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Summary

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Keywords: Natural Gas Market, Futures, Hedging Ratio, Natural Gas Price Risk

JEL Classification: G11, L95

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European natural gas seasonal effects on futures hedging*

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Abstract

This paper is the first to discuss the design of futures hedging strategies in European natural gas markets (NBP, TTF and Zeebrugge). A common feature of energy prices is that conditional mean and volatility are driven by seasonal trends due to weather, demand, and storage level seasonalities. This paper follows and extends the Ederington and Salas (2008) framework and considers seasonalities in mean and volatility when minimum variance hedge ratios are computed. Our results show that hedging effectiveness is much higher when the seasonal pattern in spot price changes is approximated with lagged values of the basis (futures price minus spot price). This fact remain true for short (a week) and long (one, three and six months) hedging periods. Furthermore, volatility of weekly price changes also has a seasonal pattern and is higher in winter than in summer. A simple volatility seasonal model that is based on sinusoidal functions on the basis improves the risk reduction obtained by strategies in which hedging ratios are estimated with linear regressions. Seasonal hedging strategies, linear regression based strategies, or even a naïve position, perform better than more sophisticated statistical methods.

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1. Introduction

A common feature of natural gas prices is that spot price changes are partially predictable due to weather, demand, and storage level seasonalities. Further to this, the volatility of natural gas prices is seasonal. In winter, the active storage management is less flexible and price jump buffers are more difficult than in summer. Moreover, higher marginal cost production, demand inelasticity, and winter weather shocks trigger price jumps that produce a higher volatility than in summer.[1]

Ederington and Salas (2008) have adapted the standard minimum variance hedge ratio approach (Ederington, 1979) to the case where spot price changes are partially predictable. In this context, they show that the riskiness of the spot position is overestimated, the achievable risk reduction underestimated, and more efficient estimates of the hedge ratios are obtained. Ederington and Salas (2008) propose to use the basis (futures price minus the 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). This new approach is applied to European gas markets for the first time in this paper.

The UK natural gas market is the most liquid market in Europe.[2] The vast majority of gas contracts are over-the-counter but the regulated futures market is growing in importance (Heather, 2010). The futures British gas market is operated by InterContinental Exchange (ICE) Europe. The ICE natural gas futures contract for NBP was launched in January 1997 and has become the

[1] See Mu (2007), Suenaga et al. (2008), Alterman (2012), Henaff et al. (2013) and Efimova and Serletis (2014).

[2] Liberalization of the natural gas market began in the UK with the 1995 Gas Act. The following year, the Network Code created the National Balancing Point (NBP) hub enabling third party access to the British gas network. The National Transition System then changed the balancing regime from monthly to daily. Thereafter, all gas in the UK must be traded through the NBP hub. The Network Code also included the NBP`97 contract, a common standardized trading contract required for trading gas in the British market and in which all the natural gas agreements must be based. This contract, along with changes in the balancing, enabled the development of the British hub. Important changes in the contractual conditions and trading system were introduced in the British natural gas market in 2004-2005 after the Enron and TFX collapse, resulting in a new regulation, the Uniform Network Code in 2005. The equivalent of NBP`97 is ZBT`2000 in Zeebrugge and EFET for TTF.

benchmark for natural gas trading in Britain and in continental Europe.[3] Continental gas markets were developed following the path the British had marked. The UK and continental Europe are linked through *The Interconnector* – a gas pipeline which connects the UK gas entry point at Bacton to the Belgian port of Zeebrugge (ZEE henceforth). It has been open since 1998 and enables the flow of gas between British and continental markets. Since its launch, UK prices have converged progressively to continental prices (Heather (2012)).

The Title Transfer Facility (TTF, henceforth) was established in 2003 in the Netherlands. It is the virtual trading point for the Dutch natural gas market. It is the most developed natural gas market in continental Europe, comparable to NBP for hedging and balancing purposes. TTF is intended to be the leading gas hub in Europe, because of its location in the heart of Europe, LNG import facilities, and storage capacity. Futures contracts on TTF and ZEE are also negotiated on the Intercontinental Exchange (ICE).

There are several questions tackled in the literature on risk management in energy markets that we will try to answer for the special case of European natural gas markets. The first question is the existence of seasonal patterns in first and second moments of price returns and the implications for futures hedging. In a similar context, Chang et al. (2010) found that futures hedging effectiveness of a covariance model specification can change depending on the market trend (bull/bear) in energy markets (oil and gasoline). The influence of seasonality in energy prices for hedging purposes has also been studied in Suenaga et al. (2010). In their opinion, seasonal hedging turns out to be quite discretional under strong seasonality in prices. Long spot positions from the peak to off-peak price season would be senseless and it is better not to have these positions. Nevertheless, in our opinion, risk measures should take into account the Ederington and Salas (2008) framework where predictable seasonal price movements are incorporated to compute the unexpected spot price movement both in the hedging ratio computation and in the measurement of hedging effectiveness. Furthermore, the influence of energy variance seasonality on futures hedging performance has not

[3] According to the International Energy Agency (IEA, 2013) more than 50% of all the gas sold in Europe is priced linked to hubs – with prices linked to oil becoming less important in long-term contracts.

yet been explored. This is the first paper dealing with this issue and we have checked if hedge ratios and their effectiveness have a significant seasonal pattern. Finally, in the last few years non-conventional shale gas has become abundant and represents a downward pressure on winter prices. Furthermore, the increased number of cooling systems and the growing use of natural gas as a fuel are raising summer prices (see Henaff et al. (2013)). Both effects reduce price seasonality on the US market. It would be interesting to check if seasonality in mean and volatility persists in European natural gas markets.

A second question that our research enables us to answer is if the degree of integration between European natural gas markets enables a successful cross-market hedging strategy. Schultz and Swieringa (2013) have studied price discovery in European gas markets using intraday data for futures and spot prices (NBP, ZEE and TTF). NBP spot in the short run and its futures prompt traded in the ICE in the short and long run are leading the equilibrium. It is also found that spot markets are weakly linked – suggesting significant market frictions may exist between the various natural gas hubs in Europe. Results in Kao and Wan (2009) shows that NBP futures lead spot (mean and volatility) and volatility leverage effect (reverse) does not exist in NBP futures – but does exist in spot prices. Is it then possible to obtain a successful cross-market hedge in European natural gas markets?

This paper presents empirical results on hedging natural gas price risk with futures when an early cancellation of futures positions is made. The empirical study is made with the three most important benchmarks in European natural gas markets: NBP, ZEE and TTF. Using monthly futures contracts and daily spot prices, several combinations of hedging period lengths (one week, and one, three, and six months) are examined. Results can be summarized in the following points: (i) hedging performance improves as hedging duration increases. That is, one month hedges perform better than one-week hedges and so on; (ii) minimum variance hedge ratios are unconditionally estimated with the Ederington and Salas (2008) approach for all hedge periods and conditionally estimated for weekly hedging periods with the multivariate GARCH model proposed by Engle and

Kroner (1995). We further designed a simple conditional covariance model using sinusoidal functions. The highest risk reduction for the NBP and ZEE is obtained with the seasonal model. For the TTF market, the simple naïve strategy maximizes risk reduction. The OLS hedge ratio estimation proposed by Ederington and Salas (2008) produces the second best risk reduction (only slightly lower). The worst performance is found for all the tested GARCH covariance models. Consequently, it does not seem that improving statistical price modeling will guarantee better performance in our empirical application; (iii) it is found that the basis has a clear seasonal pattern with positive on-peak values in winter and negative off-peak values in summer. The basis has an important predictive power for explaining spot price changes (between 10% and 50%), consequently, the Ederington and Salas (2008) framework perfectly suits our experiment and unexpected spot price changes must be computed using the information contained in the basis; (iv) a strong and persistent seasonal pattern in both spot and futures returns volatility exists, but we do not find any significant seasonal pattern on futures hedge ratios and their effectiveness in reducing risk. This seasonal pattern is captured more smoothly with a sinusoidal function in the basis as the basis is more stable than price returns; (v) it is shown that very large risk reductions are achievable by using the new approach proposed in Ederington and Salas (2008) and optimizing the futures contract selection as described above. Specifically, risk reduction values vary between 30% and 90% – depending on the hedging duration (one week to six months) and the analyzed sub-period (in-sample and out-of-sample sub-periods); (vi) direct-market hedges significantly beat cross-market hedges – thereby showing that further European natural gas market integration is needed to make a joint risk-portfolio management possible.

This article is divided into seven sections. In Section 2, hedging ratios and their effectiveness measure are defined. In Section 3, the econometric model used to obtain conditional estimates of hedging ratios is presented. Section 4 contains the data description and some preliminary analysis. Estimation and hedging results are shown in Section 5. The paper finishes with conclusions and cited references.

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 in normality or mean-variance utility functions. These are unrealistic hypotheses. Furthermore, assuming futures prices are martingale, the high volatility in energy prices points to the 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. 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).

The conventional minimum variance hedge ratio is defined in a one-period model. At the beginning of the period, or 't', an individual is committed to a given position in the spot market. To reduce the risk exposure, the individual may choose to hedge at time 't' in the futures market with the same underlying asset. At the end of the period, say, '$t + 1$', the hedger's result per unit of spot is calculated as follows

$$x_{t+1} = \Delta S(t) - b_t \, \Delta F(t,T) \qquad (1)$$

where x_{t+1} is the value variation between t and t+1, $\Delta S(t) = (S(t+1) - S(t))$ is the spot value variation, $\Delta F(t,T) = (F(t+1,T) - F(t,T))$ the futures value variation of a futures contract maturing at T, and b_t is the hedging ratio. If b_t is positive (negative), short (long) positions are taken in futures.

The hedger will choose b_t to minimize 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. The risk of a hedge strategy is calculated as the variance of x_{t+1},

$$VAR[x_{t+1}|\psi_t] = VAR[\Delta S(t) - b_t \Delta F(t,T)|\psi_t] \tag{2}$$

The most used definition for the optimal hedge ratio[4] is the *minimum variance hedge ratio* that can be obtained by minimizing equation (2)

$$b_t = \frac{cov(\Delta S(t), \Delta F(t,T)|\psi_t)}{var(\Delta F(t,T)|\psi_t)} \tag{3}$$

where second moments are conditioned to the information set available at the beginning of the hedging period, ψ_t. When an unconditional probability distribution is used, the hedge ratio in equation (3) can be estimated from a linear relationship between spot and futures returns. That is, estimating the linear relationship appearing in equation (1) by ordinary least squares (OLS henceforth) but adding an intercept and white noise

$$\Delta S(t) = a + b\Delta F(t,T) + \varepsilon(t) \tag{4}$$

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

In this case, the OLS estimator of b is the unconditional definition of the optimal hedge ratio appearing in equation (3) (Ederington, 1979).

Ederington and Salas (2008) have adapted the above approach to the case where spot price changes are partially predictable and futures prices are unbiased estimators of future spot prices. In this context, they show that the riskiness of the spot position is overestimated and the achievable risk reduction underestimated. Under this new approach, the unexpected result of the hedge in equation (1) can be reformulated as

$$x_{t+1} = (\Delta S(t) - E[\Delta S(t) | \psi_t]) - b_t' \Delta F(t,T) \tag{5}$$

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

$$VAR[x_{t+1} | \psi_t] = VAR[(\Delta S(t) - E[\Delta S(t) | \psi_t]) - b_t' \Delta F(t,T) | \psi_t] \tag{6}$$

and the minimum variance hedge ratio obtained after minimizing equation (6) is

$$b_t' = \frac{cov((\Delta S(t) - E[\Delta S(t) | \psi_t]), \Delta F(t,T) | \psi_t)}{var(\Delta F(t,T) | \psi_t)} \tag{7}$$

Ederington and Salas (2008) propose using the basis (futures price minus the 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 (7) can be obtained by estimating the following linear regression using OLS

$$\Delta S(t) = a' + b'\Delta F(t,T) + \lambda(F(t,T) - S(t)) + \varepsilon'(t) \quad (8)$$

where $\lambda(F(t,T) - S(t))$ is used to estimate $E[\Delta S(t)|\psi_t]$. Ederington and Salas (2008) show that OLS estimation of equation (8) produces an unbiased and more efficient estimation of the unconditional minimum variance hedge ratio (b') than that obtained by using equation (4). This is providing that 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 $\hat{\lambda}\,(F(t,T) - S(t)) = E[\Delta S(t)|\psi_t]$).

Measuring hedging effectiveness

The risk reduction is computed to compare the hedging effectiveness of each strategy. 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 every time a new observation is considered. The variance of a hedge strategy is calculated as the variance of the hedged portfolio – as shown in equation (6). In this equation, the OLS estimated approximation of the expected spot price change using the basis is introduced ($\hat{\lambda}\,(F(t,T) - S(t)) = E[\Delta S(t)|\psi_t]$). The risk reduction achieved for each strategy is computed by comparison with the variance of the spot position ($b_t = 0$ for all t in equation (6)).

In the empirical application presented in Sections 4 and 5, futures with different maturities ($F(t,T_i)$ with i =1, 3, and 6 months; and $T_i = t + i$) are considered to hedge the spot price variation. Furthermore, four hedging lengths are considered: one week and 1, 3, and 6 months. Table 1 shows the four types of hedges carried out in this paper, one per row. This typology enables a study of the influence of the hedging length. It is expected that hedging performance improves as hedging length increases.[5] The second and third columns contain the spot and futures price variations implied in each hedging operation. Finally, the last column in Table 1 reports the basis used to approximate the expected spot price change in equations (6) and (8). It is important to note that only one basis is used per hedging period.[6]

In the empirical application in Section 5, five hedging strategies are compared. The hedging ratio obtained after estimating equation (4) is labeled 'OLS without basis' – and the hedging ratio obtained after estimating equation (8) is identified as 'OLS with basis'. In the following section, the alternative conditional covariance model enables the estimation of the hedging ratio appearing in equation (7). The first strategy is labeled as 'seasonal', the second strategy 'seasonal-basis' and the third strategy is identified as 'BEKK'. Hedging analysis is completed with the 'naive' 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 (*i.e.* $b_t = 1$ for all t).

[Insert Table 1 about here]

3. The econometric framework

One of the objectives of this paper is to compare the hedging effectiveness of conditional and unconditional minimum variance hedge ratio estimates. To obtain conditional estimates of the second moments, a two-step estimation procedure is followed. Firstly, a model in means is estimated and then the residuals of this model are taken in the second step as an input to model the conditional variance. In a similar empirical study, Efimova and Serletis (2014) model daily natural gas prices in the US by introducing storage levels and temperature in the mean equation to cope with seasonality in prices. As the basis contains all this information we have introduced the lagged

[5] Lindahl, 1992.

[6] The unhedged spot price risk will be measured as $\mathrm{VAR}[\Delta^k S(t) - \hat{\lambda}(F(t,T_k) - S(t))]$ after estimating λ by OLS from the adapted equation (8): $\Delta^k S(t) = a' + b' \Delta^k F(t,T_i) + \lambda(F(t,T_k) - S(t)) + \varepsilon'(t)$ for k= 1 week and 1, 2, and 3 and i= 1, 2, and 3 months and $i > k$. In the *ex ante* study, the unhedged spot price risk measure is computed by repeating this procedure each time a new observation is considered, obtaining a vector of λ coefficients that is as large as the out-of-sample period.

value of the basis in the model. Furthermore, as basis can been understood as an equilibrium model deviation between spot and futures price equilibrium (Viswanath, 1993; Lien, 1996), we propose the following vector error correction model to clean any autocorrelation

$$\begin{aligned} \Delta^k S(t) &= \gamma_1 + \gamma_{10}\left(F(t,T_k) - S(t)\right) + \sum_{\tau=1}^{p} \gamma_{11\tau} \Delta^k S(t-\tau) + \sum_{\tau=1}^{p} \gamma_{12\tau} \Delta^k F(t-\tau, T_i) + \varepsilon_{1,t+k} \\ \Delta^k F(t,T_i) &= \gamma_2 + \gamma_{20}\left(F(t,T_k) - S(t)\right) + \sum_{\tau=1}^{p} \gamma_{21\tau} \Delta^k S(t-\tau) + \sum_{\tau=1}^{p} \gamma_{22\tau} \Delta^k F(t-\tau, T_i) + \varepsilon_{2,t+k} \end{aligned} \tag{9}$$

where $\Delta^k S(t) = (S(t+k) - S(t))$ with k = 1 week and 1, 3 and 6 months; $\Delta^k F(t,T_i) = F(t+k,T_i) - F(t,T_i)$ with $T_i = t+i$; i = 1, 3, and 6 months and $k < i$; represent the k differences in futures prices when 'i' periods remain to 'delivery' or settlement – approximately as futures positions are closed just before maturity (note that $F(t+k,T_i) \neq S(t+k)$ when $k = i$); the gammas are the parameters to estimate; p is the lag of the VAR and is chosen by minimizing the Hannan and Quinn (1979) information criteria, thereby eliminating any autocorrelation patterns. The VAR model is estimated by OLS (Engle & Granger, 1987). The vector of residuals, $\varepsilon_{t+k} = (\varepsilon_{1t+k}, \varepsilon_{2t+k})'$, are saved and used as observable data to estimate seasonal and multivariate GARCH covariance models. This two-step procedure (Kroner & Ng, 1998; Engle & Ng, 1993) reduces the number of parameters to estimate in the second step, decreases the estimation error, and enables a faster convergence in the estimation procedure. In the VAR model in equation (9), the basis described in the last column of Table 1 appears as an external variable. The basis can be seen as an error correction term when spot and futures prices are cointegrated, as this is the case (Viswanath, 1993; Lien, 1996). The inclusion of the basis in the VAR specification implies an efficient conditional estimation of the minimum variance hedge ratio (see equation (7)) as it contains important information for anticipating spot price changes. A robustness check was made regarding the adequacy of the proposed model in equation (9), and an expanded model including an annual sinusoidal trend was estimated. The expanded estimated model did not report any sinusoidal trend coefficient significantly different to zero at one per cent of significance level. Moreover, the computation of the likelihood ratio test between the expanded model and the model in equation (9) rejects the significance of any expansion. These results are available upon request.

The BEKK covariance model

The number of published papers modeling conditional covariance is quite small compared to the enormous bibliography on time-varying volatility. The three 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) and; (3) the BEKK model of Engle and Kroner (1995). Each model imposes different restrictions on the conditional covariance and can lead to substantially different conclusions in any application that involves forecasting conditional covariance matrices.[7] Asymmetries are introduced following the Glosten *et al.* (1993) approach. This is the most common method for introducing asymmetries in multivariate GARCH modeling (Gagnon and Lypny, 1995; Hendry and Sharma, 1999; Bekaert & Wu 2000). In the empirical applications appearing in the following sections, we only report results for the asymmetric version of the BEKK model. 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 not change.

The two-dimensional asymmetric BEKK model in its compacted form can be written as follows:

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'\eta_{t-1}\eta'_{t-1}G \qquad (10)$$

[7] Myers (1991) and Baillie and Myers (1991) have used the VECH specification, without the asymmetric extension, in spot-futures covariance modelling for hedging purposes for various agricultural commodities. The CCORR model has often been used for modelling spot-futures covariance dynamics. Some examples are: Cecchetti *et al.* (1988) in public debt; Kroner and Sultan (1993) in currencies; and Park and Switzer (1995) in stock indexes. The BEKK model has been used in Baillie and Myers (1991) (without asymmetries), and Gagnon and Lypny (1995), in modelling spot-futures covariance for agricultural commodities and interest rates, respectively.

where C, A, B and G are 2 × 2 matrices of parameters, H_t is the 2 × 2 conditional covariance matrix, and ε_t and η_t are 2 × 1 vectors containing the shocks and threshold terms series. Therefore, the unfolded covariance model is written as follows:

$$\begin{bmatrix} h_{11t} & h_{12t} \\ . & h_{22t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11t-1} & h_{12t-1} \\ . & h_{22t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1t-1}^2 & \varepsilon_{1t-1}\varepsilon_{2t-1} \\ . & \varepsilon_{2t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' \begin{bmatrix} \eta_{1t-1}^2 & \eta_{1t-1}\eta_{2t-1} \\ . & \eta_{2t-1}^2 \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \tag{11}$$

where c_{ij}, b_{ij}, a_{ij}, and g_{ij} for all $i, j = 1, 2$ are parameters, ε_{1t} and ε_{2t} are the unexpected shock series obtained from equation (9). $\eta_{1t} = \max\,[0,-\varepsilon_{1t}]$ and $\eta_{2t} = \max\,[0,-\varepsilon_{2t}]$ are the Glosten et al. (1993) dummy series capturing negative asymmetries from the shocks and h_{ijt} for all $i, j = 1, 2$ are the conditional second moment series. The dot [.] appearing in some matrices in equation (3) means that these matrices are symmetric.

The seasonal covariance model

Benth and Benth (2007) propose a truncated Fourier series expansion describing the conditional variance of Stockholm temperature. In a similar way, we apply this idea to the bivariate case. Our empirical results for weekly data frequency show that there is only an annual seasonal pattern and any higher frequency seasonality is significant. Therefore, we will use the following bivariate specification,

$$\begin{bmatrix} h_{11t} & h_{12t} \\ . & h_{22t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ \cdot & c_{22} \end{bmatrix} \circ \begin{bmatrix} c_{11} & c_{12} \\ \cdot & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ \cdot & a_{22} \end{bmatrix} \circ \begin{bmatrix} sin(2\pi t/52) & sin(2\pi t/52) \\ \cdot & sin(2\pi t/52) \end{bmatrix}$$
$$+ \begin{bmatrix} b_{11} & b_{12} \\ \cdot & b_{22} \end{bmatrix} \circ \begin{bmatrix} cos(2\pi t/52) & cos(2\pi t/52) \\ \cdot & cos(2\pi t/52) \end{bmatrix} \tag{12}$$

where c_{ij}, a_{ij} and b_{ij} for all $i, j = 1, 2$ are parameters, t indicates week number within the year and ° is the Hadamard product operator (element-by-element matrix multiplication). We tried many other specifications and combinations, but this simple specification was the most powerful and did not present offer difficulties in the estimation procedure.

The seasonal-basis covariance model

Based on returns volatility and basis seasonality, we propose the following covariance model where the seasonal pattern in the conditional covariance is introduced using the sinusoidal function previously estimated for the basis:

$$B(t) = a + b\,sin(2\pi t/52) + c\,cos(2\pi t/52)$$
$$\begin{bmatrix} h_{11t} & h_{12t} \\ \cdot & h_{22t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ \cdot & c_{22} \end{bmatrix} \circ \begin{bmatrix} c_{11} & c_{12} \\ \cdot & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ \cdot & a_{22} \end{bmatrix} \circ \begin{bmatrix} \hat{B}(t-1) & \hat{B}(t-1) \\ \cdot & \hat{B}(t-1) \end{bmatrix} \tag{13}$$

where c_{ij}, and a_{ij} for all $i, j = 1, 2$ and a, b and c are parameters.

The parameters of the bivariate covariance models are estimated by maximizing the conditional log-likelihood function:

$$L(\theta) = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln\left|H_t(\theta)\right| + \varepsilon_t^{'} H_t^{-1}(\theta)\varepsilon_t\right) \tag{14}$$

where T is the number of observations, N is the number of equations in the system, and θ denotes the vector of all the parameters to be estimated. The log likelihood function is estimated by using the BFGS algorithm via *quasi-maximum likelihood estimation* (QMLE). Bollerslev and Wooldridge (1992) show that the standard errors calculated by using this method are robust even when the normality assumption is violated.

4. Data and preliminary analysis

Natural gas futures and spot prices are directly obtained from Platts and the ICE respectively. The spot price is computed and published daily for delivery next working day after assignment. This spot is the reference for derivative contracts traded at the ICE and those contracts traded OTC in the respective hub. There is a wide range of natural gas derivative contracts (forward, futures, and options) traded at the ICE. At the moment, the most important of the regulated contracts are monthly futures, especially the front month contract, the most liquid of all the traded contracts. The vast majority of contracts currently traded are OTC contracts, but futures contracts are becoming more important over time as markets become more liquid and more reliable.

To select which futures/forward contracts can be included in this study two important considerations are necessary: (i) firstly, a large number of observations are required to obtain insightful results; (ii) secondly, non-overlapping futures contracts are preferable in order to avoid artificially introducing autocorrelation in the data series. Therefore, it is necessary to balance the data frequency and delivery period length of the contracts to avoid introducing autocorrelation in the data series. Following these premises, the present study has focused on short-time hedges using weekly frequency, the front futures contract, and long-time hedges of one, three, and six months using monthly frequency data for the first, third and sixth to maturity monthly futures contracts. We are confident that our results, estimates, and conclusions are unaffected by autocorrelation.

Futures and forwards contracts have coexisted from the beginning, but the majority of trades are through OTC contracts. Futures negotiated at the ICE are increasing its importance and liquidity over time and they represent more than one-third of all gas negotiated at NBP (Heather, 2010). The ICE trades monthly, quarterly, seasonal, and yearly futures contracts in the three markets (the monthly futures being the most liquid). To avoid low liquidity problems the study has been limited to the first six monthly contracts nearest to delivery and the corresponding spot. With this information four type of hedges are designed as described in Table 1. Three and six months hedges are only available for the UK market. The data period for the NBP market goes from December 3, 1997 until March 26, 2014; that is, 196 months or 852 weeks in the NBP. For the ZEE market the data sample goes from October 20, 1999 until March 26, 2014; that is, 174 months or 754 weeks. For the TTF market the data sample goes from January 7, 2004 until March 26, 2014; that is, 123 months or 534 weeks.

In the ICE, final futures settlement covers the difference between the last closing price of the futures contract and the system price in the 'delivery period'. The day ahead price is used as spot price reference in the three markets. In monthly contracts, the spot reference is the spot average of all the calendar days of the month.

Figure 1 exhibits the time series for the spot and front contract in each market on a weekly frequency. Futures prices are taken on Wednesday, or the day before if non-tradable.[8] The most relevant jumps corresponds to events mostly related with geopolitics: the dispute between Russia and Ukraine about the price of gas and transit combined with abnormally cold weather (3 March 2005, 22 November 2005, January 2009, February 2012) and the Libyan civil war (spring 2011). But the most dramatic shortcoming and peak was during February and March 2006 when a cold spell was combined with a fire at the Rough natural gas storage facilities in the North Sea – preventing access to nearly over 80% of total UK storage just as withdrawals from storage were about to begin (see Giulietti et al., 2011).

[Insert Figure 1 about here]

A preliminary analysis follows. Table 2 displays the basic statistics of spot and futures price differences. Mean values deserve the first important comment. Whereas spot mean values are positive but not significantly different from zero, futures means are negative and significantly different from zero in all cases. Furthermore, the mean values of $\Delta^k F(t,T_i)$, take values varying

[8] Wednesday is the standard day in financial markets for weekly time series. Taking Wednesday prices avoids some of the anomalies (Monday effect and weekend effect) that are very common in financial markets. Chordia and Swaminathan (2000) find that return autocorrelations based on closing prices of any weekday other than Wednesday are either too low or too high.

between -0.31 (k=w) and -4.10 (k=6m) for the NBP. In the classical view of hedging pressure as a determinant of futures premiums (also known as a *forward bias* or *forward premium*) when a significant declining pattern is found in futures prices (futures prices above expected spot prices) it would be said that the futures market is in *contango* (long hedging pressure). The Kruskal-Wallis test contrasts the null of median equality between spot and futures time series. Results show that the null is rejected in all cases.

Table 2 also displays the standard deviation of the analyzed series. A pair-wise comparison between spot and futures standard deviation shows that the former is always higher. The Levene test contrasts the null of variance equality between spot and futures differenced series. Results show that the null is rejected in all markets at 5% of significance level for weekly returns but not for longer periods.

Significant skewness is found in 3 out the 16 time series analyzed in Table 2: one week futures and one month spot returns in the TTF and six month spot returns time series in the NBP. The kurtosis results indicate that all the time series appearing in Table 2 have significant excess kurtosis. In accordance with the above results, normality distribution hypothesis is clearly rejected in all cases. Maximum and minimum values help to explain the above results, especially the high kurtosis. Finally, the Ljung-Box test with twenty lags detects significant autocorrelation and heteroscedasticity.

The statistical behavior of futures and spot differences has some significant discrepancies that might be critical obstacles to overcome in order to design a successful hedging strategy. The two most insightful results are that futures have a declining pattern as maturity approaches, and that spot prices are more volatile than futures prices. This disparity produces a lower correlation than usual for linking futures and the spot position to hedge. This correlation appears in Table 3 and varies between 0.43 and 0.75. The highest correlation between spot and futures are obtained for one-month price variations and lowest values correspond to three and six months. This is an interesting point to keep in mind when considering the choice of the optimal hedging strategy.

Nevertheless, later it will be shown that hedging effectiveness increases as the hedging period increases, then a hasty interpretation of the correlation coefficient in terms of choosing the best hedging alternative may be wrong. In this case, the strong seasonal pattern on prices and volatility makes it necessary to use unexpected price changes to avoid misunderstandings.

[Insert Table 2 about here]

[Insert Table 3 about here]

Seasonality in basis and volatility

Basis has a strong seasonal pattern when convenience yield, weather, and storage costs vary during the year (Whei and Zhu (2006)). Basis is positive in winter and negative in summer. In winter, demand is great and so storage levels decrease and storage costs increase (positive convenience yield), producing a positive basis. In summer, demand for natural gas is lower because of warm weather and storage prices decrease and storage levels increase (negative convenience yield) and the combination of these effects results in a negative basis. Basis and price volatility have a similar seasonal pattern, see Figures 2 and 3. Basis and returns volatility are high in winter and low in summer. Furthermore, the basis contains information of those variables (storage levels, weather, demand, and risk premiums) that reflect uncertainty in the natural spot-futures markets necessary to obtain futures prices. Finally, in contrast to spot and price levels where jumps are frequently found, the basis is more stable as the liaison between spot and futures prices is constrained by the arbitrage arguments. The basis-seasonal model tries to cope and mix both seasonal effects in a covariance model, see equation (13).

Seasonal effects are further studied in Table 4. Using the weekly database, the year is divided in two seasons in the same way as the futures *seasonal contracts* in the ICE market: winter from October to March and summer from April to September. Results show that mean equality between basis, spot, and futures returns cannot be rejected. In contrast, the winter volatility of these variables is significantly higher than summer volatility.

In Table 5 some evidence of the predictive ability of the basis for the spot and futures price changes is presented. As this table shows, the basis has an important predictive power for explaining unexpected spot price changes (between 10% and 32%). However, the basis has less ability to forecast futures price changes. These results coincide with the Ederington and Salas (2008) approach where spot price changes are partially predictable; but futures prices results agree with the martingale hypothesis in most cases.

[Insert Figure 2 about here]

[Insert Figure 3 about here]

[Insert Table 4 about here]

[Insert Table 5 about here]

5. Results

The estimation of the conditional covariance models (see equations (9) to (13)) is carried out by maximizing the sample log-likelihood function (see equation (14)). The estimation outputs for the first five years used as ex post period in the three conditional covariance models are reported in Tables 6, 7 and 8. Looking at the results appearing in Panel (B) in all these tables, autocorrelation problems completely disappear. Nevertheless, heteroscedasticity is almost eliminated with the BEKK model but persists in seasonal models. Skewness and kurtosis statistics remain in similar values to the original data appearing in Table 2. Many other specifications were tried but results did not improve, so we decided to exhibit the most representative. [9]

[9] We tested the ADC GARCH model in Kroner and Ng (1998) and its nested models (constant correlation, VECH, and BEKK) and several diagonal versions, with normal and t-Student distributions. We also tried to insert in the GARCH specification a seasonal trend or a dummy variable for the winter season. Any of these models improved the BEKK model we reported and many halted the program because positive semi-definite matrix was not guaranteed.

Figures 4 and 5 display, respectively, the estimated conditional second moment and hedging ratios.[10] It can be seen how second moments in Figure 4 have a very clear pattern model similar to the raw data appearing in Figure 3. That is, volatility increases in all winter seasons and there was a special period of high volatility beginning in the winter between 2005 and 2006. Furthermore, volatility is about twice as high in spot as in futures prices. Finally, the strength of the seasonal pattern appears to soften towards the end of the sample period.

In Figures 5(a) and 5(b) it can be seen how conditional hedging ratio values move around linear regression based hedge ratios. In all cases, average hedge values decrease from the beginning until the end of the sample. One interesting fact is to test if hedge ratios in summer and winter are equal in mean. In the *ex post* period, hedge ratios are significantly higher in summer for the BEKK, and significantly lower in summer in seasonal models; nevertheless, equality in mean cannot be rejected in the *ex ante* period in both cases at 5% of significance level.[11] These results can partially be related with Chang et al. (2010) results, who found that risk reduction in bull markets (low volatility) is higher than risk reduction in bear markets (high volatility) in oil markets. We have tested if risk reduction values change by seasons. In this case, we obtain similar results to those reported in Table 9 for both seasons but the results are not displayed to save space. Consequently, as shown by the results of the *ex ante* period, the various hedging strategies offer no significant differences between seasons.

[Insert Table 6 about here]

[Insert Table 7 about here]

[Insert Table 8 about here]

[Insert Figure 4 about here]

[10] Results for the seasonal model are not included in Figures 4 and 5 because they are very similar to the seasonal-basis model.

[11] We tested the mean equality between winter and summer hedges (H_0: $\mu_W = \mu_S$) using the following t-test with asymptotic normal distribution $t_{H_0} = (\mu_W - \mu_S) \Big/ \sqrt{\sigma_W^2 / n_W + \sigma_S^2 / n_S}$, been μ_W, μ_S, σ_S^2, σ_W^2, n_W and n_S the means, variances, and sample sizes of hedge values for winter and summer, respectively. In the BEKK model we obtained μ_W =1.79, μ_S =1.86 and t-statistic of -6.24 in the *ex post* period and μ_W =1.54, μ_S =1.54 and a t-statistic of 0.11 in the *ex ante* period. In the seasonal-basis model we obtained μ_W =1.77, μ_S =1.52 and a t-statistic of 29.32 in the *ex post* period and μ_W =1.50, μ_S =1.47 and t-statistic of 1.51 in the *ex ante* period.

[Insert Figure 5 about here]

Table 9 and 10 display the variance reduction of the different hedging methods.[12] In Table 9 risk reduction corresponding to weekly hedges in NBP, ZEE, and TTF are reported in panels A, B, and C. The first important result is that in all cases the risk reduction in the standard approach is underestimated by more than a 10%. In the *ex post* periods the naïve hedge is the worst performing strategy and the other strategy obtains similar results. Anyway, the only realistic comparison can be made in the *ex ante* period where hedge strategies are compared using forecasted hedge ratios, and models are estimated every time a new observation is considered. In this case, for the NBP and ZEE markets the seasonal-basis strategy produces the largest risk reduction (46.81% and 44.44%, respectively), somewhat larger than the risk reduction obtained using the OLS and seasonal strategies. The BEKK and the naïve strategies produce the worst outcomes. In the TTF market in Panel (C) the naïve hedge obtains first position (46.46%), followed with a slightly lower risk reduction by "OLS w/o basis" and seasonal-basis strategies. The BEKK method produces the poorest result. It is interesting to note that obtaining risk reductions below 50% is quite common when futures hedging is carried out on commodities and the standard approach is used (Carter, 1999; section 3.2).[13]

In Table 10 results corresponding 1, 3 and 6 months hedging periods are displayed. In this case, the underestimation of the risk reduction using the standard approach is critical. In the *ex ante* period the difference between these two risk reduction methods varies between 40 percent and more than the 100 percent. Particularly noteworthy is the case of the NBP in the *ex ante* period where the

[12] Transaction costs are not considered when comparing hedging methods, as the hedging theoretical framework is a one-period model for all hedging methods. Within this framework, the individual (see Section 2) must take futures positions at the beginning of the period and cancel them at the end of the period. As hedging ratio values are quite similar in all the considered methods, all the hedging strategies will have similar transaction costs. Extracted from ICE rules in May 2014, the total member trading fees for a contract will be £1.90 and €2.70 for NBP and TTF monthly contracts, respectively (about 0.003% and 0.02% of the underlying value in each case). Following Wagner (2014), the bid-ask average spreads in the most liquid European natural gas futures contracts are about 0.001£ for NBP and ZEE and 0.1€ for the TTF. These quantities respectively represent about 0.25% and 0.5% of the total underlying amount.

[13] Although not directly displayed in Tables 9 and 10 it is important to note that the Newey-West standard errors of the hedge ratios estimated using equation (8) are 50% lower on average than those obtained after using equation (4). Consequently, the introduction of the basis in the model allows more efficient minimum variance hedge ratio estimates. These results are not reported to save space, but are available on request.

standard approach offers a risk increase (negative risk reduction) in many cases. Proposition 3 in Ederington and Salas (2008) can be used to explain the "negatives" as this proposition says that the exclusion of the basis (expected price changes) in the computation of the spot position risk to hedge tends to overestimate the variance of the spot position variance by the variance of the basis (proxy of the expected spot price changes). Looking at Table 11 it can be seen that in the *ex ante* period the basis variance is very high compared with the spot return variance and it is higher in one case. When the basis has a so great a variance, the standard approach can then report a misleading risk increase because risk reduction is dramatically underestimated.

The attained risk reduction of naïve and OLS based hedges shown in Table 10 are quite similar in all the cases in the E&S(2008) approach and vary between 79% and 93% in the *ex ante* period. The naïve strategy obtains the greatest risk reduction in three out of five cases and the "OLS w/o basis" in the remaining two cases in the *ex ante* period. In the *ex post* period the "OLS with basis" wins in four out of five cases. In all the cases, we detected a positive duration effect in hedging effectiveness. The achieved risk reduction is larger in one month than in the one week hedging period. Furthermore, in the NBP case where 3 and 6 month hedges are carried out, the risk reduction obtained by the optimal hedging strategy further increases with the duration of the hedge. The level of risk reduction reached in ZEE and TTF markets for 1 month hedges is remarkable. In this case, risk reduction is very successful and it is almost as high as the 6 month hedges in the NBP. This result is interesting for futures traders who design hedging strategies as it shows that trading with the front contract in the ZEE and TTF is very successful and furthermore, the front contract is always the more liquid contract and allows tailing and steering the futures positions dynamically with low trading costs.

Differences in the risk reduction obtained by OLS methods (with and without the basis) are inconclusive. Nevertheless, in Figure 5 where OLS weekly hedge ratios for the NBP are displayed, "OLS with basis" hedge ratios are above "OLS w/o basis". In ZEE and TTF week hedges we obtain a similar pattern. We find the reverse result for longer hedging periods: "OLS w/o basis" hedge ratios are above “OLS with basis”. In the Ederington and Salas (2008) approach it is shown that when spot price returns can be partially forecasted, then more efficient estimates can be obtained using his approach. However, our approach shows that a more efficient hedge ratio estimate will not imply an improvement in the performance of the hedging strategy. Finally, when OLS and GARCH hedge ratio performances are compared, results are conclusive in favor of OLS hedge ratios. This result implies that the better statistical performance of the GARCH models does not imply a better hedging strategy performance in our empirical application. This result is not surprising in the hedging literature and agrees with the Lien and Tse (2002, page 367) review: empirical results concerning the performance of GARCH hedge ratios are generally mixed and conventional hedge strategies perform as well as or better than the GARCH strategies. Furthermore, the naive strategy obtains a similar performance to the above remaining strategies in long-term hedges and it is the best performing strategy for weekly hedges in the case of the TTF market.

Results on Schultz and Swieringa (2013) show that ICE prompt leads in the short and long run to equilibrium in the European natural gas market. This result envisages that cross-hedging between European markets using the NBP futures as the main hedging instrument could offer a good performance. In Table 3 we report the correlation between the returns in the European market. Some cross-market correlations are above 0.9 and suggest the possibility of using cross-market hedges. Specifically, correlation between spot-spot and futures-futures in ZEE and NBP markets are above 0.9 and suggest that a cross-hedged might be an interesting possibility. Our results, available upon request, contradict this intuition. In this case, one month hedges in the ZEE using the front contract in NBP obtain a risk reduction of 72% instead to the 87% obtained in Table 10 for the *ex ante* period.

[Insert Table 9 about here]

[Insert Table 10 about here]

[Insert Table 11 about here]

6. Conclusions

This paper follows the Ederington and Salas (2008) framework when considering the expected change in spot prices when minimum variance hedge ratios are computed. The use of this new approach enables a significant improvement on the poor effectiveness measures for hedging strategies obtained in some previous studies on energy markets (see Bystrom, 2003 and Moulton 2005 for electricity, and Ederington and Salas (2008) for the US natural gas market). Specifically, previous studies have overestimated the unexpected shocks in spot prices as a large part of these shocks can be partially anticipated using the information contained in the basis (between 10% and 30%). Consequently, the riskiness of the spot position in previous studies was overestimated and the achievable risk reduction underestimated. This poor effectiveness was also due to the special statistical features of most energy commodity prices. The special statistical features of natural gas prices (specifically their high volatility, kurtosis, and the high volatility of the basis) can produce very wrong computed risk reductions that can be corrected using the Ederington and Salas (2008) framework (in which past values of the basis are used to anticipate the seasonal trend of the spot price return).

Further to the use of the new approach proposed by Ederington and Salas (2008), the empirical study carried out reveals that hedging performance can be significantly improved by increasing hedging duration. Depending on the hedging duration (one week, or one, three, and six months), and the analyzed sub-period (in-sample and out-of-sample sub-periods), risk reduction attains values of between 44% and 93%.

A strong seasonality also exists in the volatility of spot and futures price returns – which have been significantly higher in winter than in summer. We have captured this seasonality introducing a sinusoidal trend in conditional second moments. This is the first paper dealing with the influence of energy variance seasonality on MV hedging ratios and its effectiveness. Seasonalities in second moments are transmitted to the hedging ratios in the *ex post* period, been higher in winter than in summer. Nevertheless, in the more realistic *ex ante* processing, this difference is not statistically significant. A simple volatility seasonal based model built fitting sinusoidal functions on the basis (futures price less spot price) improves the risk reduction obtained by those strategies in which hedging ratios are estimated with linear regressions. Seasonal hedging strategies, linear regression based strategies, or even a naïve position prove to perform better than more sophisticated statistical methods. Consequently, in the empirical application carried out for European natural gas markets it does not seem that improving statistical price modeling guarantees a better hedging performance. Finally, although European natural gas markets integrations have improved in the last few years, it does not allow for a successful cross-market hedges.

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8. Tables

Table 1. Type of hedges

This table displays the type of hedges and helps clarify notation. Spot returns are computed as $\Delta^k S(t) = S(t+k)$-$S(t)$ with k = 1 week and 1, 3, and 6 months; and represent the NBP price variation for the k period. $\Delta^k F(t,T_i) = F(t+k,T_i)$-$F(t,T_i)$ with $T_i = t+i$; i = 1, 3, and 6 months and $k \leq i$. Note that prices are taken on Wednesday (previous trading day is used if not tradable) and futures rollovers are taken the last Wednesday of the month (or second to last Wednesday of the month if the last trading day of the month is Wednesday). Note that $F(t+k,T_i) \neq S(t+k)$ when $k = i$, as this is not a direct hedge. 'Duration' column reports the hedging period. The last column reports the basis used to approximate the expected spot price change in equation (8).

Duration k	Frequency	Spot return $\Delta^k S(t)$	Futures return $\Delta^k F(t,T_i)$	Basis approximating $E\left[\Delta^k S(t) \| \psi_t\right]$
1 week	weekly	$\Delta^{w} S(t) = S(t+1 \text{ week}) - S(t)$	$\Delta^{w} F(t,T_1) = F(\text{t+1week},T_1)\text{-}F(t,T_1))$	$F(t,T_1)\text{-}S(t)$
1 month	monthly	$\Delta^{1m} S(t) = S(t+1 \text{ month}) - S(t)$	$\Delta^{1m} F(t,T_1) = F(\text{t+1month},T_1)\text{-}F(t,T_1))$	$F(t,T_1)\text{-}S(t)$
3 month	monthly	$\Delta^{3m} S(t) = S(t+3 \text{ months}) - S(t)$	$\Delta^{3m} F(t,T_3) = F(\text{t+3months},T_3)/F(t,T_3))$	$F(t,T_3)\text{-}S(t)$
6 month	monthly	$\Delta^{6m} S(t) = S(t+6 \text{ months})\text{-} S(t))$	$\Delta^{6m} F(t,T_6) = F(\text{t+6months},T_6)\text{-}F(t,T_6))$	$F(t,T_6)\text{-}S(t)$

Table 2. Summary statistics of spot and futures prices returns

The variables appearing in the heading of each column are described in Table 1. The *Kruskal-Wallis* and *Levene* statistics test median and variance equality, respectively, between $\Delta^k S(t)$ and $\Delta^k F(t,T_i)$. *Skewness* means the skewness coefficient and has the asymptotic distribution N(0,6/T) under normality, where T is the sample size. The null hypothesis tests whether the skewness coefficient is equal to zero. *Kurtosis* means the excess kurtosis coefficient and it has an asymptotic distribution of N(0,24/T) under normality. The hypothesis tests whether the kurtosis coefficient is equal to zero. The *Jarque-Bera* statistic tests for the normal distribution hypothesis. The Jarque-Bera statistic is calculated as T[*Skewness*^{2}/6+(*Kurtosis*)^2/24]. The Jarque-Bera statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis. *Q(20)* and *Q*^{2}*(20)* are Ljung Box tests for twentieth order serial correlation in the differentiated and its squared series, respectively. Marginal significance levels of the statistical tests are displayed as [.].

Panel (A): One week variations

	NBP				ZEE				TTF			
	$\Delta^w S(t)$		$\Delta^w F(t,T_1)$		$\Delta^w S(t)$		$\Delta^w F(t,T_1)$		$\Delta^w S(t)$		$\Delta^w F(t,T_1)$	
Mean	0.04	[0.83]	–0.31	[0.00]	0.05	[0.80]	–0.27	[0.00]	0.02	[0.83]	–0.15	[0.00]
Median	0.02		–0.19		0.1		–0.22		0.00		–0.10	
Kruskal-Wallis			9.98	[0.00]			7.75	[0.00]			7.91	[0.00]
S. D.	5.94		2.56		6.36		2.63		2.10		0.98	
Levene			78.31	[0.00]			49.82	[0.00]			36.16	[0.00]
Skewness	0.46	[0.00]	1.17	[0.00]	0.37	[0.00]	1.09	[0.00]	–0.41	[0.00]	-0.10	[0.33]
Kurtosis	28.66	[0.00]	19.90	[0.00]	47.91	[0.00]	16.97	[0.00]	25.89	[0.00]	6.20	[0.00]
Jarque-Bera	2.8×10^3	[0.00]	1.4×10^5	[0.00]	7.1×10^4	[0.00]	9.1×10^3	[0.00]	1.1×10^4	[0.00]	228.78	[0.00]
Maximum	55		25.23		67.25		24.32		17.35		4.55	
Minimum	-55		-17.45		–70.05		–16.45		–16.75		–4.55	
Q(20)	302.73	[0.00]	412.77	[0.00]	314.87	[0.00]	416.29	[0.00]	149.44	[0.00]	169.52	[0.00]
Q^2*(20)*	260.75	[0.00]	622.43	[0.00]	229.84	[0.00]	555.68	[0.00]	70.98	[0.00]	189.16	[0.00]

Table 2 (continued). Summary statistics of spot and futures prices returns

Panel (B): One month variations

	NBP				ZEE				TTF			
	$\Delta^{1m} S(t)$		$\Delta^{1m} F(t,T_1)$		$\Delta^{1m} S(t)$		$\Delta^{1m} F(t,T_1)$		$\Delta^{1m} S(t)$		$\Delta^{1m} F(t,T_1)$	
Mean	0.22	[0.78]	–1.36	[0.00]	0.23	[0.74]	-1.15	[0.02]	0.07	[0.82]	-0.68	[0.00]
Median	0.10		–0.66		0.22		-0.80		-0.12		-0.45	
Kruskal-Wallis			7.08	[0.00]			5.01	[0.02]			3.55	[0.06]
S. D.	10.98		5.99		9.33		6.39		3.41		2.53	
Levene			3.29	[0.07]			3.54	[0.06]			2.30	[0.13]
Skewness	2.80	[0.00]	0.36	[0.04]	2.00	[0.00]	1.07	[0.00]	0.12	[0.59]	-0.75	[0.00]
Kurtosis	40.59	[0.00]	11.39	[0.00]	22.46	[0.00]	16.78	[0.00]	4.85	[0.00]	1.88	[0.00]
Jarque-Bera	1.3×10^4	[0.00]	1.1×10^3	[0.00]	3.5×10^3	[0.00]	3.5×10^3	[0.00]	1.1×10^3	[0.00]	27.15	[0.00]
Maximum	100.55		38.01		72.05		44.37		13.27		5.47	
Minimum	-59.5		-27.20		-33.57		-28.90		-12.40		-9.95	
Q(20)	99.357	[0.00]	79.74	[0.00]	102.86	[0.00]	63.28	[0.00]	68.63	[0.00]	54.91	[0.00]
Q^2(20)	36.09	[0.01]	40.82	[0.00]	43.015	[0.00]	29.764	[0.07]	28.69	[0.09]	47.83	[0.00]

Panel (C): Three and six months returns

	NBP				NBP			
	$\Delta^{3m} S(t)$		$\Delta^{3m} F(t,T_3)$		$\Delta^{6m} S(t)$		$\Delta^{6m} F(t,T_6)$	
Mean	0.72	[0.46]	–3.22	[0.00]	1.67	[0.19]	–4.10	[0.00]
Median	0.72		–1.38		2.00		1.30	
Kruskal-Wallis			14.78	[0.00]			16.72	[0.00]
S. D.	13.75		10.25		17.53		14.24	
Levene			1.29	[0.25]			1.22	[0.27]
Skewness	1.68	[0.00]	-1.40	[0.00]	-0.06	[0.71]	-1.96	[0.00]
Kurtosis	17.80	[0.00]	5.70	[0.00]	12.22	[0.00]	5.62	[0.00]
Jarque-Bera	2499.5	[0.00]	308.1	[0.00]	1.1×10^3	[0.00]	371.89	[0.00]
Maximum	103.25		37.12		106.22		32.83	
Minimum	-53.6		-50.78		-98.75		-69.98	
Q(20)	74.97	[0.00]	36.34	[0.00]	305.39	[0.00]	603.17	[0.00]
Q^2(20)	72.31	[0.00]	34.35	[0.02]	76.016	[0.00]	229.15	[0.00]

Table 3. Correlation matrix of the spot and futures prices variations

The variables appearing in the heading of each row and columns are described in Table 1. For a sample size of T observations, the asymptotic distribution of the $\sqrt{T}$ times the correlation coefficient is a zero-one normal distribution. * indicates significance at the 1% significance level. TTF returns are converted to pence per therm dividing by (100×34.121415×€/£) been €/£ the exchange rate euro per pound sterling.

Panel (A). One-week

		NBP		ZEE		TTF	
		$\Delta^{w}S(t)$	$\Delta^{w}F(t,T_1)$	$\Delta^{w}S(t)$	$\Delta^{w}F(t,T_1)$	$\Delta^{w}S(t)$	$\Delta^{w}F(t,T_1)$
NBP	$\Delta^{w}S(t)$	1.0					
	$\Delta^{w}F(t,T_1)$	0.58*	1.0				
ZEE	$\Delta^{w}S(t)$	0.94*	0.56*	1.0			
	$\Delta^{w}F(t,T_1)$	0.59*	0.98*	0.56*	1.0		
TTF	$\Delta^{w}S(t)$	0.71*	0.45*	0.75*	0.45*	1.0	
	$\Delta^{w}F(t,T_1)$	0.33*	0.65*	0.32*	0.65*	0.59*	1.0

Panel (B). One-month

		NBP		ZEE		TTF	
		$\Delta^{1m}S(t)$	$\Delta^{1m}F(t,T_1)$	$\Delta^{1m}S(t)$	$\Delta^{1m}F(t,T_1)$	$\Delta^{1m}S(t)$	$\Delta^{1m}F(t,T_1)$
NBP	$\Delta^{1m}S(t)$	1.0					
	$\Delta^{1m}F(t,T_1)$	0.63*	1.0				
ZEE	$\Delta^{1m}S(t)$	0.92*	0.64*	1.0			
	$\Delta^{1m}F(t,T_1)$	0.70*	0.92*	0.75*	1.0		
TTF	$\Delta^{1m}S(t)$	0.67*	0.50*	0.79*	0.62*	1.0	
	$\Delta^{1m}F(t,T_1)$	0.39*	0.72*	0.47*	0.75*	0.71*	1.0

Panel (C). Three-month

	NBP	
	$\Delta^{3m}S(t)$	$\Delta^{3m}F(t,T_3)$
$\Delta^{3m}S(t)$	1.0	0.45*
$\Delta^{3m}F(t,T_3)$		1.0

Panel (D). Six-month

	NBP	
	$\Delta^{6m}S(t)$	$\Delta^{6m}F(t,T_6)$
$\Delta^{6m}S(t)$	1.0	0.43*
$\Delta^{6m}F(t,T_6)$		1.0

Table 4. Summer and winter mean and volatility

This table reports the weekly mean and volatility (standard deviation) of basis, spot, and futures returns in winter (October to March) and summer (April to September). Marginal significance levels of the *Kruskal-Wallis* and *Levene* statistics test for median and variance equality, respectively, are reported.

	Summer Mean	Winter Mean	Equality Test	Summer Volatility	Winter Volatility	Equality Test
$F(t,T_1)$-$S(t)$						
NBP	1.26	1.16	0.19	4.34	8.40	0.00
ZEE	0.40	0.56	0.33	3.97	8.29	0.00
TTF	0.54	0.53	0.31	1.68	3.13	0.00
$\Delta^{w}S(t)$						
NBP	-0.04	0.12	0.93	3.14	7.74	0.00
ZEE	0.01	0.11	0.98	3.04	8.37	0.00
TTF	0.01	0.03	0.76	2.71	1.20	0.00
$\Delta^{w}F(t,T_1)$						
NBP	-0.18	-0.44	0.01	1.61	3.22	0.00
ZEE	-0.16	-0.38	0.12	1.70	3.28	0.00
TTF	-0.06	-0.25	0.04	0.77	1.14	0.00

Table 5. The basis as a predictor of the change in spot and futures prices

This table displays the results of the regression between spot and futures changes appearing in the first column on the basis as defined in the second column for the whole sample period. Between brackets *t*-statistic values computed with Newey-West standard errors are reported. Significant coefficients at the 1%, 5%, and 10% of significance level are highlighted with one (*), two (**) and three (***) asterisks, respectively.

Panel (A). Week returns

	Dependent variable	basis	Intercept	Basis coefficient	Adjusted R^2
NBP	$\Delta^w S(t)$	$F(t,T_1)$-$S(t)$	–0.33 (–1.85) ***	0.31 (4.93)*	11.88%
	$\Delta^w F(t,T_1)$	$F(t,T_1)$-$S(t)$	–0.23 (–2.69) *	–0.07(–3.41)*	3.09%
ZEE	$\Delta^w S(t)$	$F(t,T_1)$-$S(t)$	–0.34 (–1.67) ***	0.36 (3.99)*	14.03%
	$\Delta^w F(t,T_1)$	$F(t,T_1)$-$S(t)$	–0.21 (–2.19) **	–0.06(–2.32)**	2.38%
TTF	$\Delta^w S(t)$	$F(t,T_1)$-$S(t)$	–0.13 (–1.53)	0.26 (3.51)*	9.79%
	$\Delta^w F(t,T_1)$	$F(t,T_1)$-$S(t)$	–0.10 (–2.29) **	–0.09(–4.11)*	5.08%

Panel (B). One-month returns

NBP	$\Delta^{1m} S(t)$	$F(t,T_1)$-$S(t)$	–1.22 (–2.16)**	0.78 (2.76)*	30.93%
	$\Delta^{1m} F(t,T_1)$	$F(t,T_1)$-$S(t)$	–1.09 (–2.51)**	–0.34 (–0.83)	3.61%
ZEE	$\Delta^{1m} S(t)$	$F(t,T_1)$-$S(t)$	–1.00 (–1.86)	0.73 (3.25)*	24.39%
	$\Delta^{1m} F(t,T_1)$	$F(t,T_1)$-$S(t)$	–0.98 (–2.09)**	–0.09 (–0.49)	0.93%
TTF	$\Delta^{1m} S(t)$	$F(t,T_1)$-$S(t)$	–0.40 (–1.62)	0.51 (2.93)*	16.48%
	$\Delta^{1m} F(t,T_1)$	$F(t,T_1)$-$S(t)$	–0.38 (–1.73)***	–0.33 (–2.55)**	12.19%

Panel (C). Three month returns

NBP	$\Delta^{3m} S(t)$	$F(t,T_3)$-$S(t)$	–1.84 (–1.68)***	0.60 (3.08)*	31.48%
	$\Delta^{3m} F(t,T_3)$	$F(t,T_3)$-$S(t)$	–0.34 (–1.83)***	–0.33 (–1.83)***	1.80%

Panel (C). Six month returns

NBP	$\Delta^{6m} S(t)$	$F(t,T_6)$-$S(t)$	–1.89 (–1.07)	–0.40(3.00)*	31.55%
	$\Delta^{6m} F(t,T_6)$	$F(t,T_6)$-$S(t)$	–1.67 (–0.98)	–0.40(–2.22)**	22.27%

Table 6. BEKK model estimates

Using the pair of variables $\Delta^w S(t)\ \Delta^w F(t,T_1)$ as described in Table 1 a VECM model as described in equation (9) is estimated. From each VECM, an innovation vector $(\varepsilon_{1t}, \varepsilon_{2t})'$ is obtained without autocorrelation problems. Panel (A) of this table displays the quasi maximum likelihood estimates of the BEKK model in equation (11) for the *ex post* sample. Panel (B) reports some statistics for the standardized residuals: *Skewness* coefficient has the asymptotic distribution N(0,6/T), where T is the sample size. The null hypothesis tested is that the standardized residual skewness coefficient is equal to zero. The excess *Kurtosis* coefficient has an asymptotic distribution of N(0,24/T). The hypothesis tested is that standardized residual kurtosis coefficient is equal to zero. *Q(20)* and *Q^2(20)* are Ljung Box tests for twentieth order serial correlation in the standardized residuals and its squared value; these two statistics are distributed as $\chi^2(20)$ under the null hypothesis of no autocorrelation. Significant coefficients or rejection of the null hypothesis at the 1%, 5%, and 10% of significance level are highlighted with one (*), two (**) and three (***) asterisks, respectively.

Panel (A). BEKK model

	NBP	ZEE	TTF
c_{11}	-0.56*	-1.87*	-0.35*
c_{22}	0.02	7.6×10^{-8}	-0.35*
c_{12}	-0.12*	-0.90*	2.7×10^{-10}
a_{11}	0.20*	0.44*	-0.66*
a_{12}	0.12*	0.05	0.61*
a_{21}	0.63*	-0.34***	0.06*
a_{22}	0.23*	0.47*	0.95*
b_{11}	0.93*	0.71*	0.10*
b_{12}	0.03*	-0.09*	0.66*
b_{21}	-0.29*	-1.19*	0.35*
b_{22}	0.82*	-0.19**	-1.61*
g_{11}	-0.05	-0.34*	-0.61
g_{12}	-0.03	-0.04	0.03*
g_{21}	-0.92*	0.34	-0.30***
g_{22}	0.31*	0.05	0.38*

Panel (B). Summary statistics for the standardized residuals

	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$
Skewness	1.07*	0.45*	8.15*	0.46*	1.62*	0.46
Kurtosis	6.31*	1.99*	119.68*	2.81*	10.77*	1.67
Q(20)	20.48	15.58	6.43	5.19	15.31	14.36
Q^2(20)	15.05	33.83**	19.80	21.73	6.08	47.31*

Table 7. Seasonal model estimates

This table reports the estimates of equation (12). Other comments are identical to those of Table 5.

Panel (A). Volatility seasonal model

	NBP	ZEE	TTF
c_{11}	3.12*	3.12*	2.56*
c_{22}	1.05*	1.30*	1.10*
c_{12}	1.37*	1.54*	1.37*
a_{11}	-1.95*	-2.32*	-1.15*
b_{11}	8.05*	6.90*	5.84*
a_{22}	0.01*	-0.34*	-0.47*
b_{22}	0.44*	0.73*	0.67*
a_{12}	-0.19*	-0.40*	-0.64*
b_{12}	1.00*	1.11*	1.41*

Panel (B). Summary statistics for the standardized residuals

	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$
Skewness	0.52*	1.02*	1.42*	0.78*	0.29*	0.38*
Kurtosis	10.77*	11.15*	19.19*	7.88*	15.20*	3.01*
Q(20)	18.98	8.84	25.21	14.69	16.43	13.63
$Q^2(20)$	291.05*	223.01*	74.70*	157.80*	35.53**	60.73*

Table 8. Seasonal model estimates

This table shows the estimates of equation (13). Other comments are identical to those of Table 5.

Panel (A). Volatility seasonal model

	NBP	ZEE	TTF
c_{11}	3.47*	3.50*	2.87*
c_{22}	1.10*	1.41*	1.18*
c_{12}	1.46*	1.67*	1.49*
a_{11}	-2.21*	-2.27*	-1.93*
a_{22}	-0.11*	-0.25*	-0.21*
a_{12}	-0.27*	-0.37*	-0.45*
a	1.04*	1.10*	0.86*
b	1.29*	1.44*	0.87*
c	-3.49*	-2.88*	-2.98*

Panel (B). Summary statistics for the standardized residuals

	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$	$\varepsilon_{1t}/\sqrt{h_{11t}}$	$\varepsilon_{2t}/\sqrt{h_{22t}}$
Skewness	0.53*	1.01*	1.43*	0.79*	0.21**	0.32*
Kurtosis	10.81*	10.97*	19.30*	7.94*	15.37*	3.83*
Q(20)	18.92	8.57	25.93	14.74	16.37	12.24
$Q^2(20)$	289.82*	52.35*	183.09*	155.45*	32.78**	66.86*

Table 9. Hedging effectiveness in weekly hedges

This table displays the risk reduction achieved by each hedging strategy: naive, OLS without the basis (see equation (4)), OLS with the basis (see equation (8)), BEKK (see equation (11)), seasonal (see equation (12)) and seasonal-basis (see equation (13)). The *in sample* results are computed for the first 5 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 to calculate the risk reduction achieved with each hedging strategy. This variance is computed as $VAR[\Delta^k S(t)]$ and $VAR[\Delta^k S(t) - \hat{\lambda}(\log(F(t,T_k)/S(t)))]$ in the 'standard' and Ederington and Salas (2008) approaches, respectively. Variance of each hedging strategy is computed as $VAR[\Delta^k S(t) - \hat{b}_t \Delta^k F(t,T_i)]$ and $VAR[\Delta^k S(t) - \hat{b}_t \Delta^k F(t,T_i) - \hat{\lambda}(\log(F(t,T_k)/S(t)))]$ in the standard and 'E&S(2008)' approaches, respectively. Spot and futures variations are defined as in Table 1 and b_t represents the hedging ratio. *Ex ante* hedging ratios are forecasted values in t–1 and each time the moving window sample moves ahead the model is estimated again. Those strategies with largest risk reduction in each panel are indicated with an asterisk (*).

	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 NBP				
Period	Dec. 3rd, 1997 – Feb.19th, 2003		Feb. 26th, 2003 – Mar. 26th, 2014	
Spot variance (no hedged)	13.14	9.95	45.76	42.81
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naive (b=1)	16.76	24.91	31.83	42.55
OLS w/o basis	19.40	30.01	31.85	45.91
OLS with basis	19.26	30.19*	30.48	46.12
Seasonal	19.06	29.98	30.31	45.79
Seasonal-basis	19.03	30.15	31.83	46.81*
BEKK	16.87	29.04	8.69	17.04
Panel (B). Hedging one-week spot risk in ZEE				
Period	Oct. 20th, 1999 – Jan.5th, 2005		Jan. 12th, 2005 – Mar. 26th, 2014	
Spot variance (no hedged)	11.39	8.76	52.38	57.25
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naive (b=1)	19.87	28.80	29.65	39.52
OLS w/o basis	19.96	29.53	29.94	43.61
OLS with basis	18.68	30.79	28.38	42.71
Seasonal	17.98	30.64	29.30	43.52
Seasonal-basis	17.81	30.64	30.91	44.44*
BEKK	22.02	33.17*	28.94	41.52
Panel (C). Hedging one-week spot risk (($\Delta^{1w}S(t)$).TTF				
Period	Jan. 7th, 2004 – Mar. 25th, 2009		Apr. 1st, 2009 – Mar. 26th, 2014	
Spot variance (no hedged)	7.90	6.75	1.34	1.32
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naive (b=1)	33.62	41.65	34.18	46.46*
OLS w/o basis	34.36	44.65	33.14	46.18
OLS with basis	31.58	46.95	26.28	44.71
Seasonal	29.38	47.37*	27.73	42.96
Seasonal-basis	28.51	46.83	30.94	45.04
BEKK	30.99	47.28	26.36	40.55

Table 10. Hedging effectiveness in long-time hedges

This table is similar to Table 6, but using monthly data frequency and only linear regression and naïve hedges because of data sample restrictions. The *in-sample* results are computed from the beginning of each time-series until March 2006. In the *out-of-sample* period, OLS hedging ratios b_t (see equations (4) and (8)) are forecasted values and each time a new observation is added the model is estimated again.

	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 NBP.				
Period	December 1997 – March 2006		April 2006 – March 2014	
Spot variance (not hedged)	185.98	94.93	54.30	74.53
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (*b*=1)	43.69	81.09*	19.88	78.58
OLS w/o basis	55.82	78.98	-24.01	78.98*
OLS with basis	54.75	69.38	-34.41	76.23
Panel (B). Hedging one month spot risk in ZEE.				
Period	October 1999 – March 2006		April 2006 – March 2014	
Spot variance (not hedged)	129.58	76.48	53.50	57.12
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (*b*=1)	59.23	75.83	46.01	85.87
OLS w/o basis	63.82	75.28	37.24	87.22*
OLS with basis	62.50	77.45*	38.61	86.97
Panel (C). Hedging one month spot risk in TTF.				
Period	January 2004 – March 2006		April 2006 – March 2014	
Spot variance (not hedged)	26.84	12.68	8.89	10.86
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naïve (*b*=1)	48.16	75.47	46.73	87.63*
OLS w/o basis	50.81	85.16	42.59	85.58
OLS with basis	47.11	89.19*	17.00	87.55
Panel (D). Hedging three-month spot risk in NBP				
Period	December 1997 – March 2006		April 2006 – March 2014	
Spot variance (not hedged)	226.35	101.36	151.71	190.65
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naive (*b*=1)	34.72	70.70	-21.45	92.10*
OLS w/o basis	36.87	73.31	-13.16	83.56
OLS with basis	36.75	73.56*	-51.83	91.23
Panel (E). Hedging three-month spot risk in NBP				
Period	December 1997 – March 2006		April 2006 – March 2014	
Spot variance (not hedged)	235.89	91.67	370.18	420.71
Hedging Strategy	**Risk reduction (%)**		**Risk reduction (%)**	
Naive (*b*=1)	16.55	66.80	-6.54	93.08*
OLS w/o basis	16.66	69.71	11.79	74.11
OLS with basis	15.25	73.39*	-32.86	92.25

Table 11. Variances of spot returns and basis

This table reports the variances of spot returns ($\Delta^k S(t)$) and basis ($F(t,T_k)$- $S(t)$) for hedges of 1, 3, and 6 months using the monthly frequency data set. The *in-sample* results are computed from the beginning of each time-series until March 2006. In the *out-of-sample* period, results are computed from April 2006 until March 2014.

	In the sample		**Out of the simple**	
	Spot return	basis	Spot return	basis
1 month (NBP)	172.69	63.74	68.65	57.60
1 month (ZEE)	130.15	43.24	53.50	36.75
1 month (TTF)	22.49	12.38	8.89	5.95
3 months (NBP)	216.72	146.88	160.57	166.80
6 months (NBP)	237.38	269.17	368.45	258.26

9. Figures

Figure 1. European spot and futures natural gas markets.
Spot price (——) and the first to 'delivery' futures price (- - -)

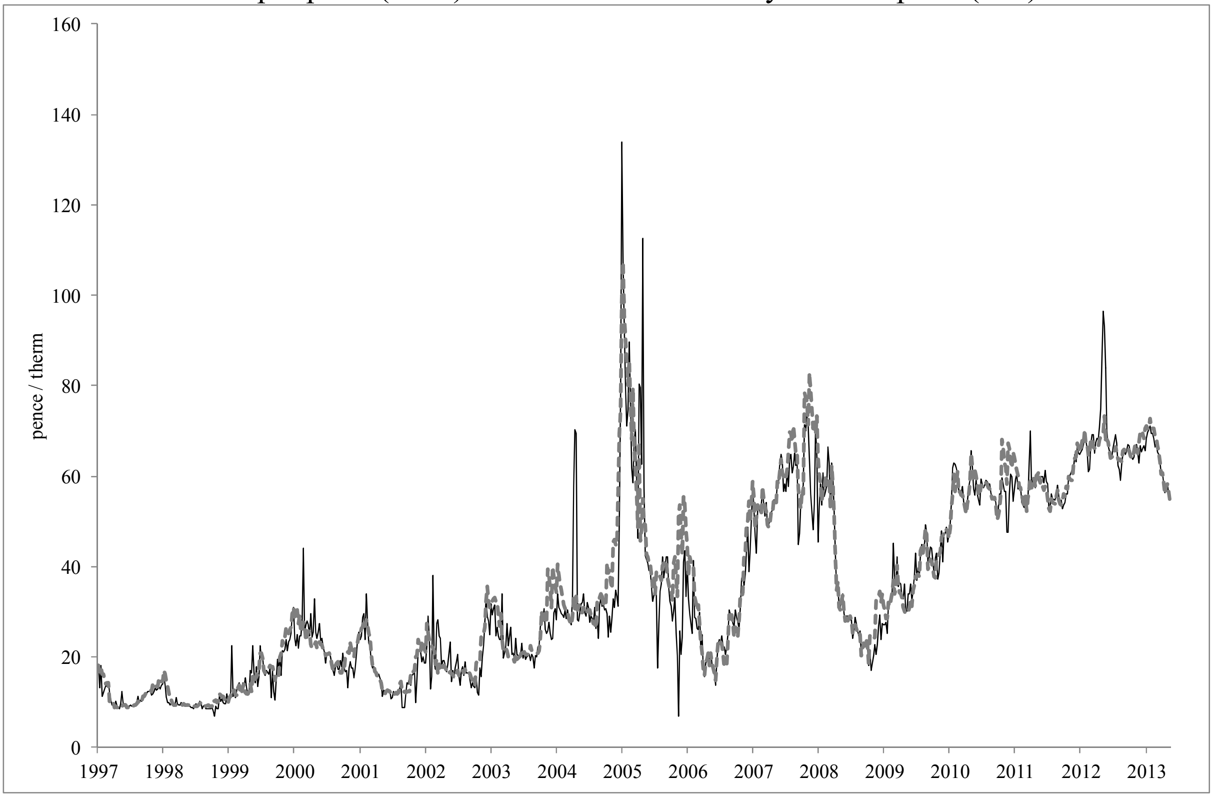

Figure 1(a). NBP spot and fist to 'delivery' futures contract.

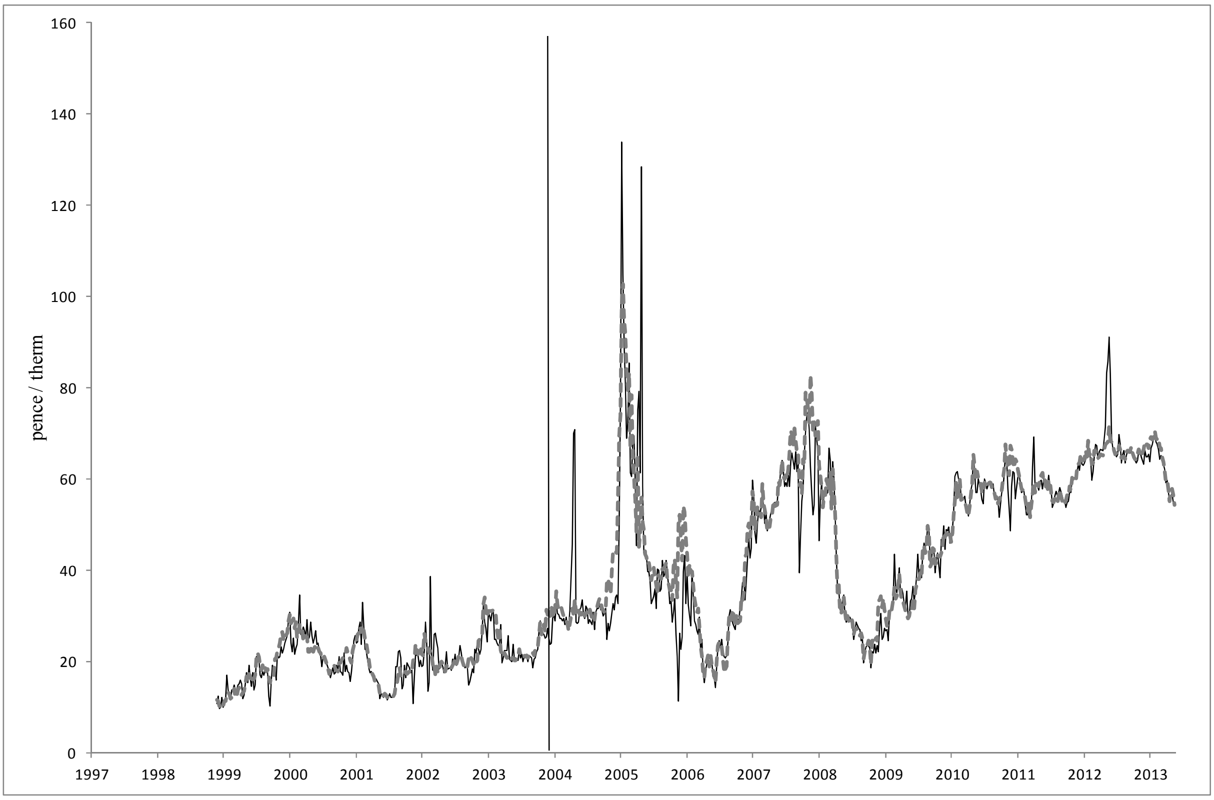

Figure 1(b). Zeebrugge spot and first to ‘delivery’ futures contract.

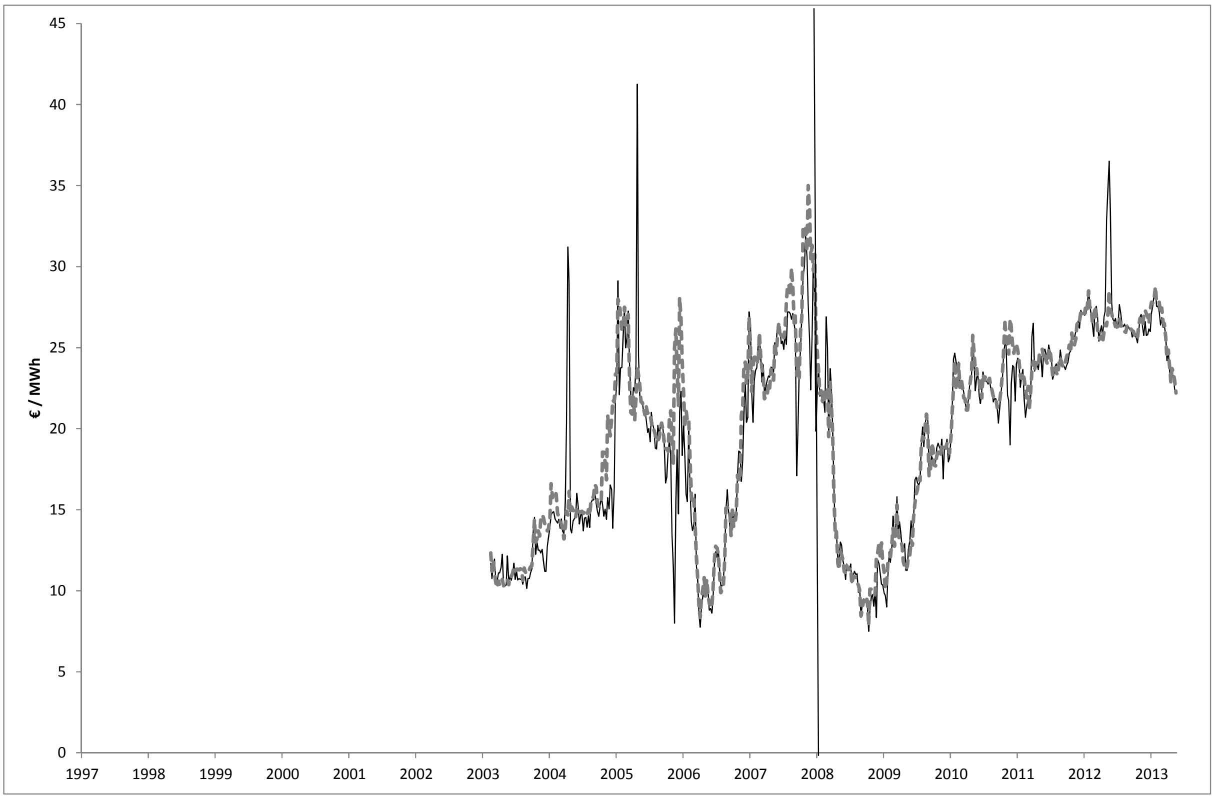

Figure 1(c). TTF spot and first to 'delivery' futures contract.

Figure 2. Seasonal basis.

13-week centered moving average basis at NBP (——), Zeebrugge (¯ ¯ ¯), and TTF (¨) are computed as the futures front contract price minus daily spot price.

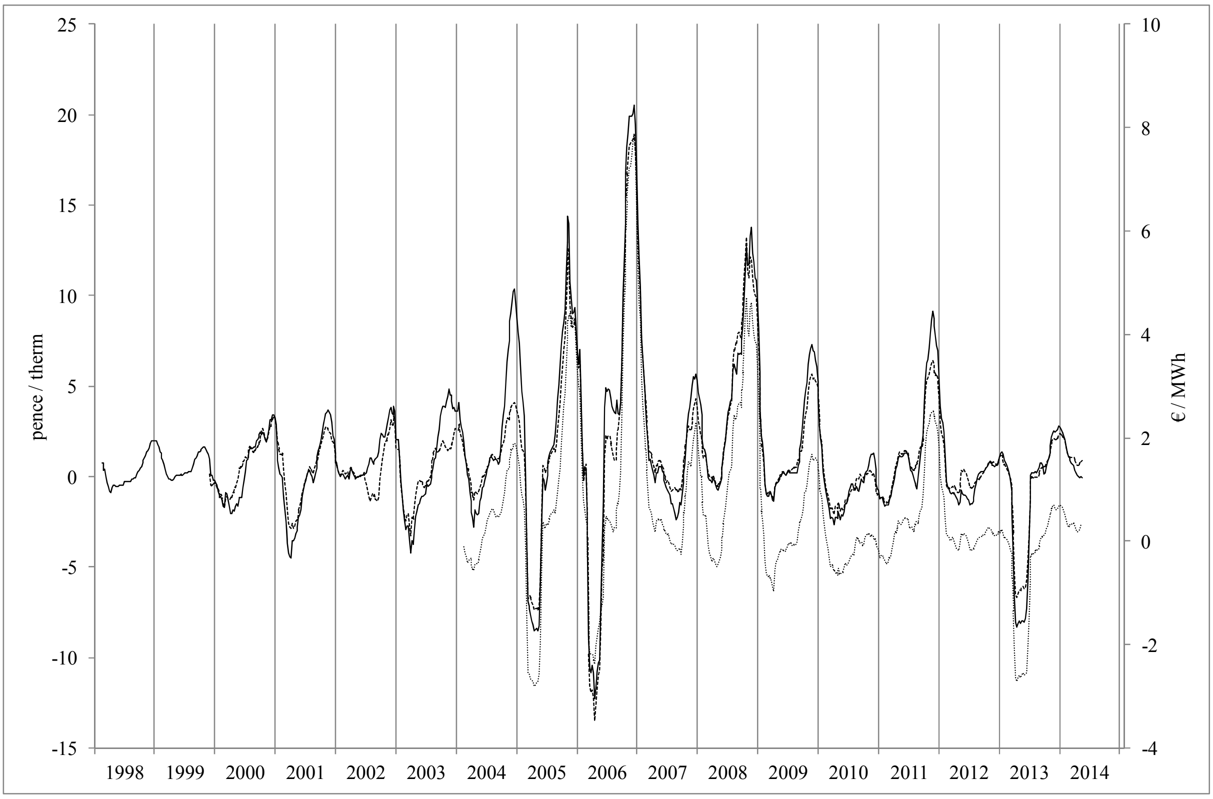

Figure 3. Seasonal volatility

NBP spot volatility (——) and its front monthly futures volatility (- - -). Standard deviation of a 13-week centered moving window returns are reported.

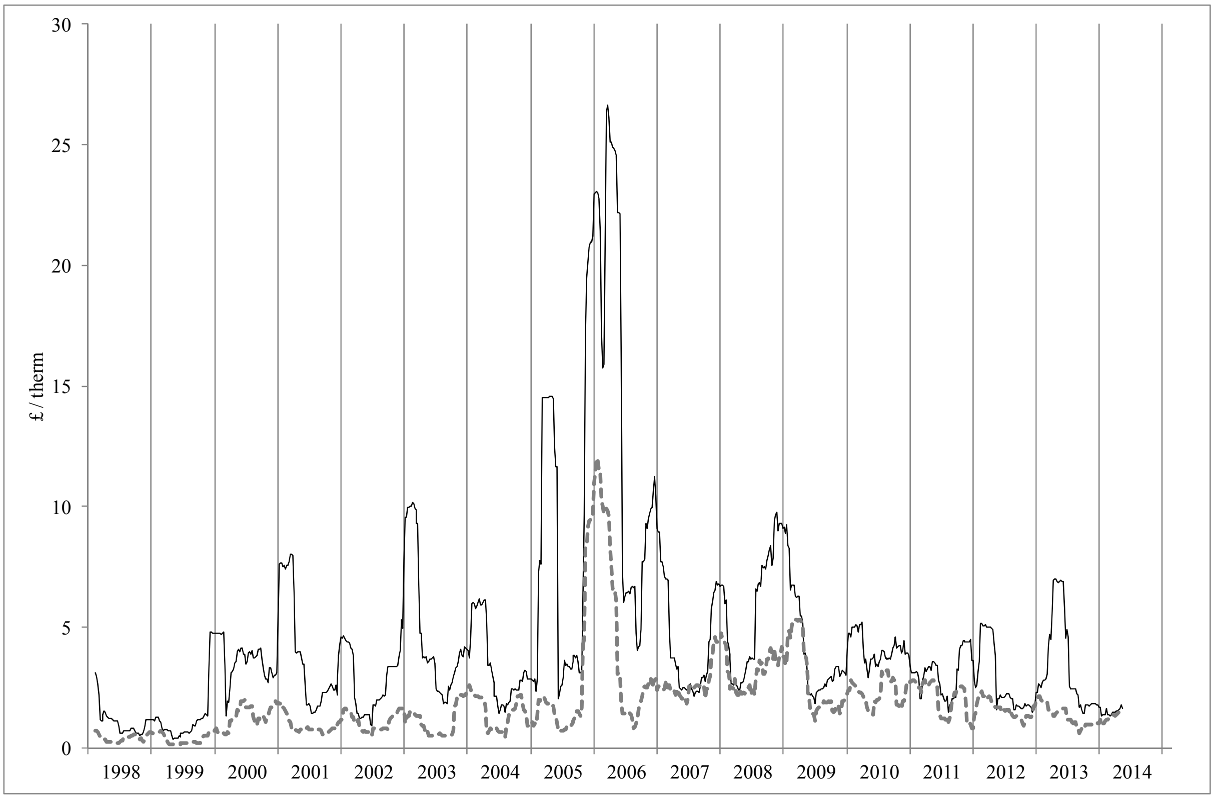

Figure 4. Annualized conditional volatilities

Notes. In each graph, the solid line (——) and the dashed line (- - -) corresponds to the annualized conditional volatility for the seasonal-basis and BEKK models, respectively. The displayed conditional volatilities are estimated in the 'one-week' hedging period models. The vertical line separates the *ex post* and *ex ante* (five year moving window) hedging periods.

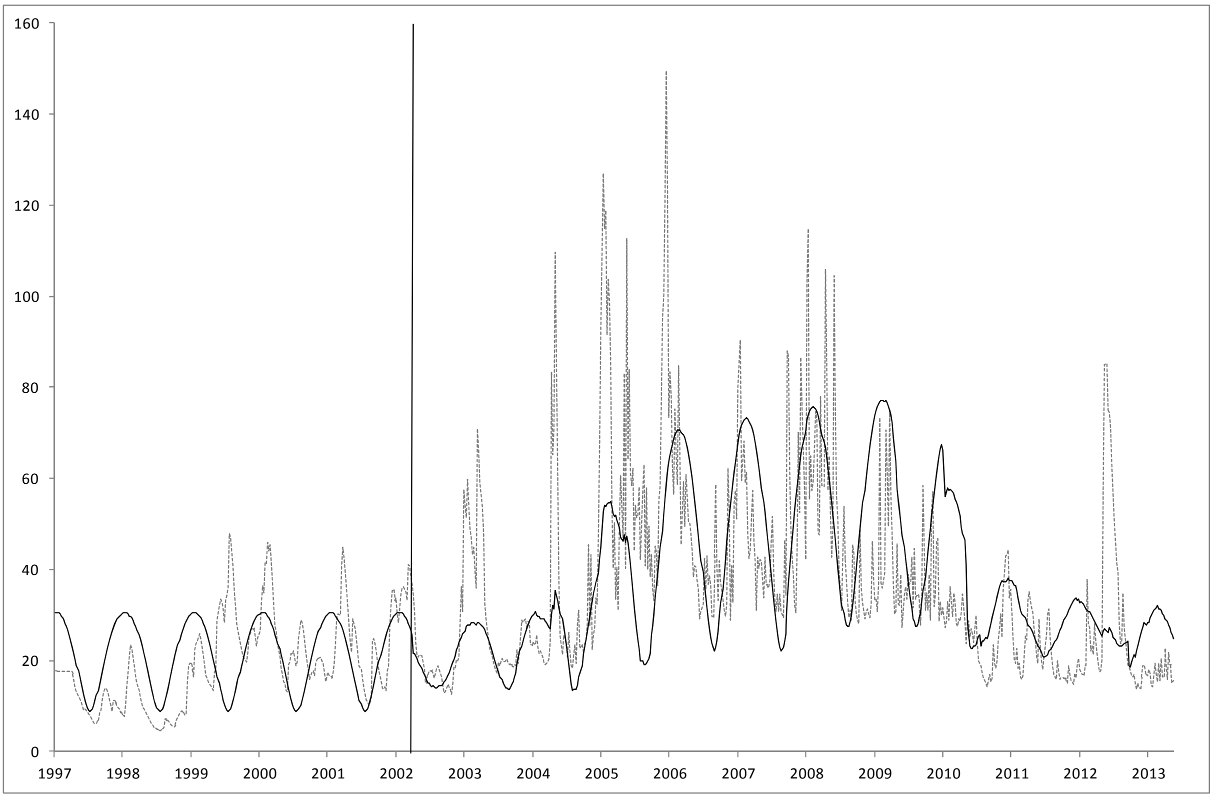

Figure 4(a). Spot annualized volatility

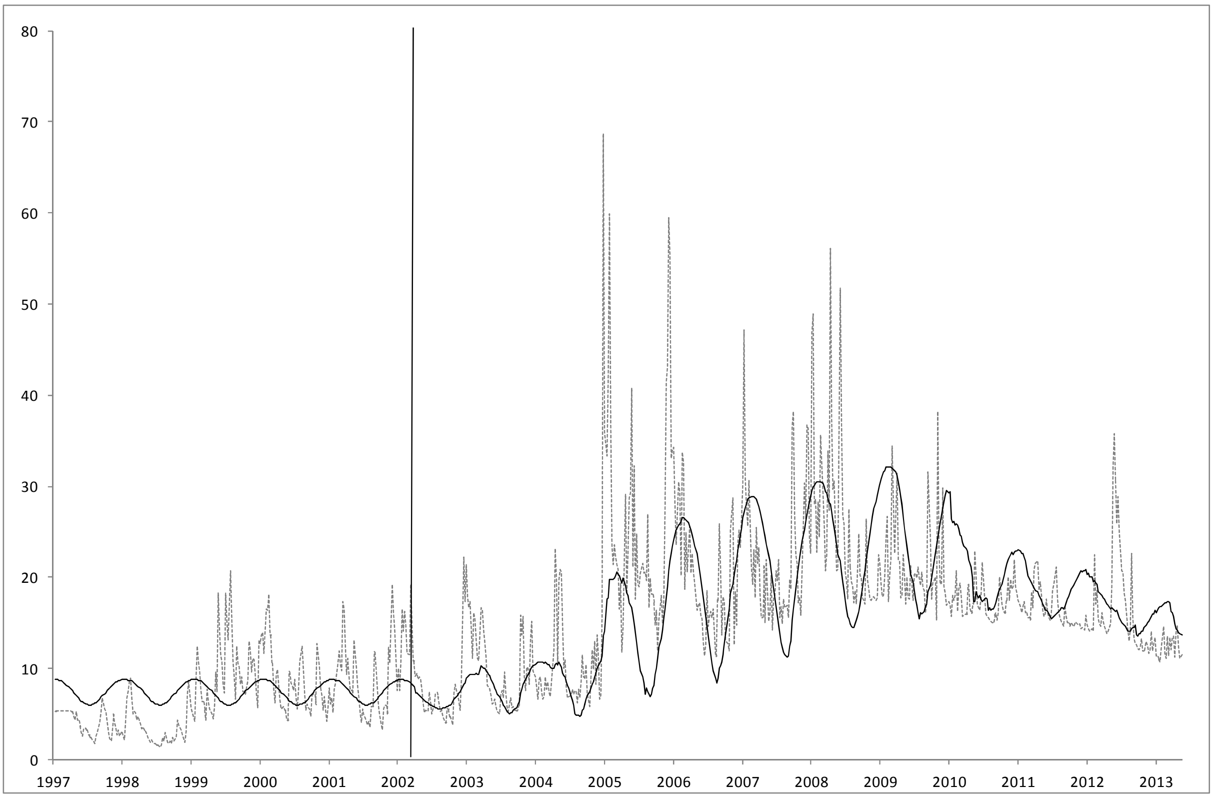

Figure 4(b). First to 'delivery' annualized volatility

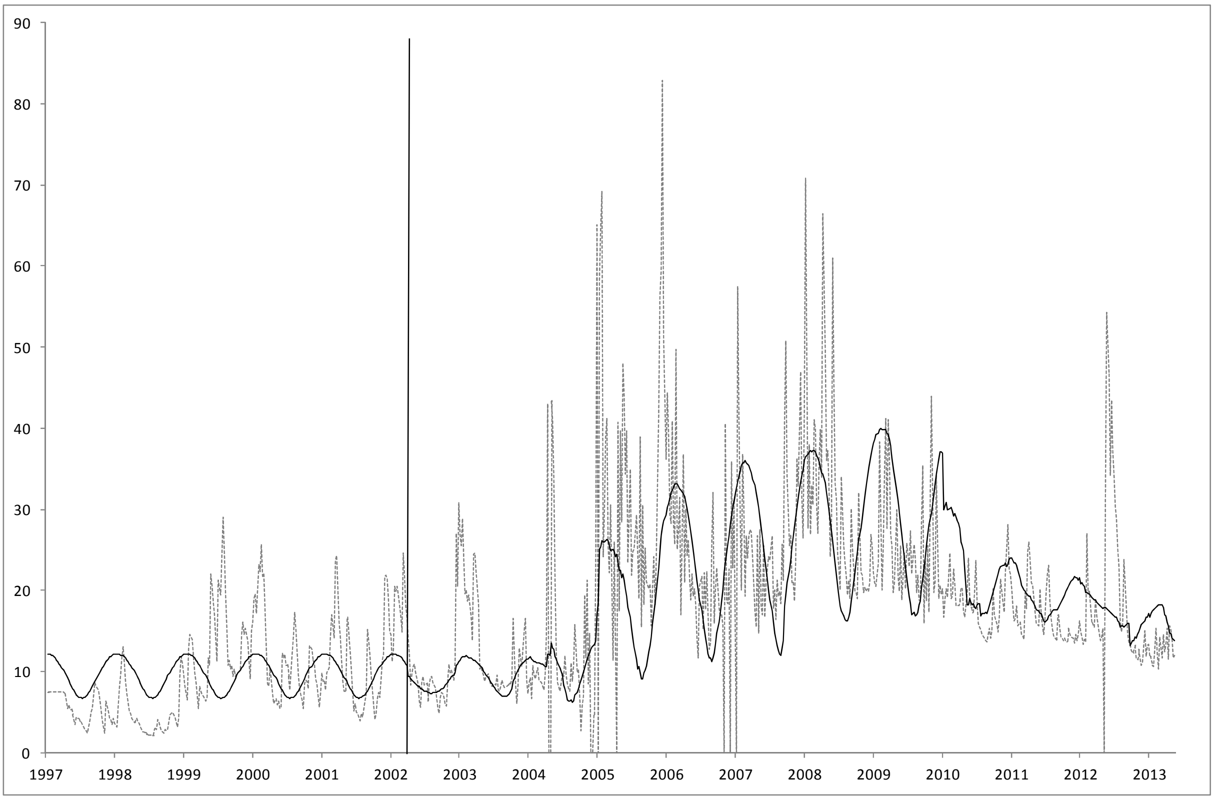

Figure 4(c). Annualized covariance between spot and futures

Figure 5. Hedging ratios.

Notes. The vertical line separates the *ex post* and *ex ante* hedging periods. The vertical line separates the *ex post* and *ex ante* (five years moving window) hedging periods.

Figure 5(a). OLS hedging ratios estimated with equation (8) are represented with continuous lines (——) and OLS hedging ratios estimated with equation (4) are represented with dashed lines (- - -).

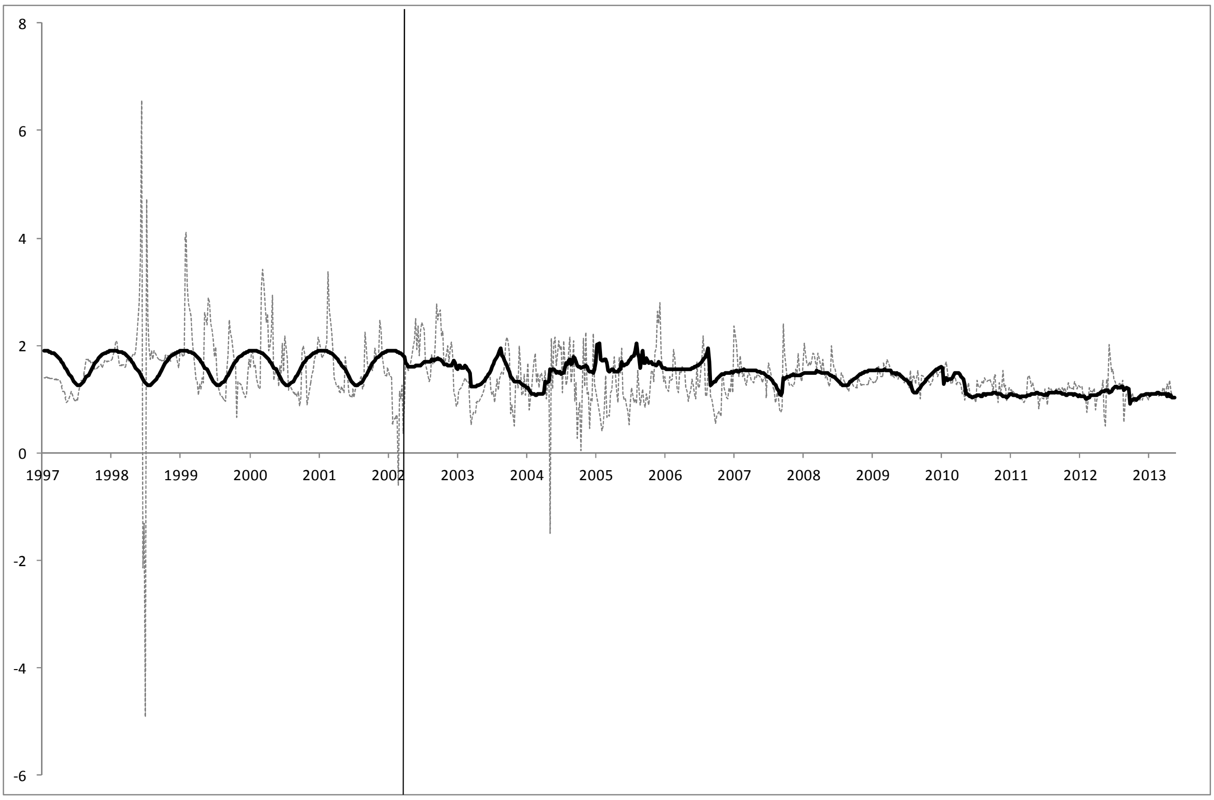

Figure 5(b). BEKK hedging ratios are represented with continuous lines (——) and seasonal hedging ratios are represented with dashed lines (- - -).

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