Optimal hedging under biased energy futures markets[*]

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Abstract

Optimal futures hedging positions for those agents trying to maximise their expected utility will depend on their view about the evolution of the market and on how risk adverse they are. The most risk adverse agents will probably decide to full-cover their positions. But when a futures bias exists, hedgers with moderate or low degree of risk aversion can alter their strategy depending on the expected gains in futures markets. In our application to the UK natural gas market, we find a statistically significant time-varying negative futures bias that can be forecasted with confidence. As a result of this bias, most effective and best performing hedging strategies for moderate risk-averse agents are those involving short (long) hedging in winter (summer) with a hedging ratio above (below) the minimum variance hedge ratio. These findings are of great interest to practitioners in the UK natural gas markets and the methodology can be extrapolated to other energy markets.

JEL Classification: G11, G13 and L95.

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1. Introduction

One important feature of energy prices is the presence of a strong seasonal pattern due to weather, demand, and storage levels.[1] Seasons with high demand, low storage levels, and adverse weather conditions generate higher price volatility and an increase in the probability of price jumps. Related to these economic risks and the willingness of different market participants to bear them, futures prices for energy commodities can contain a risk premium, also known as futures premium or futures bias. Risk premiums more probably exist in those futures contracts whose underlying spot commodity is not storable, like electricity, and where the cash-and-carry pricing framework cannot be applied. But premiums are also likely to exist in most energy fuels for which jumps in demand can be difficult to buffer under technical restrictions on supply production, demand inelasticity and uncertainty about storage costs, interest rates, convenience yield and/or transaction costs (see Duffie (1989, p. 98)). Because of this, though not in an obvious way, risk premiums in energy futures prices may describe a seasonal behaviour that should be considered by any model when attempting to improve forecast accuracy (Sadorsky, 2002). Particularly, in the specific case that concerns this work, Cartea and Williams (2008) pointed out that UK natural gas spot prices as well as their volatility tended to be higher in winter than in summer due to higher marginal production cost in the cold season together with winter weather shocks and demand inelasticity. Additionally, Martínez and Torró (2018) found that risk premiums exhibited a seasonal pattern in the UK natural gas market, being significantly higher in winter than in summer. From these results, we expect to obtain a negative futures bias in the UK natural gas futures benefiting (harming) short (long) hedging strategies. Furthermore, if this negative bias is expected to be larger in winter than in summer, short hedgers will have an incentive to over-increase (decrease) its hedging ratio in winter (summer). The reverse reasoning could be applied to long hedgers.

[1] See Mu (2007), Lucia and Schwartz (2002), Bessembinder and Lemon (2002), Cartea and Villaplana (2008) and Longstaff and Wang (2002).

Risk premiums are defined as the current futures price minus the expected spot price at maturity. To apply this definition to empirical studies, some authors (see for example Fama and French (1987) or Szymanowska et al. (2014)) compute the futures bias as the current futures price minus the same futures contract price at maturity or some days before maturity. In this way, the futures bias is the return of a short position maintained until maturity.

The minimum variance approach is the conventional methodology to obtain hedging ratios when basis risk arises, due to maturity mismatches or cross-hedging strategies. Ederington (1979)'s seminal work presented the standard methodology to estimate the Minimum Variance Hedge Ratio (MVHR henceforth) and to measure the hedging effectiveness by regressing historical spot returns on futures returns. Since then, most efforts have been put on improving this statistical method, (see Lien and Tse (2002) for an excellent survey on futures hedging literature). Recently, Chun et al. (2019) and Shrestha et. al. (2018) have compared the hedging effectiveness of several sophisticated statistical methods estimating the MVHR. These methods include quantile estimation, stochastic volatility models and GARCH models. The list of statistical methods applied in this context is endless. The minimum variance approach has also been recently applied to simultaneously hedge positions in spot markets of several closely-related energy commodities, like the spark spread risk, involving natural gas and electricity, since the former is burned to produce the latter (Martínez and Torró (2018b)) or the crack spread risk, which results from the difference between the price of crude oil and a composite of gasoline and heating oil prices (Alexander et al. (2013)). In addition, the interest of using energy commodity futures for hedging stock price risk has augmented in the last few years. In fact, there is an increasing number of studies on cross-hedging stock market portfolios using energy commodities futures. Maghyereh et al. (2017) found that equities of the Gulf Cooperation Council countries cannot be hedged using oil and gold futures. Nevertheless, for the same area, Mensi et al. (2019) found that the effectiveness of this cross-hedge is very high using portfolios of bank stocks. Similarly, Batten et al. (2019) have studied the cross-hedge of global stock market indexes and oil futures contracts. Results show the economic significance of the cross-hedge is always positive and specially increases during the global financial crisis. Sourhir et al. (2019) find that Nord Pool electricity can be used to diversify and hedge against stock market risk.

An alternative approach to the minimum variance is the optimal hedging of a spot position using futures contracts in a one-period portfolio selection model, which has been adopted in several previous papers since the pioneer work of Anderson and Danthine (1980 and 1981). Under this approach, the weight of the futures asset in the hedged portfolio is obtained by maximizing the expected utility of the hedger. Myers and Thompson (1989), Gagnon and Lypny (1995) and Kroner and Sultan (1993) applied this approach to financial assets and agricultural commodities. Optimal hedging approach has also been applied to energy markets, see Cotter and Hanly (2010) and Cotter and Hanly (2012). As Cotter and Hanly (2012) point out, the risk attitude of hedgers has an important role to play in the determination in what is considered as optimal from a hedging perspective. As will be shown in the following section, optimal futures hedging positions can be split into two parts: the minimum variance hedge ratio and a second part that depends on the agents' risk aversion and the futures bias (Anderson and Danthine (1980 &1981)). When the futures bias is zero, that is, when futures prices are martingale, and/or for those agents with extreme risk aversion, the optimal futures hedging position collapses to the well-known MVHR. In any other case, the minimum variance approach does not provide optimal hedging ratios. Therefore, the well-known minimum variance approach is a special case of the broader optimal hedging approach.

As previously explained, a forecastable futures bias may exist in energy commodities. So, the optimal hedging position may be different to the MVHR for agents with low or moderate risk aversion. Specifically, optimal hedging may imply over/under hedging regarding the MVHR, depending on the futures bias sign and the position to be taken in the futures markets (long or short).

Furthermore, the optimal hedging approach can be related to the corporate finance literature on selective hedging[2] initiated by Stulz (1996). Under this view, many corporations decide to take a mix between pure hedging and speculative positions in futures based on the managers' alleged

[2] Selective hedging is a practice in which the risk manager´s view of future price movements influences the percentage of the exposure that is hedged (Stulz, 1996).

informational advantage in predicting the direction of the market. Brown et al. (2006), Adam and Fernando (2006) and Adam et al. (2017) have studied the performance of selective hedging strategies in the gold industry. The evidence show that selective hedging does not create value to the shareholder. The gains from selective hedging appear to be small at best and mostly due to the presence of risk premia in forward markets (Adam and Fernando, 2006). On the other hand, Conlon et al. (2016) investigate how preferences on hedging horizons, risk aversion and selective hedging impact the optimal expected utility futures hedging strategy. A key difference between the hedging strategies analysed by this previous literature and our work is that we are able to estimate expected futures returns as a measure of the expected bias that can be incorporated in the portfolio selection model, without needing to make any assumption about their expected values based on a supposed greater ability of business managers to predict the evolution of market prices, which is in itself a contribution to literature.

From an empirical point of view, two previous steps are necessary to apply this view for optimal hedging. Firstly, it is important to test if there is evidence of any significant futures bias and describe how its variation in sign and size is across time. In a second step, a reliable forecasting model for the futures bias is needed. Following Lucia and Torró (2011), a bivariate vector autoregressive (VAR henceforth) model with the futures bias and the futures basis (futures price minus spot price) is proposed. The futures basis has econometric properties and economic content. The basis decreases as the futures maturity approaches, which makes it easy to predict. Furthermore, the futures basis contains all the intertemporal information agents use to link current and expected prices. For example, the basis is low (high) when storage levels of the energy commodity are low (high) because convenience yield is usually high (low) in this scenario. Risk premiums are also contained in the basis and will respond to unexpected shocks in demand and other sources of uncertainty, by increasing or decreasing, depending upon the sign of the unexpected shock.

Martínez and Torró (2018a) show that there are significant and seasonal varying risk premiums in the UK natural gas futures prices. Lucia and Torró (2011) obtained a similar result for electricity futures prices in the Nord Pool. In particular, Martínez and Torró (2018a) find that, for the period 2000-2015, the average non-annualised risk premium for futures contracts with maturities in the summer months (April to September) increases from about 2.5 to 10 per cent as time to maturity increases from 1 to 6 months. For winter maturities (October to March) these values are more than twice as high than in the summer season and vary between 6 and 20 per cent. Then, agents using futures to manage the risk assumed in the spot market shape their position in futures contracts depending on their risk-return preferences. This is especially so when futures risk premiums vary in a predictable way.

The objective of this paper is to design and evaluate optimal hedging strategies considering agent risk-return preferences based on a predictable behaviour of futures returns. Thereby, this paper also contributes to literature by identifying a bias in the futures returns of one of the benchmarks for natural gas in Europe, i.e. National Balance Point (NBP). Besides, this key finding is shown to affect the design of optimal hedging strategies and it does so in a different way depending on the degree of risk aversion of hedgers.

2. Theoretical model

The conventional hedging framework 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. The risk to be hedged is the so-called price (or market) risk, which refers to the probability of loss occurring from adverse movements in the market price of an asset. To reduce the risk exposure, the individual may choose to hedge at time '*t*' in the futures market with the same underlying asset. The idea behind hedging using futures contracts is to take a position in futures contracts so that results from the futures trading offset results from the spot market. A short hedge is appropriate when the hedger owns the asset (or will be owned at some time in the future), expects to sell it in the future and wants to lock in a price at the beginning of the period. In contrast, a long hedge is appropriate when the hedger knows she will have to purchase a certain asset in the future and wants to lock in a price at the beginning of the period. Therefore, a short (long) hedge involves taking a short (long) position in the futures market to offset a long (short) position in the spot market.

At the end of the period, say, '$t + 1$', the short hedger's result per unit of spot is calculated as follows

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

where x_{t+1} is the portfolio value variation between t and $t+1$, $\Delta S(t+1) = (S(t+1) - S(t))$ is the spot value variation, $\Delta F(t+1, T) = (F(t+1, T) - F(t, T))$ the futures value variation of a futures contract maturing at T, and b_t is the hedging ratio. The portfolio value variation for a long hedge per unit of spot will be computed as $x_{t+1} = -\Delta S(t+1) + b_t \Delta F(t+1, T)$). Assuming the investors face a mean-variance expected utility function[3]

$$E[U(x_{t+1})|\psi_t] = E[x_{t+1}|\psi_t] - ½\, \lambda\, VAR[x_{t+1}|\psi_t] \quad (2)$$

where λ is the degree of risk aversion parameter that can be understood as the coefficient of relative risk aversion. The hedger will choose b_t to maximise the expected utility

[3] The use of other utility functions (such as logarithmic, exponential, and power) can be considered as special cases of the mean-variance utility functions, taking this as a second-order approximation to any utility function, see Levy and Markowitz (1979). The theoretical framework of Pratt-Arrow for premium risk can be used at this point. Let the investor have an initial wealth of W_t and a Von Neumann-Morgenstern utility function, U, defined over the end of period wealth. This utility function is increasing, strictly concave, and double differentiable ($U' > 0$, $U'' < 0$). This investor will pay the risk premium π for not bearing the risk of an investment whose return x_{t+1} is a random variable with zero mean and variance σ_t^2. It can be easily shown that an approximation to the risk premium is $\pi \cong ½\sigma_t^2 \left(-W_t(U''(W_t)/U'(W_t))\right) = ½\sigma_t^2\lambda$, where λ is the infamous Pratt-Arrow relative risk aversion measure (our measure for the investor risk aversion degree). In this way, the proposed optimal hedging framework in this section for a wide range of λ values takes a general nature. Therefore, following the standard methodology (Anderson and Danthine (1980 & 1981) and Kroner and Sultan (1993)), the study is restricted to a specific case: the mean-variance utility function. Cotter and Hanly (2010 and 2012) estimate the coefficient of relative risk aversion in energy markets, obtaining a mean value for λ of 2.52 for monthly frequency when using a market index for the energy sector. Each hedging strategy utility is computed using λ values of 1, 4, and 10 to see how sensitive the results are to the aversion degree parameter. Results for $\lambda = 1$ are not reported because this risk-return preference will be more typical of a speculator than a hedger.

$$\max_{b_t} \quad E[U(x_{t+1})|\psi_t] = E[\Delta S(t+1)|\psi_t] - b_t\, E[\Delta F(t+1,T)|\psi_t] - ½\,\lambda\left[\sigma_s^2 + b_t^2\sigma_f^2 - 2b_t\sigma_{sf}\right] \tag{3}$$

where σ_s^2, σ_f^2 and σ_{sf} are the spot variance, the futures variance, and the covariance between spot and futures returns conditioned to the information available in t, ψ_t. The futures position optimizing the expected utility in (3) is

$$b_t = \frac{\sigma_{sf}}{\sigma_f^2} - \frac{E[\Delta F(t+1,T)|\psi_t]}{\lambda\sigma_f^2} = \beta - \frac{E[\Delta F(t+1,T)|\psi_t]}{\lambda\sigma_f^2} \tag{4}$$

For a long hedger (an investor with a short position in the spot market and a long position in futures contracts) the optimal position in futures will be

$$b_t = \frac{\sigma_{sf}}{\sigma_f^2} + \frac{E[\Delta F(t+1,T)|\psi_t]}{\lambda\sigma_f^2} = \beta + \frac{E[\Delta F(t+1,T)|\psi_t]}{\lambda\sigma_f^2} \tag{5}$$

From the above two equations it is clear that for highly adverse investors the optimal hedging ratio will collapse in the first part, β, that is the MVHR, regardless of whether there is a bias in in the futures contracts. The second part of the optimal hedging ratio depends on the futures bias and the risk aversion parameter. This second part represents the speculative part of the total position. For investors with a medium or low risk aversion, the optimal position can be different for long and short hedgers if there is a forecastable bias in futures prices. In this way, if $E[\Delta F(t+1,T)|\psi_t] > 0$, then $b_t < \beta$ for short hedgers and $b_t > \beta$ for long hedgers. Analogously, if $E[\Delta F(t+1,T)|\psi_t] < 0$, then $b_t > \beta$ for short hedgers and $b_t < \beta$ for long hedgers. Note that for high and negative (positive) futures bias and low risk aversion parameters, the optimal hedging ratio for long (short) hedgers can become negative – implying that long (short) hedgers will take short (long) positions in the futures markets. Obviously, this case will correspond to a speculator rather than a hedger.

To estimate the hedging parameters and measure the variance of the spot and hedged position we adopt the Ederington and Salas (2008) framework. Ederington and Salas (2008) have adapted the Ederington (1979) standard methodology to the case where spot price changes are partially predictable and applied it to the US natural gas case. Martínez and Torró (2015) find that the same framework is suitable for hedging with futures in UK natural gas. Ederington and Salas (2008) show that the riskiness of the spot position is overestimated, and the achievable risk reduction underestimated. Under this approach, the unexpected result of the hedge in equation (1) can be reformulated as

$$x_{t+1} = (\Delta S(t+1) - E[\Delta S(t+1)|\psi_t]) - b_t \Delta F(t+1,T) \tag{6}$$

The variance of the hedged strategy appearing in equation (2) is reformulated as

$$VAR[x_{t+1}|\psi_t] = VAR[(\Delta S(t+1) - E[\Delta S(t+1)|\psi_t]) - b_t \Delta F(t+1,T)|\psi_t] \tag{7}$$

The risk reduction attained by a hedging strategy will be computed by comparing (7) to the variance of the unexpected spot return $VAR[\Delta S(t+1) - E[\Delta S(t+1)|\psi_t]|\psi_t]$. 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. Ederington and Salas (2008) shown that an unconditional estimate of the MVHR can be obtained by estimating the following linear regression using OLS

$$\Delta S(t+1) = \alpha + \beta \Delta F(t+1,T) + \gamma(F(t,T) - S(t)) + \varepsilon_t \tag{8}$$

where $\gamma(F(t,T) - S(t))$ is used to estimate $E[\Delta S(t+1)|\psi_t]$. Ederington and Salas (2008) show that the inclusion of $\gamma(F(t,T) - S(t))$ produces unbiased and more efficient OLS estimation of the unconditional β. 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 $\hat{\gamma}(F(t,T) - S(t)) = E[\Delta S(t+1)|\psi_t]$).[4]

3. Data and preliminary analysis

We built a time series for UK natural gas futures and spot prices. National Balancing Point (NBP) futures prices from one to six months to maturity were retrieved from the Intercontinental Exchange. The system average price (SAP), computed as the average price of all the natural gas traded via the on-the-day commodity market mechanism, was taken as the spot price for UK natural gas and was obtained from the APX-ENDEX market. The data time series are built at the monthly frequency. Thus, each month spot and futures prices are compiled the day before the last trading day of the front futures contract. The time period starts in April 2000, finishes in March 2019, and contains 228 monthly observations.

Table 1 reports the descriptive analysis of the futures log-returns corresponding to a long position in futures, opened 6 (5, 4, 3 and 2) months before maturity and closed one day before the last trading day of the futures contract. The results for the corresponding short position are the same but with the opposite sign. For the whole sample period, the mean futures returns are significant in all cases and vary between -4% for 1-month hedging period to -9% for 5-months period. The same calculation though for winter months shows significant and higher absolute values varying between -5% and -15%, according to time to maturity. The summer season mean futures returns are significant (at 10 per cent of significance level) for 2, 3, and 4 months to maturity, with values fluctuating between -2% and -4%.[5] The mean values for December, January, February, and March are significant

[4] The theoretical framework of the Ederington and Salas (2008) and Martínez and Torró (2015) is the Minimum Variance approach. Our approach encompasses this approach as the optimal hedging approach contains the minimum variance as a special case. Both approaches will coincide when agents are infinitely risk averse or when futures prices do not contain any bias.

[5] For the period April 2000 to February 2015 the summer mean returns are significant at 1% of significance level and have somewhat higher absolute values.

in almost all cases and their values vary between -9 and -23 per cent. Equality of mean and median returns between winter and summer seasons are rejected in all cases, whereas the volatility equality hypothesis between these two seasons cannot be accepted for 1 to 4-month time to maturity at 10 per cent of significance level (being higher in winter in all cases). From the results in Table 1, it can be concluded that futures returns have a significant bias that increases with the time to maturity and that is higher and more volatile in winter than in summer. This bias may imply positive (negative) returns to short (long) positions in futures markets, which should be taken into account before trading by market participants. For example, a long hedger in winter must be aware that long positions during several winter months in futures contracts would probably lead to sizable negative returns in the futures market.[6]

The aim of this paper is not to study futures pricing on UK natural gas market nor to detect any anomaly in this market.[7] In a previous paper, also focused on this market, Martínez and Torró (2018a) found the existence of risk premiums, priced according to risk considerations and not merely being a bias without economic significance. Specifically, they found that risk premium variation could be explained by unexpected shocks in demand, unexpected shocks in reservoir levels and volatility. These three variables exhibit seasonal patterns, which leads us to expect futures returns (as a proxy for futures risk premiums) to become more easily predictable.

Once we have measured the futures bias, the second step is to design a procedure to obtain reliable estimations of $E\left[\Delta^i F(t,T)|\psi_t\right]$ with $\Delta^i F(t,T) = F(t+i,T) - F(t,T)$. Inspired by Lucia and Torró (2011), we use a VAR model between the futures returns and the basis in order to capture the linear interdependencies among these time series. In the preliminary data analysis, we obtained that the *ex post* average values of $\Delta^i F(t,T)$ were time varying, negative on average and with larger

[6] Mean and variance equality tests between winter and summer monthly spot returns cannot be rejected at 10% of significance level.
[7] Anyway, we have computed the Sharpe Ratio for the futures returns analysed in Table 1. As futures positions do not require any investment (apart from margins) we compute the Sharpe Ratio as the mean return to volatility quotient. For the whole period this ratio varies between 0.3 and 0.4 across the different futures time-series. Sharpe Ratio for monthly returns in the same period in the UK stock index FTSE 100 is equal to -0.02. We use 1-month Libor rate to compute a proxy of the risk-free rate. Therefore, the investment in UK natural gas futures has a very attractive risk-return profile.

absolute values in winter than in summer. With this seasonal pattern, it makes sense to design an autoregressive model. Furthermore, the basis has a high informational content related to the cost of carrying the commodity and the expected spot prices at futures maturity (Fama and French, 1987). In all the hedging strategies, the futures positions are closed out the day before the last trading day of the front contract, and we expect the basis will be useful to forecast $\Delta^i F(t,T)$. Therefore, the proposed VAR model is the following:

$$\begin{aligned}\Delta^i F(t,T) &= c_i + \textstyle\sum_{j=1}^{p} a_{i,j}\Delta^i F(t-j,T) + \sum_{j=1}^{p} b_{i,j}B(t-j,T) + \varepsilon_{i,t} \\ B(t,T) &= c_i^{'} + \textstyle\sum_{j=1}^{p} a_{i,j}^{'}\Delta^i F(t-j,T) + \sum_{j=1}^{p} b_{i,j}^{'}B(t-j,T) + \varepsilon_{i,t}^{'}\end{aligned} \tag{9}$$

Where $\Delta^i F(t,T) = F(t+i,T) - F(t,T)$ and $B(t,T) = F(t,T) - S(t)$ for $i = 1, \dots, 5$; and $T = t + i + 1$. The p-order of the VAR is chosen to minimize the corrected Akaike information criterion. We will not show the results of the estimated VARs. Instead, we report the optimal lag and the adjusted determination coefficient for each equation of the VAR in Table 2. As can be seen, the explanatory power of the VAR increases with the hedging period. With the exception of 1-month hedges, high adjusted determination coefficients are obtained, which is a good starting point. Figure 1 reports the *ex post* futures returns for the whole period and the forecasted values for the *ex-ante* period (from October 2008 to March 2019) for the 3-month horizon. From a visual inspection of Figure 1, it is observed that forecasted and realized returns have a very similar pattern.[8]

4. Hedging results

In previous sections we have presented all the elements we need to design an optimal hedging strategy. As seen in equations (4) and (5), we need to compute β using equation (8) and estimate

[8] The main statistics for forecasted returns have also been computed and are very similar to those displayed in Table 1 for realized returns. Figures for forecasted and observed futures bias are also very similar for the remaining hedging horizons. These results are kept to save space but are available from the corresponding author, upon request.

$E[\Delta F(t+1,T)|\psi_t]$ using the VAR model in equation (9). Figure 2 presents optimal hedging ratios for 3-month hedging periods. Figure 2 displays the MVHR or β, and the optimal hedge ratio for short and long hedgers (see equations (4) and (5), respectively), differentiating medium and high degrees of risk aversion (λ = 4 and λ = 10, respectively). As can be seen, optimal short (long) hedging ratios are usually above (below) β because the obtained negative expected futures return favour (harms) short (long) hedging strategies. It is important to highlight that reported biases in Figure 1 vary both in sign and size. As can be seen in Tables 1 and 2, they are negative most of the time and exhibit important seasonal variations. Thus, in the *ex-ante* period, the highest negative expected values correspond to the 2009 winter (about 50% return) whereas the highest positive expected values to the beginning of the 2018 summer (about 18%). In 2009 winter, the optimal hedging ratio (see Figure 2) for a moderate risk-averse hedger takes a value of 3.2 for short hedges (about three times β) and -1.0 for long hedges. This last value implies that a large negative expected bias can make a moderate risk-averse long hedger change the sign of its hedge; that is, taking short instead of long positions in futures. In the beginning of the 2018 summer, the reverse holds.[9]

Therefore, a short (long) hedger with a medium or high-risk aversion will increase (reduce) the expected benefits (losses) of futures trading by increasing (decreasing) its short (long) positions in the futures markets. Table 3 presents the results for the long and short hedgers and for hedging periods of 1-month to 5-months in Panels A to E, respectively. In each panel, results for the mean and the variance of the returns, as well as risk reduction, for $b_t = \beta$, λ = 4 and λ = 10, computed for the whole (*ex-ante)* period as well as separately for the summer and the winter seasons are reported. Thus, each time a new observation is incorporated in the sample, the VAR, the expected bias, and the hedging ratios are re-estimated, making the hedging experiment similar to a real situation. The main results can be summarized as follows: (i) for the whole *ex-ante* sample period and winter season, all the short hedging strategies obtain positive mean returns that decrease with λ; (ii) for the whole *ex-ante* sample period and winter season, long hedging strategies obtain negative or very low positive

[9] Figures for the remaining hedging horizons are skipped to maintain space since they are very similar.

returns for high aversion risk hedger ($\lambda = 10$), whereas they are positive though small for medium aversion risk ones ($\lambda = 4$); (iii) for the summer season, results are mixed. Thus, for 1 and 2-month hedging periods, short-hedge mean returns are positive and higher than those from long hedges, whereas for 3, 4 and 5-month hedging periods, long- hedge mean returns are positive and larger than those from short-hedging strategies; (iv) variance reduction is notably higher for high risk-aversion traders than for moderate risk-aversion ones, who will obtain poor risk reduction or might even increase the risk and finally, (v) risk reduction improves with the length of the hedging horizons, being higher during summer.

It is interesting to note that while winter season returns are much more volatile than summer season returns, risk reductions attained are higher in the summer season for all horizons. That is, riskier situations are more difficult to manage. A comparable situation is observed in Chang et al. (2010) for crude oil and gasoline, where greater risk reductions are achieved in bull than bear markets, being the former less volatile. Our results are consistent with those by Conlon and Cotter (2013) for heating oil. They obtain that hedging effectiveness decreases with risk uncertainty, whereas it improves as hedging horizon increases.

Table 4 reports the hedging ratios for each strategy. We obtain the mean of the optimal hedge ratios for the whole *ex-ante* sample as well as for the winter and summer seasons, separately. As mentioned above, short (long) hedging ratios for the whole sample are shown to be on average above (below) β. This result implies that short (long) hedgers with $\lambda = 4$ might take further short (long) futures positions of about 25 percent over (under) β to maximize their expected utility. To see whether hedging ratios exhibit any seasonality, we have computed hedging ratios separately for summer and winter seasons. Thus, according to our results, for $b_t = \beta$, that is, the MVHR approach, there are no significant differences between winter and summer hedge ratios. Nevertheless, when including different degrees of risk-aversion in the analysis, it can be observed significant differences between hedging ratios in winter and summer. Hedging ratios for short positions in winter are significantly higher than in summer and the reverse happens for long positions. This important result comes from the fact that there is a significantly negative bias in futures prices in winter (Table 1).

As explained in section 3, a negative bias in futures returns would imply optimal hedging ratios being above (below) the MVHR for short (long) hedging strategies. As previously stated, this forecastable bias can be considered as a proxy for the risk premiums analysed in Martínez and Torró (2018a) for the NBP market. They found that risk premiums variations can be explained by unexpected shocks in demand, unexpected shocks in reservoir levels and volatility. These three risk factors exhibit a clearly seasonal pattern and our intuition is that futures returns for short positions, as a proxy of the futures risk premiums, will be higher in winter than in summer. In general, production of natural gas is steady throughout the year. In contrast, the demand fluctuates between summer and winter. Storage is used to help balance the market, so that in summer, when demand is lower, natural gas is progressively put into storage, whereas in winter it is withdrawn to meet the demand needs. The colder the winter, the higher the demand for natural gas, and the increase in demand has the effect of pushing prices up.

In summary, natural gas prices are highly susceptible to weather, production and fluctuations in inventory levels. After the summer months of higher stock piles, during the cold winter, prices tend to rise reflecting the high marginal production costs, the low demand elasticity and the reduced inventories or even the fear to a stock-out.

5. Hedging effectiveness.

Under the optimal hedging approach, hedgers introduce futures contracts in their commodity portfolio with the aim to maximize their mean-variance utility. Following Cotter and Hanly (2010) and Batten et al. (2019), we compute their expected utility and compare it with the expected utility of the unhedged spot position to measure the effectiveness of each hedging strategy. For short and long hedgers, this measure will be obtained, respectively, as:

$$HE_{Short\ Hedgers} = E[U(\Delta S(t) - b_t \Delta F(t,T))|\psi_t] - E[U(\Delta S(t))|\psi_t] \quad (10)$$

$$HE_{Long\ Hedgers} = E[U(-\Delta S(t) + b_t \Delta F(t,T))|\psi_t] - E[U(-\Delta S(t))|\psi_t] \quad (11)$$

with the expected utility defined as in equation (2). Furthermore, the Sharpe Ratio (SR) has also been computed, in order to compare the risk-return performance of each hedging strategy, independently of the risk attitude:

$$SR = \frac{E[x_{t+1}|\psi_t] - r}{\sqrt{VAR[x_{t+1}|\psi_t]}} \quad (12)$$

where r represents the risk-free return. In order to obtain a proxy of the risk-free return we have computed the average of the Libor rate from 1 to 5 months for the same sample period used to compute the portfolio return and volatility. These time series were retrieved from the Bank of England web site.[10]

Table 5 displays the results for the hedging effectiveness, measured as the difference between the expected utility of the hedged and the unhedged portfolio for short and long hedgers (equations 10 and 11, respectively). The first insightful result is that hedging effectiveness increases as the risk aversion decreases.[11] Furthermore, the hedging effectiveness improves as the hedging period increases. Specifically, this happens with short hedging strategies for the whole sample period and for winter, as well as with long hedging strategies for the summer season. Finally, the hedging effectiveness measure is positive in all cases for the whole period and for the winter season with short hedges. In contrast, with long hedges, it is positive mostly for the summer season.[12] These results are consistent with those previously highlighted (section 4): increasing the hedging ratio in winter above

[10] https://www.bankofengland.co.uk/. Last accessed: September 2019.

[11] Long hedges for 2-months in the whole period and 1-month hedges in the summer season are the only two exceptions.

[12] 1-month hedges in the summer season is the only exception.

the MVHR for short hedging strategies and reducing the hedging ratio in summer below the MVHR for long hedging strategies is an optimal strategy to obtain a positive variation in the expected utility when futures returns show a negative bias. Of course, the more precise the prediction of the future bias, the higher the achieved utility.

As an additional robustness test, Table 6 reports the performance of each hedging strategy through the Sharpe ratio. According to the obtained results, the following conclusions can be drawn: (i) hedging performance generally improves as the risk aversion decreases. (ii) A pairwise comparison between long and short hedgers for the same degree of risk aversion shows that in all cases short hedges performs better than long hedges for the whole and winter periods. In summer, 1, 2 and 3-months short hedges perform better than long hedges, but for 4- and 5-months hedges, the reverse holds. (iii) Finally, it can be observed improvements in the hedging performance as hedging period increases in the following cases: short hedges for the whole sample and for winter (with the only exception of 4-month hedge and $b_t = \beta$), as well as long hedges for summer. Once again, results are consistent with those previously shown through the variation in expected utility at the beginning of this section (Table 5) and those presented in Tables 3 and 4 and discussed in section 4. To summarize, it can be concluded that most effective and best performing hedging strategies are those involving over-hedging in winter for short hedgers and under-hedging in summer for long hedgers, with several months as their hedging horizons.

6. Conclusions

Energy commodity prices are characterised by a seasonal behaviour, both in price and volatility, due to weather, demand, and storage level seasonalities. Some previous research has found that risk premiums contained in energy futures prices can also be described by a seasonal trend that enables reliable predictions. Focused on the UK natural gas market, after confirming the finding of previous literature that there exists a statistically significant futures bias, we use this result to design Optimal Hedging strategies with futures, based on the approach of expected utility maximization.

Our approach can be linked to that of *selective hedging* of corporate finance, according to which many companies trades futures with the aim of increasing profits and little concerned with reducing the company's risk exposure. Thereby, their hedge ratio appears not to be frequently the one corresponding to a pure hedging position. Contrarily, evidence is found that they consider their beliefs about the direction of the market when deciding the level of their hedge ratios. So, they do not hedge their exposure in a systematic way but define the extent of their hedge depending on their views about future movements in prices with the aim of benefiting from subjective intuition. However, according to Stulz (1996), *selective hedging* will only increase shareholder value if managers have an informational advantage relative to other market participants. Otherwise, it will result in a higher variability of cash flows; namely, it will expose firms to a higher risk due to hedging decisions based on inaccurate or erroneous private information. Our work uses a methodology that differentiates from the one employed by *selective hedging* as defined in Stulz (1996) in that we estimate future movements in prices in an econometric way, based on previously identified seasonal patterns in risk premiums, and make optimal hedge ratios depend on those obtained estimates as well as on risk aversion.

As long as the expected futures returns of the hedging strategy are equal to zero and/or the hedger has infinite risk aversion, the optimal futures hedging ratio will become the minimum variance hedge ratio. Nevertheless, there is some evidence in previous literature that energy futures contain sizable bias that can be characterised by a seasonal behaviour due to weather, demand fluctuations, and/or storage levels (see Szymanowska et al. (2014) and Lucia and Torró (2011)). Therefore, those agents with a moderate or low degree of risk aversion might decide to take advantage of it and not to merely use the MVHR but take into account this expected bias to optimise their futures hedging positions. In this way, whenever a significantly negative bias is expected, short (long) hedgers may increase (decrease) the hedging ratio over (below) the MVHR.

We obtain evidence for the presence of a significant and seasonally varying futures bias in the UK natural gas futures contracts and propose to use a bivariate VAR model including past values of the futures bias and the basis to obtain reliable forecasts of the futures bias. Specifically, futures bias is shown to be negative and statistically significant for the whole year, and especially in the winter season. Besides, it increases with the hedging period. The hedging effectiveness and compared performance of all considered strategies shows that most effective and best performing hedging strategies are those involving short hedging in winter and long hedging in summer, with several months as their hedging horizons.

To conclude, according to our results, it is optimal for moderate risk-averse short (long) hedgers to over-hedge (under-hedge) in winter, whereas moderate risk-averse long (short) hedgers should under-hedge (over-hedge) in summer, when over-hedging (under-hedging) means choosing a futures position larger (smaller) than the MVHR.

The obtained results are of great interest to practitioners in not only the natural gas sector but also in the electricity sector, since natural gas and electricity prices are strongly linked to each other in a twofold way. On the one hand, they are substitutive goods and the former is an input for the production of the latter. Furthermore, the results are relevant to financial assets portfolio managers, who take positions in commodities such as natural gas with hedging (cross-hedging), diversification or merely speculative purposes. Lastly, the performed analysis can be extended to other energy markets.

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8. Tables

Table 1. Futures returns

This table reports the results for a long position in futures (*log*-prices) during 1, 2, 3, 4 and 5 months, closing the position one day before the last trading day of the futures contract. Log-returns are defined as $\Delta^j F(t,T) = \big(F(t+j,T) - F(t,T)\big)$, for $j = 1, \ldots, 5$ and $t + j < T$. Mean values are displayed jointly with the zero hypothesis tests between brackets. Winter season is defined taking the following months: October, November, December, January, February and March. For the summer season, the remaining months are taken. In the 'Mean equality', 'Median equality' and 'Variance equality' rows, the *t*-statistic, the Kruskal-Wallis, and the Levene test statistics and their *p*-values in brackets are reported.

	1 month	2 months	3 months	4 months	5 months
Whole period	-0.04 [0.00]	-0.06 [0.00]	-0.08 [0.00]	-0.09 [0.00]	-0.09 [0.00]
January	-0.09 [0.01]	-0.17 [0.00]	-0.20 [0.00]	-0.22 [0.01]	-0.20 [0.01]
February	-0.05 [0.27]	-0.13 [0.01]	-0.18 [0.00]	-0.21 [0.00]	-0.23 [0.01]
March	-0.02 [0.42]	-0.06 [0.21]	-0.12 [0.02]	-0.14 [0.02]	-0.17 [0.01]
April	-0.03 [0.28]	-0.03 [0.28]	-0.05 [0.32]	-0.10 [0.11]	-0.11 [0.11]
May	0.03 [0.52]	-0.02 [0.58]	-0.01 [0.79]	-0.02 [0.76]	-0.06 [0.33]
June	-0.05 [0.07]	-0.00 [0.98]	-0.03 [0.55]	-0.02 [0.75]	-0.02 [0.74]
July	-0.02 [0.46]	-0.05 [0.12]	0.01 [0.82]	-0.01 [0.84]	0.00 [0.98]
August	-0.04 [0.21]	-0.04 [0.29]	-0.07 [0.08]	-0.02 [0.68]	-0.03 [0.57]
September	0.00 [0.93]	-0.02 [0.62]	-0.03 [0.49]	-0.05 [0.24]	0.00 [0.96]
October	-0.05 [0.12]	-0.04 [0.37]	-0.06 [0.14]	-0.07 [0.13]	-0.08 [0.11]
November	-0.04 [0.41]	-0.07 [0.27]	-0.06 [0.33]	-0.07 [0.25]	-0.08 [0.23]
December	-0.08 [0.02]	-0.12 [0.02]	-0.14 [0.04]	-0.13 [0.07]	-0.13 [0.07]
Winter	-0.05 [0.00]	-0.10 [0.00]	-0.13 [0.00]	-0.14 [0.00]	-0.15 [0.00]
Summer	-0.02 [0.12]	-0.03 [0.05]	-0.03 [0.09]	-0.04 [0.09]	-0.04 [0.12]
Mean equality	1.98 [0.04]	8.38 [0.00]	3.44 [0.00]	3.25 [0.00]	3.12 [0.00]
Median equality	2.98 [0.08]	5.50 [0.02]	8.24 [0.00]	8.19 [0.00]	8.09 [0.00]
Winter volatility	0.15	0.22	0.18	0.26	0.29
Summer volatility	0.12	0.14	0.24	0.21	0.25
Variance equality	3.71 [0.05]	13.78 [0.00]	5.41 [0.02]	3.67 [0.05]	1.40 [0.24]

Table 2. Optimal VAR *p*-order and adjusted determination coefficient of each VAR equation (in percent)

$$\Delta^i F(t,T) = c_i + \sum_{j=1}^{p} a_{i,j}\Delta^i F(t-j,T) + \sum_{j=1}^{p} b_{i,j} B(t-j,T) + \varepsilon_{i,t}$$
$$B(t,T) = c_i^{'} + \sum_{j=1}^{p} a_{i,j}^{'}\Delta^i F(t-j,T) + \sum_{j=1}^{p} b_{i,j}^{'} B(t-j,T) + \varepsilon_{i,t}^{'}$$

where $\Delta^i F(t,T) = F(t+i,T) - F(t,T)$ and $B(t,T) = F(t,T) - S(t)$ for $i = 1,\ldots,5$; and $T = t + i + 1$. The *p*-order of the VAR is chosen by minimizing the corrected Akaike Information Criterion. Adjusted determination coefficients, expressed as a percentage, are reported ($\bar{R}^2$).

	p	$\bar{R}^2$ in $\Delta^i F(t,T)$ equation	$\bar{R}^2$ in $B(t,T)$ equation
1-month hedges ($i = 1$)	12	11.25	24.66
2-month hedges ($i = 2$)	12	46.85	43.27
3-month hedges ($i = 3$)	12	57.24	54.19
4-month hedges ($i = 4$)	12	70.78	59.46
5-month hedges ($i = 5$)	6	73.62	60.95

Table 3. Hedging strategies: mean of returns, variance of returns and risk reduction

This table reports the *ex ante* mean and variance of returns, as well as the variance reduction, for each of the optimal hedging strategies (from October 2008 to March 2019), distinguishing between the winter season, the summer season and the whole sample. During the *ex-ante* period, hedging ratios are recalculated each time a new observation is included that is conditioned to the information known in that moment.

	Long hedge b_t with $\lambda = 4$	Long hedge b_t with $\lambda = 10$	Long hedge $b_t = \beta$	Short hedge $b_t = \beta$	Short hedge b_t with $\lambda = 10$	Short hedge b_t with $\lambda = 4$
Panel A. 1-month hedge.						
Mean return (%)						
Whole sample	0.50	-1.29	-2.48	2.48	3.68	5.47
Winter	1.04	-1.56	-3.30	3.30	5.04	7.64
Summer	-0.10	-0.01	-1.60	1.60	2.21	3.12
Variance×100 (Reduction %)						
Whole sample	1.15 (45.33)	0.63 (70.09)	0.57 (72.78)	0.57 (72.78)	0.75 (64.41)	1.45 (31.11)
Winter	1.91 (33.38)	1.05 (63.32)	0.97 (66.08)	0.97 (66.08)	1.29 (55.09)	2.50 (12.80)
Summer	0.32 (74.08)	0.18 (85.52)	0.14 (88.38)	0.14 (88.38)	0.16 (87.45)	0.26 (78.91)
Panel B. 2-month hedge.						
Mean return (%)						
Whole sample	-1.57	4.23	-4.62	4.62	8.16	13.48
Winter	3.71	-4.70	-8.81	8.81	13.81	21.32
Summer	4.81	1.87	-0.09	0.09	2.05	4.98
Variance×100 (Reduction %)						
Whole sample	4.67 (-40.81)	1.14 (65.69)	0.61(81.42)	0.61 (81.42)	1.56 (52.91)	5.73 (-72.77)
Winter	8.12 (-82.28)	1.93 (56.65)	1.00 (77.46)	1.00 (77.46)	2.63 (40.84)	9.88 (-121.79)
Summer	0.81 (59.24)	0.28 (85.69)	0.19 (90.12)	0.19 (90.12)	0.32 (83.96)	0.89 (54.91)
Panel C. 3-month hedge.						
Mean return (%)						
Whole sample	4.04	-3.14	-6.42	6.42	10.60	16.87
Winter	-2.16	-10.63	-14.04	14.04	18.79	25.92
Summer	10.75	4.58	1.84	-1.84	1.73	7.07
Variance×100 (Reduction %)						
Whole sample	3.88 (6.79)	1.06 (74.45)	0.59 (85.78)	0.59 (85.78)	1.25 (70.11)	4.34 (-4.05)
Winter	4.79 (-1.37)	1.50 (68.25)	0.98 (79.35)	0.98 (79.35)	1.79 (62.18)	5.51 (-16.57)
Summer	2.96 (12.15)	0.61 (81.88)	0.17 (94.85)	0.17 (94.85)	0.64 (81.01)	3.03 (9.98)
Panel D. 4-month hedge.						
Mean return (%)						
Whole sample	4.58	-3.71	-8.43	8.43	13.64	21.46
Winter	-5.45	-14.32	-19.53	19.53	25.17	33.62
Summer	15.46	7.57	3.59	-3.59	1.16	8.27
Variance×100 (Reduction %)						
Whole sample	4.90 (13.10)	1.20 (78.76)	0.60 (89.38)	0.60 (89.38)	1.50 (73.48)	5.64 (-0.07)
Winter	6.08 (2.44)	1.69 (72.87)	9.82 (84.24)	9.82 (84.24)	2.05 (67.15)	6.98 (-11.85)
Summer	3.69 (21.55)	0.68 (85.54)	0.18 (96.11)	0.18 (96.11)	0.89 (81.02)	4.23 (10.26)
Panel E. 5-month hedge.						
Mean return (%)						
Whole sample	2.44	-5.13	-9.56	9.56	14.36	21.56
Winter	-10.94	-19.62	-23.93	23.93	29.12	36.91
Summer	16.94	9.81	6.09	-6.09	-1.64	4.92
Variance×100 (Reduction %)						
Whole sample	4.13 (41.67)	1.06 (84.98)	0.60 (91.45)	0.60 (91.45)	1.41 (79.99)	5.01 (29.20)
Winter	5.51 (28.68)	1.59 (79.36)	0.10 (87.11)	0.10 (87.11)	2.00 (74.04)	6.53 (15.39)
Summer	2.70 (55.28)	0.50 (91.66)	0.18 (96.97)	0.18 (96.97)	0.78 (87.14)	3.38 (43.97)

Table 4. Winter and summer hedging ratios

This table reports the mean of the optimal hedging ratios for the *ex-ante* period (October 2008 to March 2019). In the *ex-ante* period, hedging ratios are recalculated each time a new observation is included, conditioned to the information known in that moment. Hedging ratios are computed as described in Section 3. Mean values are displayed jointly with the zero hypothesis tests within brackets. Winter season is defined by taking the following months: October, November, December, January, February and March. For the summer season, the remaining months are taken. In 'Mean equality' rows, the equality between the mean value of the hedging ratios in winter and summer seasons is tested (the *t*-statistics together with their *p*-values within brackets are reported).

	Long hedge	Long hedge	Long/Short hedge	Short hedge	Short hedge
	b_t with $\lambda = 4$	b_t with $\lambda = 10$	$b_t = \beta$	b_t with $\lambda = 10$	b_t with $\lambda = 4$
Panel A. 1-month hedge.					
Whole sample	0.82	1.02	1.15	1.28	1.48
Winter	0.71	0.98	1.15	1.33	1.59
Summer	0.94	1.07	1.15	1.23	1.36
Mean equality	-3.08	-3.04	-0.86	3.15	3.12
	[0.00]	[0.00]	[0.39]	[0.00]	[0.00]
Panel B. 2-month hedge					
Whole sample	0.83	1.01	1.13	1.25	1.43
Winter	0.73	0.97	1.13	1.29	1.53
Summer	0.84	1.06	1.13	1.20	1.31
Mean equality	-1.91	-1.91	-0.71	1.91	1.91
	[0.06]	[0.06]	[0.39]	[0.06]	[0.06]
Panel C. 3-month hedge					
Whole sample	0.78	0.95	1.06	1.17	1.34
Winter	0.64	0.89	1.06	1.23	1.49
Summer	0.94	1.01	1.06	1.11	1.19
Mean equality	-3.08	-3.08	-1.08	3.08	3.09
	[0.00]	[0.00]	[0.28]	[0.00]	[0.00]
Panel D. 4-month hedge					
Whole sample	0.81	0.97	1.07	1.17	1.33
Winter	0.69	0.94	1.07	1.23	1.46
Summer	0.95	1.03	1.08	1.12	1.20
Mean equality	-2.53	-2.53	-1.19	2.54	2.54
	[0.01]	[0.01]	[0.23]	[0.01]	[0.01]
Panel E. 5-month hedge					
Whole sample	0.86	0.98	1.07	1.15	1.28
Winter	0.75	0.94	1.07	1.19	1.38
Summer	0.97	1.03	1.07	1.11	1.16
Mean Equality	-2.55	-2.54	-1.16	2.55	2.55
	[0.01]	[0.01]	[0.25]	[0.01]	[0.01]

Table 5. Hedging effectiveness: Expected utility variation.
This table reports the hedging effectiveness of each strategy, calculated as described in equations (10) and (11) for the *ex-ante* whole period (October 2008 to March 2019), winter and summer seasons and for different hedging horizons (from 1-month to 5-month).

	Long hedge b_t with $\lambda = 4$	Long hedge b_t with $\lambda = 10$	Long hedge $b_t = \beta$	Short hedge $b_t = \beta$	Short hedge b_t with $\lambda = 10$	Short hedge b_t with $\lambda = 4$
Panel A. 1-month hedge.						
Whole sample	0.50	-1.23	-1.73	3.26	3.77	5.50
Winter	1.02	-1.50	-2.39	4.21	5.08	7.61
Summer	-0.08	0.04	-1.05	2.15	2.26	3.14
Panel B. 2-months hedge						
Whole sample	-1.64	4.30	-3.31	6.01	8.29	13.47
Winter	3.57	-4.64	-7.15	10.47	13.83	21.14
Summer	4.82	1.94	0.79	0.97	2.12	4.99
Panel C. 3-months hedge						
Whole sample	3.99	-3.04	-4.69	8.27	10.81	16.93
Winter	-2.26	-10.58	-12.40	15.68	18.83	25.81
Summer	10.74	4.70	3.42	-0.26	1.84	7.05
Panel D. 4-months hedge						
Whole sample	4.52	-3.56	-5.99	11.02	13.92	21.53
Winter	-5.56	-14.21	-21.44	17.62	25.26	33.49
Summer	15.45	7.74	5.82	-1.36	1.32	8.25
Panel E. 5-months hedge						
Whole sample	2.41	-4.92	-6.41	12.88	14.73	21.69
Winter	-11.03	-19.44	-20.25	27.61	29.28	36.80
Summer	16.97	10.05	8.98	-3.20	-1.41	4.94

Table 6. Hedging performance: Sharpe ratio.

This table reports the Sharpe ratio, computed as described in equation (12) for the *ex-ante* whole period (October 2008 to March 2019), winter and summer seasons and for different hedging horizons (from 1-month to 5-month).

	Long hedge b_t with $\lambda = 4$	Long hedge b_t with $\lambda = 10$	Long hedge $b_t = \beta$	Short hedge $b_t = \beta$	Short hedge b_t with $\lambda = 10$	Short hedge b_t with $\lambda = 4$
Panel A. 1-month hedge.						
Whole sample	-0.01	-0.24	-0.41	0.25	0.35	0.40
Winter	0.03	-0.21	-0.40	0.27	0.39	0.44
Summer	-0.13	-0.15	-0.60	0.26	0.40	0.49
Panel B. 2-months hedge						
Whole sample	-0.10	0.33	-0.68	0.50	0.60	0.53
Winter	0.11	-0.39	-0.95	0.81	0.81	0.66
Summer	0.46	0.22	-0.18	-0.14	0.24	0.45
Panel C. 3-months hedge						
Whole sample	0.17	-0.38	-0.93	0.74	0.88	0.77
Winter	-0.13	-0.93	-1.49	1.34	1.35	1.07
Summer	0.58	0.49	0.27	-0.62	0.13	0.36
Panel D. 4-months hedge						
Whole sample	0.17	-0.41	-1.19	0.99	1.05	0.87
Winter	-0.25	-1.16	-0.65	0.60	1.70	1.24
Summer	0.77	0.83	0.67	-1.03	0.04	0.37
Panel E. 5-months hedge						
Whole sample	0.08	-0.58	-1.34	1.13	1.14	0.93
Winter	-0.50	-1.62	-7.82	7.32	2.00	1.41
Summer	0.98	1.28	1.25	-1.62	-0.28	0.22

9. Figures

Figure 1. 3-Month realized and forecasted futures biases
Futures returns (——), $\Delta^3 F(t,T) = F(t+3,T) - F(t,T)$ for the whole sample period (April 2000 to March 2019), and forecasted futures returns (------), $E[\Delta^3 F(t,T)|\psi_t]$, using the VAR model (see Table 2) for the *ex-ante* period (October 2008 to March 2019).

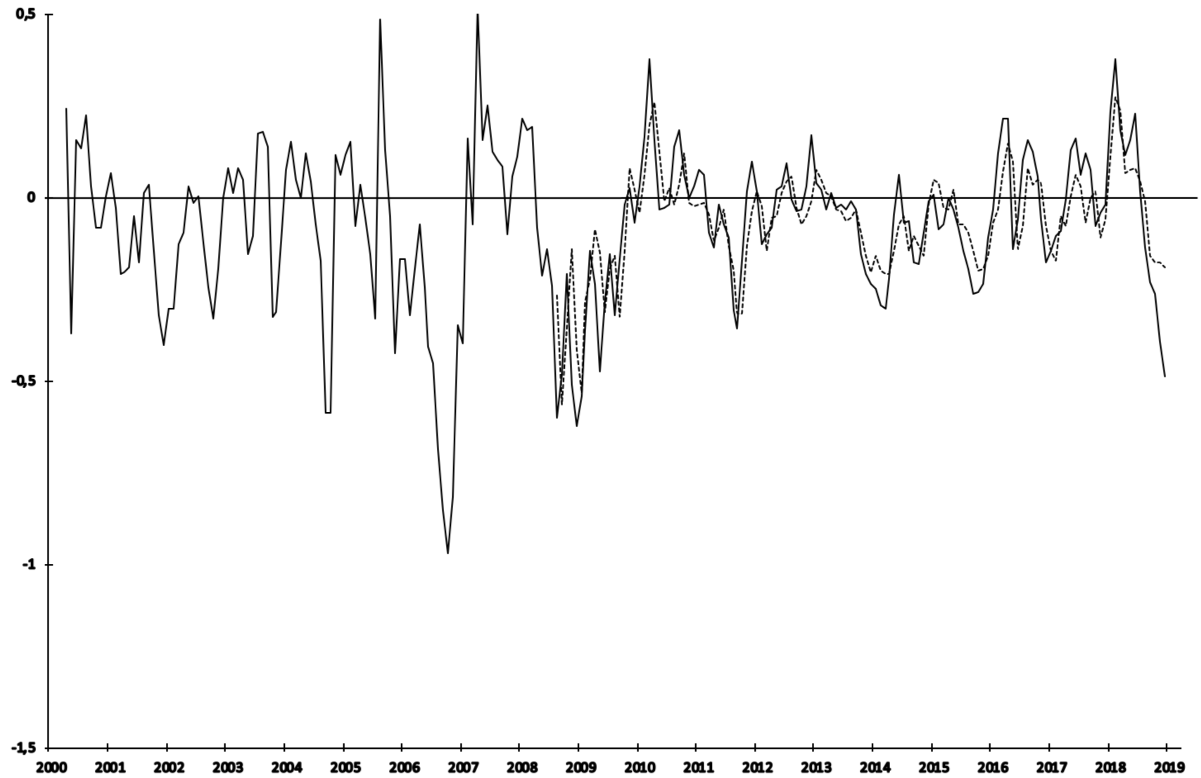

Figure 2. 3-Month hedging ratios

This figure displays the minimum variance hedge ratio (β) and the optimal hedging ratios for short hedgers and long hedgers with a degree of risk aversion of $\lambda = 4$ and $\lambda = 10$, computed as described in section 3 in Equations (3) and (4).