Hedging effectiveness of European wheat futures markets: an application of multivariate GARCH models

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Abstract

The instability of commodity prices and the hypothesis that speculative behaviour was one of its causes has brought renewed interest in futures markets. In this paper, the hedging effectiveness of European and US wheat futures markets were studied to test whether they were affected by the high price instability after 2007. In particular, the focus of the paper is to test of whether the increasing presence of financialization of commodity trading in futures markets mentioned in the literature has made them divorced from the physical markets. A multivariate GARCH model was applied to compute optimal hedging ratios. Important evidence was found of an slight improvement, after 2007, in the effectiveness of hedging with the European futures.

Keywords: Risk management, hedging ratio, multivariate GARCH model, hedging effectiveness, wheat, futures prices, commodity prices, European Commodity Exchanges.

JEL codes: Q11, Q13

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1. Introduction

The relatively recent instability of commodity prices has brought back the interest on futures markets and related derivatives, including collateralized loans (e.g., Battauz et al., 2015) and their use for hedging as a device to reduce vulnerability to risk. Furthermore, this renewed interest has extended use of futures and options contracts to the area of food security, as they have been proposed as a way in which importing countries could manage price volatility (Sarris et al., 2011).

Futures markets perform several functions as they provide the instruments to transfer price risk, they facilitate price discovery and they are offering commodities as an asset class for financial investors, such as fund and money managers who had not previously been present in these markets (United Nations, 2011).

Commercial participants use futures contracts to hedge their crops or inventories against the risk of fluctuating prices, e.g., processors of agricultural commodities, who need to obtain raw materials, would buy futures contracts to guard against future price rises. If prices rise (i.e., both cash and futures prices), then they use the increased value of the futures contract to offset the higher cost of the physical quantities they need to purchase. However, hedgers are not the only agents operating in futures markets, as one can also find non-commercial participants, who do not have any involvement in the physical commodity trade in contrast to commercial participants, such as farmers, traders and processors. These are called “speculators” and they buy and sell futures contracts in order to obtain a profit.

This paper focuses on the usefulness of futures prices for hedging against price risk. It is motivated by the relatively recent discussion on the effects that the increasing financialization of commodity trading in futures markets may have brought to commodity markets - e.g., see Bohl and Stephan (2013) for a recent literature review on the issue -; in particular, whether the increasing speculation may have made futures markets divorced from physical markets and useless for hedging.

Note that the fact that only price risk is considered in the paper means that it is dealing with the usefulness of exchange markets for most of the participants in the supply chain, except farmers, which as it is well known, are also affected by yield risk, not to mention the fact that only a minority of them tend to operate in futures markets (Blank et al., 1991; 1997).

The paper is structured as follows: first, a brief overview of the discussion of how speculation may have affected futures markets is presented. Second, a description of the methods used in the paper (i.e., data and methodological approach). The next section presents and discusses the results of the analysis and the last section offers some conclusions.

2. Financialization of commodity trading and hedging

The purpose of this section is to present an overview of of the discussion on financialization of commodity trading. The increasing dispersion observed in commodity prices since 2007 has partially been explained by the increasing use of futures markets by speculators. As pointed by Irwin et al. (2009) – referring to evidence by Gheit (2008); Masters (2008); Masters and White (2008) – it has commonly asserted that speculative buying by index funds in commodity futures and over–the–counter (OTC) derivatives markets created a “bubble” with the result that commodity prices, and crude oil prices, in particular, far exceeded fundamental values at the peak (Irwin et al., 2009).

According to UNCTAD: “Financial investors in commodity futures exchanges have been treating commodities increasingly as an alternative asset class to optimize the risk-return profile of their portfolios. In doing so, they have paid little attention to fundamental supply and demand relationships in the markets for specific commodities. A particular concern with respect to this financialization of commodity trading is the growing influence of so called index traders, who tend to take only long positions that exert upward pressure on prices. The average size of their positions has become so large that they can significantly influence prices and create speculative bubbles, with extremely detrimental effects on normal trading activities and market efficiency. Under these conditions, hedging against commodity price risk becomes more complex, more expensive, and perhaps unaffordable for developing-country users. Moreover, the signals emanating from commodity exchanges are getting to be less reliable as a basis for investment decisions and for supply and demand management by producers and consumers.” [UNCTAD, (2009), p. iv].

Irwin et al. (2009), who consider that fundamentals offer the best explanation for the rise in commodity prices, pointed out some inconsistencies in use increasing speculative buying by index funds as an explanation for the behaviour of commodity prices (i.e., the physical). Four of their points are worth noting: first, the arguments of bubble proponents are conceptually flawed and reflect misunderstanding of how commodity futures markets actually work, as they state that the money flows that go into futures and derivatives markets pressures the demand for physical commodities, when that money only operates in the futures market. There are at least two ways in which futures markets can affect the physical markets: the first one is through arbitraging between the two markets which will force both prices (futures and spot) to converge at the delivery time. The second way is through the use that commercial entities make of futures prices for pricing their products (e.g., processors selling flour for future delivery). Clearly, the latter strategy makes sense only if the entities believe that the two markets are related.

The second point cited by Irwin et al. (2009) regards a number of facts about the situation in commodity markets are inconsistent with the existence of a substantial bubble in commodity prices such as the fact that the available data do not indicate a change in the relative level of speculation to hedging. Third, the available statistical evidence does not indicate that positions for any group in commodity futures markets, including long–only index funds, consistently lead futures price changes and fourth, there is a historical pattern of attacks upon speculation as scapegoat during periods of extreme market volatility.

While Irwin et al. (2009) arguments apply for the effects of the increasing use of futures markets for speculation on the evolution of commodity prices; it is clear that if futures markets trends follow factors that are not related to fundamentals, one should expect changes in futures prices and spot prices to become divorced or less correlated.

The implication of the above disassociation between futures and the physical market is necessarily a reduction in the effectiveness of the degree in price risk that can be hedged using futures markets, as the correlation between both prices (futures and spot) is the basis for the traditional minimum variance calculation of the optimal hedge ratio (Ederington, 1979; Sanders and Manfredo, 2004). Moreover, if after computing the hedging ratio and the hedging effectiveness measures one finds that hedging in futures markets is still a useful tool for risk management, then it means that both markets are still related and the financialization of futures markets have not broken that link. This is the topic of the work of the next section.

3. Empirical work

3.1. Data

Due to their importance for food security, and to a less extent for energy (i.e., biofuels), European wheat markets were selected for the analysis. In this respect, France, Italy and the United Kingdom are three of the major wheat-growing countries in Western Europe.
The price analysis was performed using data for feed wheat contracts from the London International Financial Futures and Options Exchange (NYSE LIFFE London abbreviated LIFFE) and for milling wheat contracts from the Marché à Terme International de France (NYSE LIFFE Paris abbreviated MATIF). In order to provide a comparison data from the Chicago Mercantile Exchange Group (abbreviated in CBOT) wheat contracts were also used.
For LIFFE and CBOT contracts the data comprised the period 1988 until February 2014, while for MATIF contracts the data were available only since 1998. As hedging performance requires the contemporary evaluation of cash price changes, spot prices from East Anglia (UK), Rouen (France), Bologna (Italy) and Chicago (USA) were also collected. Descriptive statistics for the price data in levels and first difference are presented in Table 1.

3.2. Methods

While the economic theory behind hedging is still the minimum variance portfolio approach (Ederington, 1979), i.e., market participants in futures markets choose a hedging strategy that reflects their attitudes toward risk and their individual goals, the econometrics when estimating hedging ratios has evolved with the progress on time series statistics. Lien and Tse (2002) provide an overview of relatively recent econometric methods to compute the hedging ratio.
The return of a portfolio containing spot and futures positions is given by (1):

$$R_{H,t} = R_{S,t} - \gamma_t R_{F,t} \qquad (1)$$

Where $R_{H,t}$ is return of the hedged portfolio, $R_{S,t}$ and $R_{F,t}$ are the return of the spot and future position, and γ_t is the hedge ratio, i.e., the number of future contracts that the hedger must sell for each using of spot commodity on which the price risk is borne (Chang et al., 2011). The variance of the hedged return conditional to the information in t-1 is given by (2):

$$\mathrm{Var}\left[R_{H,t}\middle|\Omega_{t-1}\right] = \mathrm{Var}\left[R_{S,t}\middle|\Omega_{t-1}\right] - 2\gamma_t \mathrm{Cov}\left[R_{S,t}, R_{F,t}\middle|\Omega_{t-1}\right] + \gamma_t^2 \mathrm{Var}\left[R_{F,t}\middle|\Omega_{t-1}\right] \qquad (2)$$

Where $\mathrm{Var}\left[R_{S,t}\middle|\Omega_{t-1}\right]$, $\mathrm{Var}\left[R_{F,t}\middle|\Omega_{t-1}\right]$ and $\mathrm{Cov}\left[R_{S,t}, R_{F,t}\middle|\Omega_{t-1}\right]$ are the conditional variance and covariance of the spot and futures returns. The optimal hedging ratio, γ_t^*, is then defined as the value of γ_t that minimises (2). The result is given by:

$$\gamma_t^* = \frac{\mathrm{Cov}\left[R_{S,t}, R_{F,t}\middle|\Omega_{t-1}\right]}{\mathrm{Var}\left[R_{F,t}\middle|\Omega_{t-1}\right]} \qquad (3)$$

Hedging effectiveness (HE_t) is then defined as the reduction in the variance of the unhedged portfolio due to the hedging and defined by (4):

$$HE_t = \frac{Variance_{unhedged} - Variance_{hedged}}{Variance_{unhedged}} \tag{4}$$

In this paper, the conditional variance and covariance of spot and future prices (and therefore the optimal hedging ratios) were estimated using a restricted version of the BEKK model, i.e., the diagonal BEKK model (Engle and Kroner, 1995; Chang et al., 2011). The BEKK model is a multivariate generalised autoregressive conditional heteroskedasticity model (MGARCH), which allows model the dynamics of conditional variance and covariance of the series of interest (i.e., in this case the spot price and the nearby futures price) and in addition it has the attractive property that the conditional covariance matrices are positive definite (therefore, the estimation will not produce negative variances).
The choice of restricted version of the BEKK model instead of its full version was not only due to the fact that it is more parsimonious but also because it was found to perform better than the full BEKK model (Chang, 2011). The diagonal BEKK model for MGARCH(1,1), i.e., one lag for the residuals and for the GARCH term, is given by:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{5}$$

With the parameters matrices defined as (for the bivariate case):

$$C = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix};\ A = \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix};\ B = \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}$$

With $a_{ii}^2 + b_{ii}^2 < 1$, i=1,2 for stationarity. The conditional means of the model were estimated following Moschini and Myers (2002) as:

$$R_{S,t} = \beta_0 + \beta_1(T - t) + \beta_2 D_2 + \beta_3 D_4 + \beta_4 P_{t-1}^S + \beta_5 P_{T,t-1}^F + u_{1t} \tag{6}$$

$$R_{F,t} = \delta_0 + u_{2t} \tag{7}$$

Where $P_{T,t}^F$ is the nearby future price at t for delivery at expiration date T, P_t^S is the spot price at t, D_2 and D_4 are quarterly dummies for the 2nd and 4th quarters, $u_{1,t}$ and $u_{2,t}$ are random shocks. In addition, the model considers the time to maturity (T-t). The returns were computed as the difference of the price series considering several hedging length 5, 22, 44 and 66 days.
The model comprising equations (5), (6) and (7) was estimated by quasi maximum likelihood (Moschini and Myers, 2002).

4. Results and discussion

Table 2 presents the results of the unit root tests for the data. As shown in the Table all the prices in levels showed the presence of unit roots, while the series in differences were free of them.
The market efficiency hypothesis requires that the current futures prices and the future spot price are cointegrated, meaning that futures prices are unbiased predictors of spot prices at maturity (Chang et al., 2011). Table 3 presents the results of the Johansen test for cointegration (Johansen, 1995) between spot and futures prices. The trace test and maximum

eigenvalue test statistics are used, based on minimizing AIC. The results show that the two series are cointegrated, and there exists at least one cointegrating vector in all the cases and for all the model specifications.

Table 4 and Table 5 present the results from the estimation of the models (i.e., one per country). Table 4 presents the results from the conditional means and Table 5 the results for the diagonal BEKK model (where the coloured panels are matrices). The results show that the parameters are in general statistically significant, for both the condition means and variances. Using the BEKK model the optimal hedging ratios were constructed.

Note that while the results of the estimations are interesting, the focus of this paper is on the effectiveness of the hedging activity, and in particular whether that effectiveness was affected by the price instability observed after 2007. For this purpose Table 6 was constructed, where the concentration is on the mean of the optimal hedging ratios (OHRs) and effectiveness rather than daily results coming the estimation as the purpose is to track a structural change on the series after 2007.

Table 6 presents averages for the optimal hedging ratios and the hedging effectiveness for the entire sample and the broken down into two periods: before and since 2007 for all the markets. In addition, it reports statistical tests for differences in the means and variances of the series during the two mentioned periods.

Before any comment it is important to note that the type of hedging varies depending on the type of the operator and his (her) business. The lag length changes with the type of business and the position of the firm along the supply chain. Thus, the hedge suitable for merchants and for processors is shorter than for farmers and it is not seasonally specified. In order to evaluate hedging for farmers it would be needed to define a hedging strategy that considers the planting and the harvesting period for growing wheat. However, as mentioned in the introduction, the focus of this paper is solely on the usefulness of hedging to reduce price risk and farmers' hedging is not considered.

Merchants and processors usually hedge their physical (spot) positions all over the year holding position in the futures market for less than 5-6 months. Because of these different needs, the lengths assumed here in the paper were assumed to be 5, 22, 44 and 66 trading days. These intervals imply, approximately, one week, one month, two months and three months period respectively.

When one compares the optimal hedging ratios for the periods before and since 2007 (see Table 6), it is clear that the test for the difference in variances reject the hypothesis that the variance of the ratios remained the same, although in some situations the t test rejected that average ratios remained the same in both periods.

The OHRs change passing from the period before 2007 to the one since 2007. That is true for the majority of the averages and also for their variances. Generally speaking the US market shows more variations respect to Italy and France (which confirms unchanged the OHR for 44 and 66 days lag). In the case of a 66 days lag, the average optimal hedging ratio for US (i.e., using the CBOT exchange) increased between the two samples from 0.96 to 1.22. In the case of the UK, the ratio increase from 0.81 to 0.96; France and Italy remain unchanged at 0.94 and 0.64 respectively.

The comparison of hedging effectiveness before and since 2007 indicates that these changed in all the countries (in fact, in most of the cases, the tests rejected the hypothesis that the means and variances remained the same).

Nevertheless the levels, or the changes, in the OHRs value does not influence negatively the hedging effectiveness which improves for all the markets and mostly for the European ones. When one considers the hedging effectiveness for the entire period, the value for the US is significantly higher than the ones for the European Exchanges, but for the second period the differences lower.

Whilst hedging with CBOT reduces the price variability by 75-85 per cent for all the lags, the European Exchanges reduce significantly the price risk mostly when the lag is longer. Whilst hedging for 22 days with CBOT reduces the price variability by 78 per cent, the European exchanges only reduces the price variability by 67 per cent at most (France). The same comparison for a 66 days hedge gives the following result: 82 per cent with CBOT and 77 per cent for France..

In the case of very short term hedges the European exchanges do not perform well. Their low effectiveness in the 5 days hedge indicate that they are not sufficiently attractive for firms, in particular if one adds the costs linked with the hedging process (i.e., brokerage fees and the cost of innovations in the entrepreneurial activity).

The other aspect worthwhile to highlight from Table 6 concerns whether the increasing presence of speculation mentioned in the literature since year 2007 affected the hedging effectiveness (or what is the same the degree of association between spot and futures markets). Although in most of the cases, the mean and variance tests rejected the hypotheses that optimal hedging ratios and hedging effectiveness were the same before and since 2007, in practical terms the optimal hedging ratios changed relatively little and the hedging effectiveness improved. Note that results since 2007 are actually better than before implying that spot and future in the European markets became closer and not more divorced.

5. Conclusions

The primary aim of this paper has been to study whether hedging in futures markets can be considered as a useful instrument for price risk reduction for commercial entities operating with commodities along the wheat supply chain in US, France, Italy and UK. The focus was on two European wheat futures markets, LIFFE and MATIF, using the CBOT market for comparison purposes. In all the cases the data spanned up to the end of February 2014. Optimal hedging ratios and the corresponding hedging effectiveness are computed for four different hedging intervals.

Whilst hedging with CBOT reduces the price variability by 75-85 per cent for all the lag lengths, the European Exchanges reduce significantly the price risk mostly when the hedging periods are longer (i.e., the effectiveness increases with the length of the hedging). Whilst hedging for 22 days with CBOT reduces the price variability by 78 per cent, the European exchanges only reduces the price variability by 67 per cent at most (France). The same comparison for a 66 days hedge gives closer results: 82 and 77 per cent for US and France respectively.

The results show that in the case of the short hedge used in the paper, the US market performs better than the European wheat markets. In fact, the hedging in the US market reduces the price variances of the portfolio by 78 per cent whilst in the European market the reductions are below 35 per cent of the price risk. This result implies that very short-term hedges (1 week only) are not of great utility for participants of the wheat supply chain, except for those firms operating on the US market.

In addition, it should be noted that all these results are close to those from Revoredo-Giha and Zuppiroli (2013). However, the techniques used in this paper are supplemented by more up-to-date methods, but the operational conclusions are not as different as could suppose. This may confirm Myers and Thompson (1989) view that simple regressions using price changes provided estimates as accurate as the more flexible specification allowed by a generalized approach to optimal hedge ratio estimation.

Future extensions of this research are to expand the approach to smaller markets, which are more vulnerable to speculation and other distortions and possibly will show different results.

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Tables

Table 1. Descriptive statistics

Prices in levels	Mean	Max	Min	SD	Skewness	Kurtosis	Jarque-Bera
Spot France	153,1	296,4	94,8	51,3	1,0	2,6	687,7
Spot Italy	175,2	293,0	120,5	47,4	0,9	2,6	612,7
Spot UK	106,8	216,7	53,1	36,9	0,9	3,1	793,2
Spot USA	400,0	1194,5	192,0	146,1	1,6	5,2	5.622,4
Nearby futures CBOT	414,9	1282,5	230,8	156,8	1,7	5,6	6.670,3
Nearby futures LIFFE	109,4	225,5	57,5	37,6	0,9	3,2	949,2
Nearby futures MATIF	153,5	286,8	99,0	49,4	1,0	2,6	700,6
First differences	**Mean**	**Max**	**Min**	**SD**	**Skewness**	**Kurtosis**	**Jarque-Bera**
Spot France	0,02	55,5	-39,0	2,6	1,4	90,4	1.324.261,0
Spot Italy	0,02	30,0	-52,5	2,0	-8,0	251,7	10.748.902,0
Spot UK	0,01	20,2	-21,1	1,4	-0,5	68,3	1.167.290,0
Spot USA	0,03	116,5	-232,5	10,1	-1,6	54,6	1.020.426,0
Nearby futures CBOT	0,03	90,0	-111,0	9,0	-0,2	19,3	102.057,5
Nearby futures LIFFE	0,01	15,8	-32,8	1,5	-2,5	66,3	1.101.164,0
Nearby futures MATIF	0,02	21,8	-39,0	2,5	-1,4	34,7	174.755,9

Prices in levels	Mean
Spot France	153,1
Spot Germany	160,4
Spot Italy	175,2
Spot UK	106,8
Spot USA	400,0
Nearby futures CBOT	414,9
Nearby futures LIFFE	109,4
Nearby futures MATIF	153,5
First differences	**Mean**
Spot France	0,02
Spot Germany	0,02
Spot Italy	0,02
Spot UK	0,01
Spot USA	0,03
Nearby futures CBOT	0,03

Nearby futures LIFFE	0,01
Nearby futures MATIF	0,02

Note: CBOT and Chicago prices are in US cts/bushel, Liffe and UK prices are in GBP/tonne, and MATIF, France, Germany and Italy prices are in Euro/tonne.

Table 2. Unit root tests 1/

Prices	In levels		In differences	
	Phillips-Perron test	Sig.	Phillips-Perron test	Sig.
Spot Chicago (USA)	-3.2		-29.9	*
Spot UK	-2.0		-23.6	*
Spot France	-2.7		-17.8	*
Spot Italy	-2.4		-18.7	*
Nearby futures CBOT	-3.1		-26.1	*
Nearby futures LIFFE	-1.9		-23.7	*
Nearby futures MATIF	-2.6		-16.8	*

Notes:

1/ All the tests include constant term and linear trend.

2/ "*" denotes rejection of the null hypothesis that the series have a unit root at the 1 per cent statistical significance level.

Table 3. Cointegration test using the Johansen approach

(Number of cointegrating relationships by model)

Market	Test type	Model specification				
		No trend		Linear trend		Quadratic trend
		No intercept or trend	Intercept on CE	Intercept in CE and test VAR	Intercept and trend in CE, no intercept in VAR	Intercept intercept in CE and in VAR
US wheat	Trace test	1	1	2	1	2
	Max-Eigenvalue	1	1	2	1	2
UK wheat	Trace	1	1	1	1	1
	Max-Eigenvalue	1	1	1	1	1
France wheat	Trace	1	1	1	1	2
	Max-Eigenvalue	1	1	1	1	2
Italy wheat	Trace	1	1	1	1	2
	Max-Eigenvalue	1	1	1	1	2

Notes:

1/ CE stands for cointegrating equations and VAR for vector autoregressions.

2/ Lags were selected according to the Akaike Information Criterion (AIC).

Table 4a. Conditional mean equations for US wheat market

		$\beta_{0,}\delta_0$	β_1	β_2	β_3	β_4	β_5
5 days lag	Spot	**0.004**	**0.000**	**-0.001**	**0.003**	**-0.065**	**0.065**
	z-test	(1.8)	-(9.5)	-(2.8)	(9.2)	-(42.4)	(41.1)
	Nearby	**-0.001**					
	z-test	-(4.4)					
22 days lag	Spot	**0.040**	**0.000**	**-0.004**	**0.014**	**-0.387**	**0.381**
	z-test	(10.6)	-(24.0)	-(9.2)	(26.1)	-(157.1)	(149.6)
	Nearby	**-0.002**					
	z-test	-(5.5)					
44 days lag	Spot	**-0.137**	**0.000**	**-0.009**	**0.015**	**-0.733**	**0.756**
	z-test	-(36.7)	-(51.2)	-(28.9)	(29.7)	-(289.3)	(309.8)
	Nearby	**-0.008**					
	z-test	-(16.1)					
66 days lag	Spot	**-0.270**	**0.000**	**-0.004**	**0.010**	**-0.840**	**0.884**
	z-test	-(48.7)	-(49.6)	-(8.4)	(16.1)	-(297.5)	(318.3)
	Nearby	**-0.018**					
	z-test	-(30.6)					

Notes:

1/ The value of the log likelihood and the Akaike Information Criterion (AIC) is presented in Table 5 and the conditional mean and variance where estimated together.

Table 4b. Conditional mean equations for UK wheat market

		$\beta_{0,}\delta_0$	β_1	β_2	β_3	β_4	β_5
5 days lag	Spot	**0.000**	**0.000**	**0.007**	**0.001**	**-0.179**	**0.177**
	z-test	(0.2)	(21.4)	(19.2)	(3.1)	-(127.7)	(123.9)
	Nearby	**0.000**					
	z-test	(0.2)					
22 days lag	Spot	**-0.028**	**0.000**	**0.006**	**0.004**	**-0.508**	**0.509**
	z-test	-(9.3)	(34.4)	(10.8)	(6.1)	-(222.5)	(218.9)
	Nearby	**-0.003**					
	z-test	-(13.5)					
44 days lag	Spot	**-0.060**	**0.000**	**0.013**	**0.014**	**-0.757**	**0.761**
	z-test	-(13.6)	(25.7)	(19.9)	(16.3)	-(190.2)	(198.9)
	Nearby	**-0.006**					
	z-test	-(17.1)					
66 days lag	Spot	**-0.054**	**0.000**	**0.015**	**0.005**	**-0.845**	**0.847**
	z-test	-(9.5)	(34.5)	(20.0)	(4.7)	-(195.4)	(198.3)
	Nearby	**-0.005**					
	z-test	-(16.0)					

Notes:

1/ The value of the log likelihood and the Akaike Information Criterion (AIC) is presented in Table 5 and the conditional mean and variance where estimated together.

Table 4c. Conditional mean equations for France wheat market

		$\beta_{0,}\delta_0$	β_1	β_2	β_3	β_4	β_5
5 days lag	Spot	**-0.048**	**0.000**	**0.008**	**0.001**	**-0.298**	**0.307**
	z-test	-(13.8)	(6.8)	(16.8)	(1.5)	-(73.4)	(72.1)
	Nearby	**0.000**					
	z-test	(1.5)					
22 days lag	Spot	**-0.093**	**0.000**	**0.013**	**0.001**	**-0.789**	**0.804**
	z-test	-(16.5)	(15.0)	(17.8)	(0.9)	-(111.6)	(107.0)
	Nearby	**0.000**					
	z-test	-(0.7)					
44 days lag	Spot	**-0.113**	**0.000**	**0.019**	**0.002**	**-0.863**	**0.882**
	z-test	-(21.0)	(21.0)	(26.5)	(2.6)	-(143.5)	(135.1)
	Nearby	**0.001**					
	z-test	(2.5)					
66 days lag	Spot	**-0.152**	**0.000**	**0.017**	**0.007**	**-0.915**	**0.940**
	z-test	-(21.3)	(22.8)	(21.5)	(6.3)	-(133.9)	(124.6)
	Nearby	**-0.006**					
	z-test	-(12.4)					

Notes:

1/ The value of the log likelihood and the Akaike Information Criterion (AIC) is presented in Table 5 and the conditional mean and variance where estimated together.

Table 4d. Conditional mean equations for Italy wheat market

		β_0, δ_0	β_1	β_2	β_3	β_4	β_5
5 days lag	Spot	**0.069**	**0.000**	**-0.005**	**0.001**	**-0.099**	**0.088**
	z-test	(54.4)	-(14.4)	-(41.2)	(5.8)	-(77.9)	(77.6)
	Nearby	**0.000**					
	z-test	-(2.5)					
22 days lag	Spot	**0.354**	**0.000**	**0.012**	**0.002**	**-0.380**	**0.319**
	z-test	(75.6)	(14.2)	(28.0)	(3.2)	-(115.7)	(113.0)
	Nearby	**-0.006**					
	z-test	-(17.0)					
44 days lag	Spot	**0.514**	**0.000**	**0.008**	**0.007**	**-0.641**	**0.552**
	z-test	(79.0)	(26.1)	(13.0)	(7.4)	-(163.3)	(162.6)
	Nearby	**0.002**					
	z-test	(4.1)					
66 days lag	Spot	**0.525**	**0.000**	**0.013**	**0.011**	**-0.673**	**0.583**
	z-test	(69.2)	(32.8)	(18.0)	(10.2)	-(146.4)	(137.3)
	Nearby	**0.000**					
	z-test	(0.0)					

Notes:

1/ The value of the log likelihood and the Akaike Information Criterion (AIC) is presented in Table 5 and the conditional mean and variance where estimated together.

Table 5a. Estimation of the diagonal BEKK model for US wheat market

	Matrices					
	C		A		B	
5 days lag						
Coefficient	**0.006**		**0.724**		**0.676**	
z-test	**(103.3)**		**(78.6)**		**(187.5)**	
Coefficient	**0.012**	**0.013**		**0.735**		**0.636**
z-test	**(58.0)**	**(72.0)**		**(78.5)**		**(162.0)**
Log-likelihood	**45.153.7**					
AIC	**-9.8**					
22 days lag						
Coefficient	**0.008**		**0.868**		**0.475**	
z-test	**(121.8)**		**(58.5)**		**(79.9)**	
Coefficient	**0.017**	**0.018**		**0.881**		**0.450**
z-test	**(71.0)**	**(84.4)**		**(59.1)**		**(75.6)**
Log-likelihood	**38.498.8**					
AIC	**-8.4**					
44 days lag						
Coefficient	**0.007**		**0.893**		**0.477**	
z-test	**(109.6)**		**(57.0)**		**(77.1)**	
Coefficient	**0.018**	**0.018**		**0.894**		**0.479**
z-test	**(86.9)**	**(94.9)**		**(56.6)**		**(75.3)**
Log-likelihood	**36.250.6**					
AIC	**-7.9**					
66 days lag						
Coefficient	**0.007**		**0.888**		**0.473**	
z-test	**(130.4)**		**(52.2)**		**(66.2)**	
Coefficient	**0.019**	**0.019**		**0.888**		**0.475**
z-test	**(106.3)**	**(102.0)**		**(51.9)**		**(65.6)**
Log-likelihood	**35.026.3**					
AIC	**-7.7**					

Notes:
1/ AIC stands for Akaike Information Criterion.

Table 5b. Estimation of the diagonal BEKK model for UK wheat market

	Matrices					
	C		**A**		**B**	
5 days lag						
Coefficient	**0.008**		**0.896**		**-0.108**	
z-test	**(64.3)**		**(68.7)**		**-(9.2)**	
Coefficient	**0.006**	**0.008**		**0.818**		**0.525**
z-test	**(44.2)**	**(58.4)**		**(59.9)**		**(64.6)**
Log-likelihood	**36.095.3**					
AIC	**-11.0**					
22 days lag						
Coefficient	**0.009**		**0.978**		**-0.106**	
z-test	**(81.4)**		**(55.8)**		**-(11.1)**	
Coefficient	**0.008**	**0.011**		**0.970**		**0.090**
z-test	**(47.4)**	**(87.4)**		**(55.1)**		**(9.9)**
Log-likelihood	**30.820.4**					
AIC	**-9.4**					
44 days lag						
Coefficient	**0.011**		**0.932**		**0.333**	
z-test	**(112.8)**		**(36.0)**		**(28.4)**	
Coefficient	**0.007**	**0.010**		**0.951**		**0.259**
z-test	**(47.7)**	**(85.1)**		**(37.7)**		**(22.6)**
Log-likelihood	**28.122.7**					
AIC	**-8.6**					
66 days lag						
Coefficient	**0.012**		**0.946**		**0.293**	
z-test	**(147.8)**		**(31.6)**		**(25.6)**	
Coefficient	**0.008**	**0.010**		**0.961**		**0.233**
z-test	**(46.4)**	**(84.4)**		**(32.6)**		**(21.2)**
Log-likelihood	**26.793.8**					
AIC	**-8.2**					

Notes:
1/ AIC stands for Akaike Information Criterion.

Table 5c. Estimation of the diagonal BEKK model for France wheat market

	Matrices					
	C		**A**		**B**	
5 days lag						
Coefficient	**0.004**		**0.846**		**0.148**	
z-test	**(4.2)**		**(55.7)**		**(9.8)**	
Coefficient	**0.012**	**0.005**		**0.700**		**0.717**
z-test	**(38.8)**	**(53.4)**		**(47.2)**		**(111.8)**
Log-likelihood	**22.076.5**					
AIC	**-10.6**					
22 days lag						
Coefficient	**0.011**		**0.927**		**0.123**	
z-test	**(72.6)**		**(35.4)**		**(10.5)**	
Coefficient	**0.013**	**0.012**		**0.910**		**0.294**
z-test	**(61.5)**	**(62.5)**		**(34.3)**		**(22.9)**
Log-likelihood	**19.067.9**					
AIC	**-9.2**					
44 days lag						
Coefficient	**0.011**		**0.965**		**0.049**	
z-test	**(83.3)**		**(32.5)**		**(5.7)**	
Coefficient	**0.011**	**0.013**		**0.953**		**0.172**
z-test	**(54.5)**	**(103.3)**		**(31.9)**		**(17.8)**
Log-likelihood	**17.895.3**					
AIC	**-8.7**					
66 days lag						
Coefficient	**0.011**		**0.961**		**0.107**	
z-test	**(90.1)**		**(33.4)**		**(14.8)**	
Coefficient	**0.012**	**0.014**		**0.947**		**0.193**
z-test	**(49.2)**	**(74.0)**		**(33.0)**		**(24.0)**
Log-likelihood	**17.087.7**					
AIC	**-8.4**					

Notes:
1/ AIC stands for Akaike Information Criterion.

Table 5d. Estimation of the diagonal BEKK model for Italy wheat market

	Matrices					
	C		A		B	
5 days lag						
Coefficient	**0.003**		**1.063**		**-0.119**	
z-test	**(13.5)**		**(70.9)**		**-(10.1)**	
Coefficient	**0.003**	**0.003**		**0.705**		**0.762**
z-test	**(13.3)**	**(41.1)**		**(57.2)**		**(156.0)**
Log-likelihood	**24.001.0**					
AIC	**-11.6**					
22 days lag						
Coefficient	**0.005**		**0.820**		**-0.615**	
z-test	**(52.9)**		**(41.6)**		**-(80.9)**	
Coefficient	**0.003**	**0.009**		**0.891**		**-0.460**
z-test	**(20.7)**	**(66.0)**		**(45.6)**		**-(56.3)**
Log-likelihood	**19.565.0**					
AIC	**-9.5**					
44 days lag						
Coefficient	**0.008**		**0.945**		**0.314**	
z-test	**(82.7)**		**(30.4)**		**(37.8)**	
Coefficient	**0.006**	**0.010**		**0.897**		**0.425**
z-test	**(37.4)**	**(104.9)**		**(29.4)**		**(43.7)**
Log-likelihood	**17.688.7**					
AIC	**-8.6**					
66 days lag						
Coefficient	**0.008**		**0.935**		**0.373**	
z-test	**(83.2)**		**(34.3)**		**(48.8)**	
Coefficient	**0.005**	**0.010**		**0.904**		**0.440**
z-test	**(25.4)**	**(72.2)**		**(33.5)**		**(51.9)**
Log-likelihood	**17.035.2**					
AIC	**-8.3**					

Notes:
1/ AIC stands for Akaike Information Criterion.

Table 6. Evaluation of hedging strategy

Market	Optimal hedging ratio							Hedging effectiveness (%)						
	Entire period	Until 2007	Since 2007	Test 1/	Sig.	Test 2/	Sig.	Entire period	Until 2007	Since 2007	Test 1/	Sig.	Test 2/	Sig.
France wheat														
- 5 days lag	0.61	0.70	0.50	1.7	0.00	144.9	0.00	34.3	34.6	34.0	1.6	0.00	0.6	0.44
- 22 days lag	0.92	0.95	0.87	1.6	0.00	18.3	0.00	66.8	59.6	75.5	1.1	0.00	319.3	0.00
- 44 days lag	0.94	0.93	0.94	1.7	0.00	0.1	0.75	73.9	66.3	82.9	1.4	0.00	352.5	0.00
- 66 days lag	0.94	0.94	0.94	1.5	0.00	0.1	0.77	77.1	70.8	84.6	1.5	0.00	251.3	0.00
Italy wheat														
- 5 days lag	0.13	0.15	0.10	3.0	0.00	7.9	0.00	17.9	16.3	19.9	1.4	0.00	39.8	0.00
- 22 days lag	0.44	0.40	0.50	3.6	0.00	7.8	0.01	56.7	48.1	67.1	1.0	0.54	390.0	0.00
- 44 days lag	0.58	0.53	0.63	5.1	0.00	6.5	0.01	64.5	54.6	76.4	1.2	0.00	490.8	0.00
- 66 days lag	0.64	0.64	0.64	4.2	0.00	0.0	0.93	69.8	63.5	77.2	1.1	0.02	188.0	0.00
UK wheat														
- 5 days lag	0.34	0.33	0.35	1.6	0.00	1.3	0.25	27.4	25.5	32.1	1.5	0.00	107.7	0.00
- 22 days lag	0.65	0.60	0.78	2.9	0.00	64.6	0.00	62.0	57.9	72.1	1.1	0.00	280.5	0.00
- 44 days lag	0.82	0.79	0.88	6.6	0.00	12.5	0.00	71.5	67.4	81.7	1.4	0.00	325.7	0.00
- 66 days lag	0.85	0.81	0.96	6.2	0.00	40.1	0.00	77.6	73.4	88.1	1.9	0.00	460.0	0.00
US wheat														
- 5 days lag	1.01	0.99	1.07	1.4	0.00	46.0	0.00	77.6	77.3	79.1	1.1	0.19	9.8	0.00
- 22 days lag	0.99	0.97	1.06	1.6	0.00	18.2	0.00	77.7	77.4	78.8	1.1	0.02	4.1	0.04
- 44 days lag	0.97	0.95	1.04	2.4	0.00	8.6	0.00	78.7	77.9	82.0	1.2	0.00	30.7	0.00
- 66 days lag	1.02	0.96	1.22	3.0	0.00	60.4	0.00	81.9	81.0	85.7	1.3	0.00	47.1	0.00

Notes:

1/ Test of the hypothesis that variances of the series are equal before and since 2007 (F test).

2/ Test of the hypothesis that the means of the series are equal before and since 2007 (t test).