.4149	1.6097	3.6752	2.7173	1.8969	3.0198	1.3354	1.5544

Table 5. Correlation matrix of the spot, futures and spark spread realised returns

For a sample size of T observations, the asymptotic distribution of the $\sqrt{T}$ times the correlation coefficient is a zero-one normal distribution. Those coefficients not significantly different to zero at 5% of significance level are marked with an asterisk (*). The variables appearing in the heading of each row and columns are described in Table 4.

	$\Delta S_t^{e,peak}$	$\Delta F_t^{e,peak}$	$\Delta S_t^{e,base}$	$\Delta F_t^{e,base}$	ΔS_t^{g}	ΔF_t^{g}	$\Delta S_t^{s,peak}$	$\Delta F_t^{s,peak}$	$\Delta S_t^{s,base}$	$\Delta F_t^{s,base}$
Panel (A). One-week variations. UK.										
$\Delta S_t^{e,peak}$	1,00									
$\Delta F_t^{e,peak}$	0.29	1.00								
$\Delta S_t^{e,base}$	0.97	0.32	1.00							
$\Delta F_t^{e,base}$	0.26	0.92	0.30	1.00						
ΔS_t^{g}	0.20	(*)0.08	0.23	0.17	1.00					
ΔF_t^{g}	0.25	0.29	0.26	0.42	0.53	1.00				
$\Delta S_t^{s,peak}$	0.93	0.26	0.90	0.20	-0.17	0.06	1.00			
$\Delta F_t^{s,peak}$	0.20	0.93	0.23	0.79	-0.13	(*)-0.09	0.25	1.00		
$\Delta S_t^{s,base}$	0.85	0.27	0.86	0.20	-0.30	(*)-0.02	0.96	0.29	1.00	
$\Delta F_t^{s,base}$	0.12	0.82	0.16	0.83	-0.14	-0.16	0.18	0.91	0.23	1.00
Panel (B). One-week variations. Netherlands.										
$\Delta S_t^{e,peak}$	1.00									
$\Delta F_t^{e,peak}$	0.10	1.00								
$\Delta S_t^{e,base}$	0.98	0.08	1.00							
$\Delta F_t^{e,base}$	0.21	0.22	0.22	1.00						
ΔS_t^{g}	0.19	0.11	0.21	0.24	1.00					
ΔF_t^{g}	0.06	0.19	0.08	0.50	0.55	1.00				
$\Delta S_t^{s,peak}$	0.95	(*) 0.07	0.93	0.14	-0.11	-0.11	1.00			
$\Delta F_t^{s,peak}$	(*) 0.05	0.81	0.03	(*)-0.10	-0.23	-0.43	0.13	1.00		
$\Delta S_t^{s,base}$	0.90	(*) 0.03	0.91	0.12	-0.21	-0.16	0.98	0.13	1.00	
$\Delta F_t^{s,base}$	0.18	(*) 0.08	0.18	0.70	-0.20	-0.28	0.25	0.24	0.26	1.00
Panel (C). One-week variations. Germany										
$\Delta S_t^{e,peak}$	1.00									
$\Delta F_t^{e,peak}$	0.28	1.00								
$\Delta S_t^{e,base}$	0.94	0.27	1.00							
$\Delta F_t^{e,base}$	0.27	0.95	0.30	1.00						
ΔS_t^{g}	(*) 0.08	0.34	(*) 0.06	0.34	1.00					
ΔF_t^{g}	0.14	0.49	0.12	0.50	0.62	1.00				
$\Delta S_t^{s,peak}$	0.93	0.16	0.88	0.15	-0.27	(*)-0.07	1.00			
$\Delta F_t^{s,peak}$	0.27	0.96	0.26	0.90	0.18	0.22	0.21	1.00		
$\Delta S_t^{s,base}$	0.88	0.14	0.94	0.17	-0.29	(*)-0.10	0.94	0.19	1.00	
$\Delta F_t^{s,base}$	0.25	0.87	0.29	0.92	(*) 0.10	0.12	0.21	0.93	0.24	1.00

Table 5. Correlation matrix of the spot, futures and spark spread realised returns (cont.)

For a sample size of T observations, the asymptotic distribution of the $\sqrt{T}$ times the correlation coefficient is a zero-one normal distribution. Those coefficients not significantly different to zero at 5% of significance level are marked with an asterisk (*). The variables appearing in the heading of each row and columns are described in Table 4.

Panel (E). One-month variations. UK.

	$\Delta S_t^{e,peak}$	$\Delta F_t^{e,peak}$	$\Delta S_t^{e,base}$	$\Delta F_t^{e,base}$	ΔS_t^{g}	ΔF_t^{g}	$\Delta S_t^{s,peak}$	$\Delta F_t^{s,peak}$	$\Delta S_t^{s,base}$	$\Delta F_t^{s,base}$
$\Delta S_t^{e,peak}$	1.00									
$\Delta F_t^{e,peak}$	0.39	1.00								
$\Delta S_t^{e,base}$	0.96	0.45	1.00							
$\Delta F_t^{e,base}$	0.47	0.93	0.55	1.00						
ΔS_t^{g}	0.58	0.22	0.62	0.40	1.00					
ΔF_t^{g}	0.50	0.52	0.53	0.69	0.57	1.00				
$\Delta S_t^{s,peak}$	0.81	0.32	0.74	0.29	(*)-0.01	0.20	1.00			
$\Delta F_t^{s,peak}$	(*) 0.18	0.89	0.24	0.72	(*)-0.05	(*) 0.07	0.26	1.00		
$\Delta S_t^{s,base}$	0.65	0.36	0.67	0.32	(*)-0.18	(*) 0.13	0.93	0.35	1.00	
$\Delta F_t^{s,base}$	(*) 0.17	0.79	0.25	0.72	(*) 0.00	(*)-0.01	0.21	0.93	0.31	1.00

Panel (F). One-month variations. Netherlands.

	$\Delta S_t^{e,peak}$	$\Delta F_t^{e,peak}$	$\Delta S_t^{e,base}$	$\Delta F_t^{e,base}$	ΔS_t^{g}	ΔF_t^{g}	$\Delta S_t^{s,peak}$	$\Delta F_t^{s,peak}$	$\Delta S_t^{s,base}$	$\Delta F_t^{s,base}$
$\Delta S_t^{e,peak}$	1.00									
$\Delta F_t^{e,peak}$	0.46	1.00								
$\Delta S_t^{e,base}$	0.92	0.38	1.00							
$\Delta F_t^{e,base}$	0.45	0.65	0.50	1.00						
ΔS_t^{g}	0.34	0.33	0.28	0.43	1.00					
ΔF_t^{g}	0.42	0.55	0.43	0.78	0.61	1.00				
$\Delta S_t^{s,peak}$	0.65	0.16	0.62	0.07	-0.50	(*)-0.11	1.00			
$\Delta F_t^{s,peak}$	0.27	0.84	0.17	0.27	(*)-0.01	(*) 0.00	0.26	1.00		
$\Delta S_t^{s,base}$	0.41	(*) 0.00	0.52	(*) 0.00	-0.67	-0.21	0.92	(*) 0.13	1.00	
$\Delta F_t^{s,base}$	(*) 0.09	0.23	(*) 0.15	0.43	-0.22	-0.23	0.25	0.42	0.31	1.00

Panel (G). One-month variations. Germany

	$\Delta S_t^{e,peak}$	$\Delta F_t^{e,peak}$	$\Delta S_t^{e,base}$	$\Delta F_t^{e,base}$	ΔS_t^{g}	ΔF_t^{g}	$\Delta S_t^{s,peak}$	$\Delta F_t^{s,peak}$	$\Delta S_t^{s,base}$	$\Delta F_t^{s,base}$
$\Delta S_t^{e,peak}$	1,00									
$\Delta F_t^{e,peak}$	0,49	1,00								
$\Delta S_t^{e,base}$	0,97	0,46	1,00							
$\Delta F_t^{e,base}$	0,49	0,96	0,49	1,00						
ΔS_t^{g}	0,20	0,45	0,19	0,45	1,00					
ΔF_t^{g}	(*) 0,14	0,51	0,17	0,57	0,55	1,00				
$\Delta S_t^{s,peak}$	0,85	0,23	0,83	0,23	-0,35	-0,17	1,00			
$\Delta F_t^{s,peak}$	0,49	0,84	0,43	0,76	0,17	(*)-0,04	0,37	1,00		
$\Delta S_t^{s,base}$	0,72	(*) 0,10	0,75	(*) 0,12	-0,51	-0,22	0,96	0,26	1,00	
$\Delta F_t^{s,base}$	0,42	0,57	0,38	0,55	(*)-0,05	-0,37	0,43	0,90	0,37	1,00

takes values between 0.42 and 0.50. Consequently, these commodities are closely related. This fact is especially clear for monthly returns in the UK as the natural gas returns and all the electricity returns have correlation values between 0.50 and 0.69. Therefore, natural gas prices have an important pricing role in the electricity market. This is an expected result, as natural gas is the most import fuel source of the generation mix in the UK electricity market. As expected, the correlation between natural gas return and the spark spread return is negative in most cases and not significant in many cases. Finally, for electricity and spark spread, the correlation between base and peak load returns is very high, especially for the pair of futures and for the pair of spot returns, with values of about 0.90 in most cases. Nevertheless, each of these futures contracts with its underlying asset has a lower correlation. For example, for monthly returns, electricity futures and the underlying assets have correlations ranging between 0.39 and 0.50, with the highest values corresponding to base load pairs. The spark spreads futures-spot correlation is lower with values ranging between 0.26 and 0.37. Taking this information into account, one would expect that a successful hedge in the spark spread will be much more difficult than hedging risk with futures separately in the electricity or natural gas markets.

Weekly returns cross-lagged correlations are displayed in Table 6. In the previous paragraph, we have seen that simultaneous correlation between natural gas returns and electricity returns are high in many cases, particularly in the case of natural gas futures and base load futures. Now in Table 6, we want to examine the dynamics of this relationship computing one-week cross-lagged correlation coefficients. The highest and most significant values correspond to the first and second rows of this table. That is, an increase (decrease) in natural gas price will probably be followed by an increase (decrease) in electricity prices. The wholesale gas price and the wholesale electricity price broadly move together, as for much of the year gas-fired generation is the marginal plant and therefore sets the wholesale electricity price (UK Government, 2012). The high values of simultaneous and cross-lagged correlation between electricity and natural gas returns point to a significant degree of price shock transfer from natural gas to electricity. As we have discussed in the previous section, in the case of a perfect price shock transfer between both commodities, CCGT plants producing electricity would enjoy a natural hedge and not need to take positions in futures markets.

Table 6. Weekly cross-lagged correlations between natural gas and electricity returns

The first-order cross-correlation coefficient between two standardised data series x and y is estimated as $\rho(x_t, y_{t-1}) = \sum x_t y_{t-1} / \sqrt{\sum x_t^2 \sum y_t^2}$ of y with respect x. For a sample size of T observations, the asymptotic distribution of the $\sqrt{T}$ times the cross-correlation coefficient is a zero-one normal distribution, that is $\sqrt{T}\rho(x_t, y_{t-k}) \rightarrow AN(0,1)$ (see Cheung and Ng (1996) for more details). *, ** and ***, indicates significance at the 1%, 5% and 10% levels, respectively. The variables appearing in the heading of each row are described in Table 4.

	UK	***Netherlands***	***Germany***
$\rho(\Delta S_t^{e,base}, \Delta S_{t-1}^{g})$	*0.31	*0.18	*0.29
$\rho(\Delta S_t^{e,peak}, \Delta S_{t-1}^{g})$	*0.25	*0.15	*0.31
$\rho(\Delta F_t^{e,base}, \Delta S_{t-1}^{g})$	0.07	**0.09	0.05
$\rho(\Delta F_t^{e,peak}, \Delta S_{t-1}^{g})$	0.04	0.04	0.09
$\rho(\Delta S_t^{e,base}, \Delta F_{t-1}^{g})$	*0.14	*0.18	**0.12
$\rho(\Delta S_t^{e,peak}, \Delta F_{t-1}^{g})$	***0.09	*0.17	**0.14
$\rho(\Delta F_t^{e,base}, \Delta F_{t-1}^{g})$	0.07	0.12	-0.09
$\rho(\Delta F_t^{e,peak}, \Delta F_{t-1}^{g})$	0.06	0.06	-0.06
$\rho(\Delta S_t^{g}, \Delta S_{t-1}^{e,base},)$	*-0.17	-0.01	-0.04
$\rho(\Delta S_t^{g}, \Delta S_{t-1}^{e,peak})$	*-0.14	0.00	-0.06
$\rho(\Delta S_t^{g}, \Delta F_{t-1}^{e,base})$	*-0.14	**0.08	0.03
$\rho(\Delta S_t^{g}, \Delta F_{t-1}^{e,peak})$	**-0.13	-0.01	0.06
$\rho(\Delta F_t^{g}, \Delta S_{t-1}^{e,base},)$	-0.02	0.02	0.03
$\rho(\Delta F_t^{g}, \Delta S_{t-1}^{e,peak})$	-0.03	0.03	-0.01
$\rho(\Delta F_t^{g}, \Delta F_{t-1}^{e,base})$	-0.08	***0.07	-0.04
$\rho(\Delta F_t^{g}, \Delta F_{t-1}^{e,peak})$	**-0.10	-0.05	-0.06

4. Results

Ederington and Salas (2008) demonstrated that when spot price returns are partially predictable, the standard method of estimating hedging ratios based on Ederington (1979) is inefficient and the risk reduction obtained with the hedge is underestimated. To overcome these problems, Ederington and Salas (2008) propose approximating the expected spot return using the lagged value of the basis (see Section 2). Before applying this methodology, it is necessary to measure the predictive power of the basis on returns, particularly in the spot case. Results are reported in Table 7. For the Netherlands and Germany, lagged values of the basis explain between 17 and 60 per cent of subsequent spot returns and they have a much lower explicative power for futures returns. Moreover, the determination coefficients are higher in spot returns than in forward returns in all cases. This result agrees with Borovkova and Geman (2006) and Lucia and Schwartz (2002) when they state that seasonal patterns in spot prices and the forward curve should be significantly different.

As in most energy commodities, a seasonal feature is expected for the spark spread (see Borovkova and Geman (2006)). It is important to highlight that with the exception of the peak spark spread return for the UK, in the remaining cases, spark returns can be explained by the lagged values of their bases with determination coefficients ranging between 16.18 and 54.14 per cent. If the objective of the risk manager is to reduce the uncertainty of unexpected changes in the spark spread using futures, the expected changes must be separated from the total changes in the spark spread risk measure. This result is new in the literature and is very relevant for the design and performance measure of hedging strategies using futures contracts. The reason for the existence of these forecastable pattern in the spark spread comes from the existence of seasonal patterns in energy commodity demand due to climate oscillation throughout the year. Previous results in Torró (2011) and Martinez and Torró (2015) confirm the existence of this feature in European electricity and natural gas markets, but this is the first time it is found in spark spreads.

Table 7. The basis as a predictor of spot, futures, and spark spread returns.

This table reports the results for the whole sample period of the regression between energy price changes appearing in the first column on the corresponding basis value at the beginning of the time interval appearing in the second column. The variables appearing in the first and second columns are described in Table 4. Between brackets *t*-statistic values computed with Newey-West standard errors are reported. Significant coefficients at 1%, 5% and 10% of significance level are highlighted with one (*), two (**) and three (***) asterisks, respectively.

Panel A. Netherlands.

		Weekly returns			Monthly returns		
Dependent variable	Basis	Intercept	Basis coefficient	Adjusted R^2	Intercept	Basis coefficient	Adjusted R^2
$\Delta S_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	-0.13 (-0.55)	0.55 (6.64)*	29.39%	0.47 (1.29)	0.64 (3.35)*	30.47%
$\Delta F_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	-0.43 (-2.89)*	0.04 (0.68)	0.47%	-1.87 (-3.27)*	0.03 (0.33)	0.08%
$\Delta S_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.31 (-1.75)***	0.35 (7.92)*	17.58%	-0.84 (-1.35)	0.62 (5.14)*	24.32%
$\Delta F_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.09 (-1.11)	-0.05 (-2.33)**	2.32%	-1.01 (-1.98)**	-0.33 (-3.97)*	12.19%
ΔS_t^{g}	$F_t^{g} - S_t^{g}$	-0.01 (-0.20)	0.23 (2.37)**	5.95%	-0.23 (-0.99)	0.94 (6.42)*	22.96%
ΔF_t^{g}	$F_t^{g} - S_t^{g}$	-0.07 (-1.93)***	-0.12 (-3.79)*	4.19%	-0.61 (-2.65)*	-0.34 (-1.64)***	5.44%
$\Delta S_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	-0.04 (-0.22)	0.66 (8.01)*	35.56%	0.55 (1.61)	0.75 (5.69)*	44.43%
$\Delta F_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	-0.26 (-1.99)**	0.07 (1.12)	1.29%	-1.03 (-1.97)**	0.11 (1.61)	1.71%
$\Delta S_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	-0.45 (-1.26)	0.52 (6.21)*	24.63%	-0.72 (-1.22)	0.86 (8.19)*	39.21%
$\Delta F_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	0.02 (0.22)	-0.03 (-2.38)*	1.86%	0.07 (0.17)	-0.15 (-2.33)**	3.75%

Panel B. Germany.

$\Delta S_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	-3.18 (-9.88)*	0.68 (11.78)*	60.68%	-4.78 (-5.36)*	0.63 (4.82)*	29.20%
$\Delta F_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	-0.36 (-0.85)	0.03 (0.45)	0.19%	-0.34 (-0.41)	-0.20 (-1.67)***	4.53%
$\Delta S_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.27 (-1.39)	0.79 (9.58)*	59.78%	-1.33 (-3.21)*	0.89 (6.81)*	43.52%
$\Delta F_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.32 (-1.56)	0.01 (0.10)	0.01%	-0.86 (-1.87)***	-0.11 (-0.98)	1.42%
ΔS_t^{g}	$F_t^{g} - S_t^{g}$	-0.01 (-0.09)	0.19 (2.19)**	4.98%	-0.19 (-0.85)	0.91 (6.12)*	20.45%
ΔF_t^{g}	$F_t^{g} - S_t^{g}$	-0.06 (-1.60)	-0.14 (-4.41)*	5.45%	-0.61 (-2.64)*	-0.39 (-1.98)**	6.61%
$\Delta S_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	-2.85 (-8.27)*	0.62 (10.64)*	51.31%	-5.75 (-7.26)*	0.80 (8.35)*	42.78%
$\Delta F_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	-0.23 (-0.65)	0.03 (0.66)	0.36%	0.14 (0.19)	-0.09 (-0.97)	1.05%
$\Delta S_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	-0.18 (-0.72)	0.73 (9.34)*	52.51%	-1.13 (-2.54)**	1.07 (13.07)*	54.14%
$\Delta F_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	-0.17 (-0.93)	0.01 (0.14)	0.02%	0.43 (1.00)	-0.04 (-0.71)	0.32%

Panel B. United Kingdom.

$\Delta S_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	-0.79 (-2.19)**	0.17 (1.42)	5.84%	-0.66 (-1.12)	0.09 (0.57)	1.62%
$\Delta F_t^{e,peak}$	$F_t^{e,peak} - S_t^{e,peak}$	0.16 (0.82)	-0.08 (-1.53)	5.17%	0.66 (0.69)	-0.33 (-1.99)**	19.48%
$\Delta S_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.44 (-2.6)*	0.26 (1.87)***	8.85%	-0.52 (-1.36)	0.25 (0.96)	5.62%
$\Delta F_t^{e,base}$	$F_t^{e,base} - S_t^{e,base}$	-0.04 (-0.32)	-0.10 (-1.88)***	5.96%	-0.47 (-0.81)	-0.29 (-1.20)	8.75%
ΔS_t^{g}	$F_t^{g} - S_t^{g}$	-0.21 (-1.03)	0.32 (3.59)*	10.46%	-0.32 (-0.57)	0.52 (1.54)	9.48%
ΔF_t^{g}	$F_t^{g} - S_t^{g}$	-0.39 (-3.49)*	-0.10 (-4.69)*	4.29%	-1.66 (-2.71)*	-0.44 (-2.69)*	10.29%
$\Delta S_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	-0.91 (-2.39)**	0.22 (1.59)	8.17%	-0.65 (-1.66)***	0.12 (0.83)	3.67%
$\Delta F_t^{s,peak}$	$F_t^{s,peak} - S_t^{s,peak}$	0.38 (2.11)**	-0.06 (-1.12)	2.86%	1.19 (1.59)	-0.17 (-0.93)	5.62%
$\Delta S_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	-0.53 (-3.58)*	0.43 (2.94)*	16.18%	-0.56 (-2.53)**	0.43 (2.24)**	19.83%
$\Delta F_t^{s,base}$	$F_t^{s,base} - S_t^{s,base}$	0.20 (1.74)***	-0.08 (-1.61)	2.94%	0.29 (0.90)	0.03 (0.18)	0.12%

Tables 8 to 17 show the hedging effectiveness analysis of the strategies presented in Section 2. The five assets considered are the spark spread for the base and peak load, electricity for the base and peak load, and natural gas. In each of the above cases, weekly (Tables 8, 9, 12, 13 and 14) and monthly data frequency results are reported (Tables 10, 11, 15, 16 and 17). We considered electricity and natural gas separately because it is important information and it is not obvious that a successful separated hedging strategy for electricity and natural gas will produce a successful hedge of the spark spread.

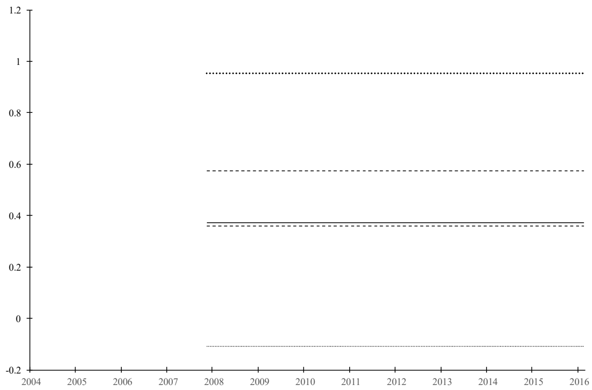
We first discuss results corresponding to the spark spreads. Figure 2 reports the hedging ratios estimated as described in Section 2 for the spark spreads for a monthly frequency. The sample period is divided into *ex post* and *ex-ante* sub-periods when the number of observations is sufficiently large. With the exception of the natural gas hedging ratio in Figure 2-a (when it is jointly estimated), all the hedging ratios are positive. It is also interesting to note hedging ratios in electricity futures when estimated jointly (case 1) or restricted (case 3), as both hedge ratios are almost equal in all the cases. This fact indicates that the optimal least squares method prioritises the electricity hedging ratio to minimise estimation errors because of electricity jumps. Looking at the best performing strategies marked with an asterisk in Tables 8 to 11, we cannot point out a hedging strategy that dominates the risk reduction achieved. The best performing hedging strategy changes across markets, periods, and data frequency. Looking at best performing strategies in each panel, we can say that risk reduction is underestimated with the conventional framework. Under the Ederington and Salas (2008) framework, risk reduction really attained improvements of between 1% and 18% in weekly hedges and between 7% and 27% in the monthly hedges. The worst results for the spark spread risk reduction correspond to the UK. In the case of the peak load spark spread at weekly frequency appearing in Panel A in Table 8, it can be observed that in the out-of-sample period no hedging strategy produces a risk reduction. In this case, it is best to leave the spot position unhedged. Monthly hedges for the UK case significantly improve the attained risk reduction. In this case, the optimal hedging strategies obtain a risk reduction of 20.05 and 25.05 per cent for the base and peak load spark spreads, respectively. Results for the Netherlands and Germany are much better. The risk reduction reached for optimal weekly hedges varies between 16.38 and 34.75 per cent. In monthly hedges in these two countries, the risk reduction can attain values ranging between 28.92 and 48.90 per cent. To sum up, the main result for the spark spread are: (i) monthly hedges obtain a better hedging performance than weekly hedges; (ii) there is no clear hedging strategy that clearly dominates the remaining strategies; (iii) results for Germany and the Netherlands are much better than the results for the UK; (iv) the best performing monthly hedging strategies can attain risk reductions ranging between 20.05 and 48.90.

To better understand spark spread hedging results we have extended the hedging analysis to individual hedges of electricity (peak and base load) and natural gas prices. Results for electricity are similar to spark spread results, see Tables 12 and 13. Weekly hedges for electricity produce poor results, and in one case even increase the risk after hedging (see Panel A in Table 13). Nevertheless, excellent results are obtained in monthly hedges, especially in the base load case. In this case (see Table 15), the risk reduction produces values ranging between 48.69 and 60.35 per cent. For the peak load case (see Table 16), these values range between 31.22 and 55.89. Electricity hedges must then be made for long periods, otherwise the result can be the opposite of what was expected.

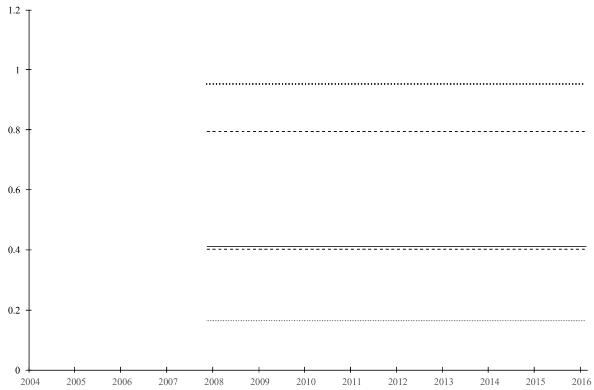
Finally, hedging results for weekly and monthly periods of the natural gas price are reported in Tables 14 and 17, respectively. Risk reduction for weekly and monthly periods are above 41.19 and 56.44 per cent, respectively. Therefore, compared with spark spread and electricity, natural gas price risk is the easiest to hedge.

Figure 2. Monthly spark spreads hedging ratios

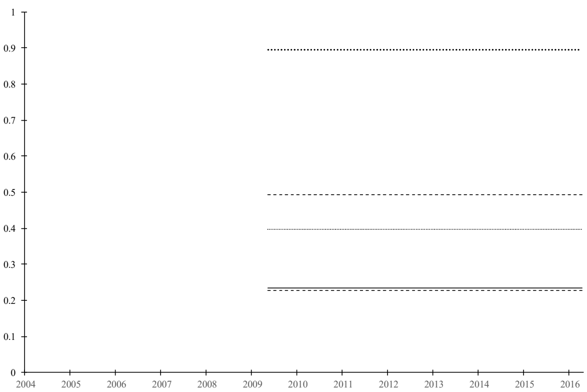
Following Ederington and Salas (2008), the estimated hedging ratios for electricity and natural gas futures corresponding to the following three cases are shown: (1) β_t^e (---) and ($\cdots$) β_t^g are jointly obtained, (2) β_t^e (---) and β_t^g ($\cdots$) are separately obtained in each market as independent problems, and (3) $\beta_t^e = \beta_t^g = \beta_t$ (—), jointly obtained but restricted to be equal.



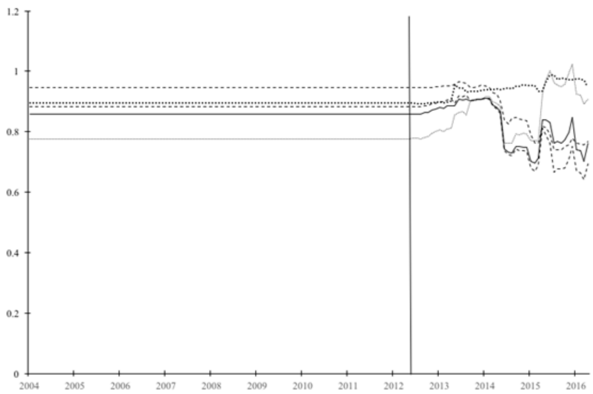
a) UK peak spark spread



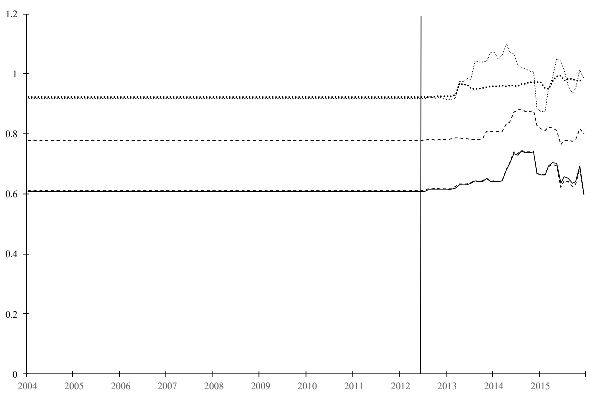
b) UK base spark spread



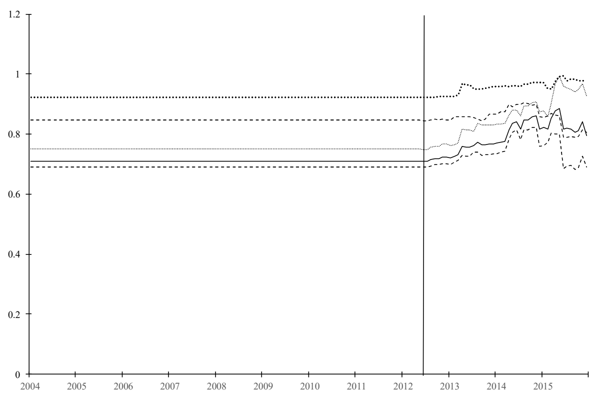
c) Netherlands peak spark spread



d) Netherlands base spark spread



e) Germany peak spark spread



f) Germany base spark spread

Table 8. Hedging effectiveness in weekly hedges. Peak spark prices.

This table displays the risk reduction achieved by each hedging strategy described in Section 2. The *in-sample* results are computed for the first five years and then a moving window of five years is used to compute the *out-of-sample* results. In the second row of each panel, the unhedged spot position variance is reported and constitutes the base for calculating the risk reduction achieved with each hedging strategy. This variance is computed as $VAR[\Delta S_t]$ and $VAR\left[\Delta S_t - \hat{\lambda}(F_t - S_t)\right]$ in the 'standard' and Ederington and Salas (2008) approaches, respectively. The variance of each hedging strategy is computed with equations (2) and (5) in the standard and 'E&S(2008)' approaches, respectively. *Ex-ante* hedging ratios for the period [t–1,t] are estimated using the information available until t–1, and the model is estimated again each time the moving window sample moves ahead. Those strategies with the largest risk reduction in each panel are indicated with an asterisk (*).

Hedging strategy		**In the sample**		**Out of the sample**	
		Standard approach	E&S (2008) approach	Standard approach	E&S (2008) approach
		Panel (A). Hedging one-week spot risk in UK			
	Period	Nov. 14th, 2007 – Nov. 7th, 2012		Nov. 14th, 2012 – Feb. 10th, 2016	
$\beta_t^e = \beta_t^g = 0$	Spot variance	100.58	94.30	24.48	17.87
		Risk reduction (%)		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		2.00	8.15	-10.40	-12.02
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	7.69	11.44	-3.85	-2.37*
	with basis	7.40	11.76	-4.71	-4.46
β_t^e and β_t^e separately	w/o basis	5.19	7.72	-4.61	-3.08
	with basis	3.71	7.06	-5.13	-5.36
β_t^e and β_t^e jointly	w/o basis	8.67	13.36	-4.16	-2.64
	with basis	8.40	13.70	-12.96	-14.56
		Panel (B). Hedging one-week spot risk in Netherlands			
		May. 6th, 2009 – Apr. 23th, 2014		Apr. 30th, 2014 – Apr. 27th, 2016	
$\beta_t^e = \beta_t^g = 0$		32.19	20.55	14.76	9.76
		Risk reduction (%)		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		-10.72	5.47	9.63	12.85
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	9.36	15.39	4.97	8.41
	with basis	8.18	16.53	6.49	7.98
β_t^e and β_t^e separately	w/o basis	10.40	18.36	11.38	13.03
	with basis	8.02	18.22	12.06	10.40
β_t^e and β_t^e jointly	w/o basis	19.24	30.73	10.58	16.46*
	with basis	18.44	30.88*	10.85	16.02

		Panel (C). Hedging one-week spot risk Germany	
	Period	Mar. 24th, 2010 – Dec. 28th, 2015	
$\beta_t^e = \beta_t^g = 0$	Spot variance	41.42	20.17
		Risk reduction (%)	
$\beta_t^e = \beta_t^g = 1$		-1.42	-5.40
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	-16.59	-45.65
	with basis	4.42	5.42
β_t^e and β_t^e separately	w/o basis	6.09	10.85
	with basis	5.84	11.59
β_t^e and β_t^e jointly	w/o basis	16.52	32.45
	with basis	16.23	33.02*

Table 9 Hedging effectiveness in weekly hedges. Base spark prices.
This table is similar to Table 8, but uses base load prices for electricity.

		In the sample		Out of the sample	
		Standard approach	E&S (2008) approach	Standard approach	E&S (2008) approach
Panel (A). Hedging one-week spot risk in UK					
Hedging strategy	Period	Jan. 7th, 2004 – Nov. 7th, 2012		Nov. 14th, 2012 – Feb. 10th, 2016	
$\beta_t^e = \beta_t^g = 0$	Spot variance	46.94	40.86	15.21	9.57
		Risk reduction (%)		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		1.71	10.78	-1.20	1.09
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	6.71	12.44	0.20	2.08
	with basis	6.08	13.17	-0.46	1.04
β_t^e and β_t^e separately	w/o basis	4.05	8.55	1.42	2.43
	with basis	2.01	7.69	1.20	4.31
β_t^e and β_t^e jointly	w/o basis	6.91	12.90	2.73	4.52*
	with basis	6.22	13.68	1.96	3.60
Panel (B). Hedging one-week spot risk in Netherland					
	Period	Jan. 7th, 2004 – Dec. 30th, 2008		Jan. 7th, 2008 – Apr. 27th, 2016	
$\beta_t^e = \beta_t^g = 0$	Spot variance	187.09	141.14	17.94	13.83
		Risk reduction (%)		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		7.31	14.64	3.98	9.71
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	7.44	15.56	3.52	8.59
	with basis	6.81	16.38*	-0.24	7.40
β_t^e and β_t^e separately	w/o basis	7.83	15.23	10.35	23.64*
	with basis	7.67	16.37	5.40	20.62
β_t^e and β_t^e jointly	w/o basis	7.31	12.56	12.76	22.81
	with basis	6.74	13.25	9.17	18.67

Panel (C). Hedging one-week spot risk Germany			
	Period	Mar. 24th, 2010 – Dec. 28th, 2015	
$\beta_t^e = \beta_t^g = 0$	Spot variance	38.84	18.44
		Risk reduction (%)	
$\beta_t^e = \beta_t^g = 1$		-1.42	-5.40
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	5.69	10.84
	with basis	5.68	10.87
β_t^e and β_t^e separately	w/o basis	7.25	16.66
	with basis	7.28	17.65
β_t^e and β_t^e jointly	w/o basis	16.40	34.47
	with basis	16.27	34.75*

Table 10. Hedging effectiveness in monthly hedges. Peak spark Prices.

This table is similar to Table 8, but uses monthly data frequency. The *in-sample* results are computed with at least the first eight years of each time-series. When more data is available, *out-of-sample* results are obtained. In these cases, hedging ratios are estimated each time a new observation is added– using past information from the beginning of each time series.

Hedging strategy		**In the sample**		**Out of the sample**	
		Standard approach	E&S (2008) approach	Standard approach	E&S (2008) approach
Panel (A). Hedging one-month spot risk in UK					
	Period	November 2007 – February 2016			
$\beta_t^e = \beta_t^g = 0$	Spot variance	30.38	29.38		
		Risk reduction (%)			
$\beta_t^e = \beta_t^g = 1$		-47.54	-35.18%		
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	13.65	18.60		
	with basis	13.30	18.95		
β_t^e and β_t^e separately	w/o basis	2.18	3.42		
	with basis	-6.19	-3.17		
β_t^e and β_t^e jointly	w/o basis	16.27	24.40		
	with basis	14.16	25.50*		
Panel (B). Hedging one-month spot risk in Netherlands					
	Period	May 2009 – April 2016			
$\beta_t^e = \beta_t^g = 0$	Spot variance	39.61	22.03		
		Risk reduction (%)			
$\beta_t^e = \beta_t^g = 1$		-17.61	-54.43		
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	6.75	4.29		
	with basis	6.05	5.56		
β_t^e and β_t^e separately	w/o basis	10.72	29.46		
	with basis	11.11	32.15*		
β_t^e and β_t^e jointly	w/o basis	7.75	5.45		
	with basis	7.02	6.78		
Panel (C). Hedging one-month spot risk in Germany					
	Period	January 2004 – April 2012		May 2012 – December 2015	
$\beta_t^e = \beta_t^g = 0$	Spot variance	146.83	81.41	48.22	27.81
		Risk reduction (%)		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		1.39	19.83	23.19	43.38*
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	13.48	33.20	16.94	29.80
	with basis	13.03	34.02	18.80	34.62
β_t^e and β_t^e separately	w/o basis	14.45	33.06	18.14	36.81
	with basis	11.58	29.71	20.53	42.20
β_t^e and β_t^e jointly	w/o basis	16.55	25.21	13.82	37.43
	with basis	11.23	34.29*	17.49	33.24

Table 11. Hedging effectiveness in monthly hedges. Base spark Prices.

This table is similar to Tables 8 and 10, but uses monthly frequency for natural gas and base load electricity prices.

Hedging strategy		**In-sample**		**Out-of-sample**	
		Standard approach	E&S (2008) approach	Standard approach	E&S (2008) approach
Panel (A). Hedging one-month spot risk in UK					
	Period	November 2007 – February 2016			
$\beta_t^e = \beta_t^g = 0$	Spot variance	18.79	14.39		
		Risk reduction (%)			
$\beta_t^e = \beta_t^g = 1$		-11.88	-16.65		
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	12.36	15.64		
	with basis	12.35	15.65		
β_t^e and β_t^e separately	w/o basis	6.57	6.54		
	with basis	-2.18	-5.68		
β_t^e and β_t^e jointly	w/o basis	13.88	19.58		
	with basis	13.49	20.05*		
Panel (B). Hedging one-month spot risk in Netherlands					
	Period	Jan 2004 – May 2012		June 2012–April 2016	
$\beta_t^e = \beta_t^g = 0$	Spot variance	110.22	69.75	35.43	17.00
		Risk reduction (%)		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		9.85	37.76	8.43	17.01
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	12.05	35.33	7.16	15.38
	with basis	9.85	38.81*	8.43	14.74
β_t^e and β_t^e separately	w/o basis	13.05	34.46	9.79	23.09
	with basis	7.56	38.77	8.11	17.52
β_t^e and β_t^e jointly	w/o basis	14.00	30.16	14.41	28.92*
	with basis	8.07	39.17	7.33	13.61
Panel (C). Hedging one-month spot risk in Germany					
	Period	January 2004 – April 2012		May 2012 – December 2015	
$\beta_t^e = \beta_t^g = 0$	Spot variance	90.74	38.39	43.83	26.63
		Risk reduction (%)		**Risk reduction (%)**	
$\beta_t^e = \beta_t^g = 1$		9.31	30.39	21.53	48.90*
$\beta_t^e = \beta_t^g = \beta_t$	w/o basis	13.01	36.21	17.67	39.69
	with basis	12.90	36.46	18.49	41.05
β_t^e and β_t^e separately	w/o basis	12.98	36.45	18.11	40.72
	with basis	12.41	34.77	12.98	46.61
β_t^e and β_t^e jointly	w/o basis	14.75	33.95	15.23	40.68
	with basis	13.61	36.67*	17.14	41.67

Table 12. Hedging effectiveness in weekly hedges. Base electricity prices.

This table is similar to Table 9, but uses only spot and futures prices on base load electricity at weekly frequency. Specifically, this table displays the risk reduction achieved by three hedging strategies applied to a single commodity: naïve; OLS without the basis; and OLS with the basis. That is, applying equations (9) and (10) to a single commodity. The variance of the unhedged position in the 'standard' and the Ederington and Salas (2008) approach is computed as $VAR\left[\Delta S_t^{e,base}\right]$ and $VAR\left[\Delta S_t^{e,base} - \hat{\lambda}(F_t^{e,base} - S_t^{e,base})\right]$, respectively. Variance of each hedging strategy is computed as $VAR\left[\Delta S_t^{e,base} - \hat{\beta}_t \Delta F_t^{e,base}\right]$ and $VAR\left[\Delta S_t^{e,base} - \hat{\beta}_t \Delta F_t^{e,base} - \hat{\lambda}(F_t^{e,base} - S_t^{e,base})\right]$ in the standard and 'E&S(2008)' approaches, respectively.

	In the sample		Out of the sample	
	Standard approach	E&S(2008) approach	Standard approach	E&S(2008) approach
Panel (A). Hedging one-week spot risk in UK				
Period	Jan. 7th, 2004 – Nov. 7th, 2012		Nov. 14th, 2012 – Feb. 10th, 2016	
Spot variance (not hedged)	44.95	43.98	12.91	10.40
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (*b*=1)	5.80	14.66	1.44	6.01
OLS w/o basis	9.85	15.39	2.33	6.06*
OLS with basis	9.17	16.09*	2.80	5.75
Panel (B). Hedging one-week spot risk in Netherlands				
Period	Jan. 7th, 2004 – Dec. 30th, 2008		Jan. 7th, 2008 – Apr. 27th, 2016	
Spot variance (not hedged)	192.06	150.27	15.96	12.82
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (*b*=1)	6.12	11.98	-6.01	0.39
OLS w/o basis	6.11	12.00	-4.13	0.28
OLS with basis	5.68	12.56*	-10.27	-3.72
Panel (C). Hedging one-week spot risk in Germany				
Period	Mar. 24th, 2010 – Dec. 28th, 2015			
Spot variance (not hedged)	35.74	14.37		
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (*b*=1)	-0.24	14.37		
OLS w/o basis	8.96	20.92		
OLS with basis	8.95	20.94*		

Table 13. Hedging effectiveness in weekly hedges. Peak electricity Prices.
This table is similar to Table 12, but using only spot and futures prices on peak load electricity at weekly frequency.

	In the sample		Out of the sample	
	Standard approach	E&S (2008) approach	Standard approach	E&S (2008) approach
Panel (A). Hedging one-week spot risk in UK				
Period	Nov. 14th, 2007 – Nov. 7th, 2012		Nov. 14th, 2012 – Feb. 10th, 2016	
Spot variance (not hedged)	99.07	92.65	22.73	16.29
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	2.05	8.20	-12.40	-15.43
OLS w/o basis	7.60	11.37	-4.46	-3.77*
OLS with basis	7.30	11.69	-5.76	-5.97
Panel (B). Hedging one-week spot risk in the Netherlands				
Period	May. 6th, 2009 – Apr. 23th, 2014		Apr. 30th, 2014 – Apr. 27th, 2016	
Spot variance (not hedged)	29.89	20.91	13.44	10.24
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	-8.71	11.57	0.16	11.75
OLS w/o basis	12.65	19.86	3.64	12.09*
OLS with basis	10.91	21.43	3.55	11.16
Panel (C). Hedging one-week spot risk in Germany				
Period	Mar. 24th, 2010 – Dec. 28th, 2015			
Spot variance (not hedged)	37.64	14.81		
Hedging strategy	**Risk reduction (%)**			
Naïve (b=1)	-17.07	-52.62		
OLS w/o basis	8.04	15.67		
OLS with basis	7.93	15.95*		

Table 14. Hedging effectiveness in weekly hedges. Natural gas prices.

This table is similar to Table 9, but using only spot and futures prices on base load electricity at weekly frequency.

	In-sample		**Out-of-sample**	
	Standard approach	E&S (2008) approach	Standard approach	E&S (2008) approach
Panel (A). Hedging one-week spot risk in UK				
Period	Jan. 7th, 2004 – Nov. 7th, 2012		Nov. 14th, 2012 – Feb. 10th, 2016	
Spot variance (not hedged)	27.44	24.90	9.73	9.60
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	29.09	43.59	30.37	39.27
OLS w/o basis	29.18	44.35	30.47	40.00
OLS with basis	28.13	45.51*	29.98	41.19*
Panel (B). Hedging one-week spot risk in Netherlands				
Period	Jan. 7th, 2004 – Dec. 30th, 2008		Jan. 7th, 2008 – Apr. 27th, 2016	
Spot variance (not hedged)	7.26	6.31	1.52	1.41
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	27.36	39.53	42.89	53.01*
OLS w/o basis	28.92	43.73	40.94	51.98
OLS with basis	28.21	44.55	36.84	50.43
Panel (C). Hedging one-week spot risk in Germany				
Period	Mar. 24th, 2010 – Dec. 28th, 2015			
Spot variance (not hedged)	1.17	1.15		
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	38.89	52.01		
OLS w/o basis	39.00	51.50		
OLS with basis	38.17	52.35		

Table 15. Hedging effectiveness in monthly hedges. Base electricity Prices.
This table is similar to Table 12, but uses monthly data.

	In the sample		Out of the sample	
	Standard approach	E&S (2008) approach	Standard approach	E&S (2008) approach
Panel (A). Hedging one-month spot risk in UK				
Period	November 2007 – February 2016			
Spot variance (not hedged)	29.71	31.29		
Hedging strategy	**Risk reduction (%)**			
Naïve (b=1)	31.40	44.60		
OLS w/o basis	33.33	46.86		
OLS with basis	21.33	48.69*		
Panel (B). Hedging one-month spot risk in Netherlands				
Period	Jan 2004 – May 2012		June 2012–April 2016	
Spot variance (not hedged)	94.50	77.19	11.55	8.81
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	9.39	58.42	32.10	64.86
OLS w/o basis	18.49	50.21	38.37	62.30
OLS with basis	11.63	58.61*	34.71	69.06*
Panel (C). Hedging one-month spot risk in Germany				
Period	January 2004 – April 2012		May 2012 – December 2015	
Spot variance (not hedged)	72.87	41.68	26.89	14.11
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	19.00	58.69	41.84	60.35*
OLS w/o basis	23.50	58.80	34.32	51.00
OLS with basis	22.40	60.00*	38.49	55.65

Table 16. Hedging effectiveness in monthly hedges. Peak electricity Prices.
This table is similar to Table 13, but uses monthly data.

	In the sample		Out of the sample	
	Standard approach	E&S (2008) approach	Standard approach	E&S (2008) approach
Panel (A). Hedging one-month spot risk in UK				
Period	November 2007 – February 2016			
Spot variance (not hedged)	47.24	47.38		
Hedging strategy	**Risk reduction (%)**			
Naïve (b=1)	-26.53	16.63		
OLS w/o basis	18.52	33.70		
OLS with basis	14.49	37.49*		
Panel (B). Hedging one-month spot risk in Netherlands				
Period	May 2009 – April 2016			
Spot variance (not hedged)	33.80	23.51		
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	1.56	-1.95		
OLS w/o basis	23.17	31.19		
OLS with basis	23.15	31.22*		
Panel (C). Hedging one-month spot risk in Germany				
Period	January 2004 – April 2012		May 2012 – December 2015	
Spot variance (not hedged)	138.32	102.00	33.88	16.18
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	13.44	53.38	43.53	55.89*
OLS w/o basis	25.05	54.89	33.08	47.58
OLS with basis	22.68	58.12*	38.94	53.15

Table 17. Hedging effectiveness in monthly hedges. Natural gas prices.
This table is similar to Table 14, but uses monthly data.

	In the sample		Out of the sample	
	Standard approach	E&S (2008) approach	Standard approach	E&S (2008) approach
Panel (A). Hedging one-month spot risk in UK				
Period	November 2007 – February 2016			
Spot variance (not hedged)	37.11	35.86		
Hedging strategy	**Risk reduction (%)**			
Naïve (b=1)	30.38	61.16		
OLS w/o basis	35.01	58.03		
OLS with basis	31.84	61.30*		
Panel (B). Hedging one-month spot risk in Netherlands				
Period	Jan 2004 – May 2012		June 2012–April 2016	
Spot variance (not hedged)	9.09	7.76	8.64	6.38
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	25.97	68.62	36.27	56.54*
OLS w/o basis	33.82	65.40	29.30	46.52
OLS with basis	30.24	69.59*	34.64	52.97
Panel (C). Hedging one-month spot risk in Germany				
Period	January 2004 – April 2012		May 2012 – December 2015	
Spot variance (not hedged)	9.49	8.11		
Hedging strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (b=1)	27.42	68.61	43.24	61.77*
OLS w/o basis	33.77	65.00	36.05	51.58
OLS with basis	30.27	69.10*	42.02	59.15

Finally, the White's test described in Section 2 was applied to test the statistical significance of variance risk reduction differences attained for the out-of-sample periods for each pair of hedging strategies. In all cases, the null hypothesis of no improvement in the risk reduction is rejected at 5% of significance level. Consequently, we can conclude that hedging performance differences are statistically significant in all cases.

5. Conclusions

There is extensive literature on price risk management using futures contracts. Nevertheless, this paper is the first (to our knowledge) to discuss spark spread within this doctrine. We have focussed on three European markets in which the natural gas share in the fuel mix for generating electricity varies considerably: Germany (10%); the United Kingdom (30%); and the Netherlands (50%). Consequently, we feel our results should be of interest for all agents in those countries and energy markets in which natural gas is part of the fuel mix for power generation.

An important preliminary result is obtained when the spark spread risk and the clean spark spread risk are compared. It is found that both variables are indistinguishable and the dimensionality of the problem can be reduced by considering only electricity and natural gas prices. This is because CO2 spot and futures prices are almost perfectly correlated and the basis risk of a hedge is the same for both spreads. Nevertheless, before burning natural gas in a CCGT plant to produce electricity, the manager must be sure that the clean spark spread level ensures a profit for the company. Hedging negative spark spreads with futures makes no sense. CCGT plants would only make an offer and enter the merit order curve if the clean spark spread is positive and consequently profitable, otherwise they will remain mothballed.

One generally accepted feature of energy prices is the presence of seasonal behaviour. We find that spark spread returns can be partially anticipated and the Ederington and Salas (2008) framework should be applied. The application of the Ederington and Salas (2008) approach highlights that risk reduction is underestimated in the standard approach (Ederington, 1978) due to the existence of a seasonal pattern that can be subtracted from the total returns. The risk underestimation varies between markets and commodities. For example, a risk reduction for monthly periods produced by optimal strategies is underestimated by between 7.56 and 27.37 per cent in the spark spreads. For the constituents of the spark spread these values are somewhat higher and more consistent across markets and strategies as it was expected from previous results in the area (see Torró, 2011, and Ederington and Salas, 2008).

Results in this paper show that an individualised risk management of electricity and natural gas prices is not always the best solution. Hedging the spark spread with futures is more difficult than hedging electricity and natural gas price risks with their respective futures contracts. Whereas spark spread risk reduction for monthly periods attains values ranging between 20.05 and 48.90 per cent, electricity price risk attains reductions ranging between 48.69 and 69.06 per cent for base load prices and between 31.22 and 55.89 per cent for peak load prices. Optimal strategies for natural gas prices for monthly periods produce risk reductions ranging between 56.54 and 61.77 per cent.

We feel our results should be of interest for electricity producers as the evolution of the spark spread is towards narrow values and, in many cases, gas-fired power plants are being mothballed while awaiting more profitable scenarios. Reducing the activity risks of these agents is an important issue. The paper is important for regulators because gas-fired power plants can back up energy from renewable energy sources because of its flexibility and reduced emission of polluting gases (compared to other fuels). And the paper is also of interest to academic audiences because of the innovative results in the scientific literature.

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