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THE OPTIMAL HEDGING RATIO FOR AGRICULTURAL MARKET

Abstract. *The objective of hedging is to reduce the variations of the value of a spot position by combining it with a contrary position taken on a different highly correlated asset. For an efficient hedging, the estimation of the optimal hedge ratio is needed. Our paper estimates the optimal hedging ratio in the case of the agricultural traded on the Chicago Board of Trade (CBOT) exchange, by three methods: the simple OLS regression, the error-correction model (ECM) and the auto regressive distributed lag model (ARDL).The results show that both the optimal hedge ratio and hedging effectiveness increase with hedging horizon. While hedging effectiveness converges to 1, the optimal hedge ratio overpasses the unit value for longer horizons. Our findings also show that the models that take into consideration the cointegration between the spot and futures prices perform better than the simple OLS regression.*

Keywords: *hedging, optimal hedge ratio, risk management, hedging effectiveness.*

JEL classification: **G13, G15, G32**

I. Introduction

Risk management represents one of the most important financial activities of a company. The main objective of hedging is to reduce the variations in the value of a spot position by combining it with a contrary position on a futures contract or on a different highly correlated asset.

The simplest way of hedging is to trade on the futures market an amount equal with the spot position. However, this naive one to one hedge ratio does not provide the most effective hedging in terms of variance reduction. In order to achieve this goal, the optimal hedge ratio (OHR) has to be estimated. Taking into consideration the importance of the topic, an extensive literature is dedicated to the determination of the OHR.

We estimate the OHR for the case of the agricultural traded on the Chicago Board of Trade (CBOT) exchange using three methods: the simple OLS regression, the error-correction model (ECM) and the auto regressive distributed lag model (ARDL). Specifically, the commodities traded on CBOT that are analyzed in this paper are: wheat, corn, soybeans and soybean oil. We chose these commodities for their importance in the global economy, the volatility in the agricultural market affecting the entire population. Given this need for managing the risks caused by the evolution of agricultural prices, the proper estimation of the OHR becomes an essential objective. Thus, the problem addressed in this article is important for both producers and companies that use agricultural products as raw materials.

The reason for selecting this specific market is that CBOT represents the most important exchange for agricultural trading and wheat, corn, soybeans and soybean oil traded here are among the most liquid commodities.

The results show that the OHR is increasing with hedging horizon length, becoming higher than the unit value for longer tenors. Hedging effectiveness also increases with the length of the hedging horizon, converging to 1 for longer term hedges. We also find that the ECM and ARDL model perform better in terms of variance reduction than the simple OLS regression. Thus, for the agricultural market, the models that take into consideration the cointegration between the spot and futures prices estimate hedge ratios that obtain higher hedging effectiveness.

The paper is organized as follows. The next section presents the main findings in the existent literature regarding the estimation of the optimal hedge ratio. In the third section are described the models, the methodology and the database of the study. Section 4 presents the main results of the paper, while in the last section the conclusions are given.

II. Literature review

Lampietti *et al.* (2011) suggested several strategies that could reduce the vulnerability to agricultural price shocks, among them being reducing the exposure to market volatility through more efficient supply chains and better use of financial instruments to hedge the arising risks. Pennings and Egelkraut (2003) highlighted the relevance of the hedging through futures contracts in the context of market liberalization.

An important literature is dedicated to the determination of the optimal hedge ratio. The models used to estimate the hedging ratio are either risk minimizing or utility maximizing. The risk-minimizing models are the most popular because they are simple to understand and easy to estimate (Barbi and Romagnoli, 2012). Johnson

(1960) derived the OHR by minimizing the portfolio risk given by variance of price changes. Ederington (1979) developed the estimation of minimum variance hedge ratio by linear regression. Chou *et al*. (1996) and Floros and Vougas (2004) used the ECM to estimate the OHR. Chen *et al.* (2004), using a database of 25 different commodities, proposed the ARDL model for OHR estimation. Turvey and Nayak (2003) estimated the OHR for Kansas City wheat by minimizing the semivariance.

The risk-minimizing hedge ratio can be static (as described in the above studies) or time varying. The time varying hedge ratios are estimated through GARCH models (Baillie and Myers, 1991; Kroner and Sultan, 1993) or through different types of rolling-window OLS (Lien *et al.*, 2002; Moon *et al.*, 2009; Bhattacharya *et al.*, 2011). Kim *et al.* (2009) estimated *ex ante* hedge ratios through a nonparametric local polynomial Kernel (LPK) for lean hogs and corn markets. Power *et al.* (2013) use a non-parametric Copula-based GARCH model to estimate the time varying hedge ratios for live cattle and corn markets.

The utility-maximizing models use specific utility functions of return and risk, discussed in Bessembinder and Lemmon (2002) and Cotter and Hanly (2012). With a focus on the agricultural market, Lence (1995, 1996) derived the OHR by maximizing the expected utility.

According to Lee and Chien (2010), various econometric models provide different conclusions regarding the estimation and performance of the OHR. A significant number of studies in the literature found that GARCH models do not improve significantly the hedging effectiveness. Lien *et al.* (2002) compared a constant correlation vector GARCH model with a rolling window OLS model and found better results for the OLS hedge ratio. Bystrom (2003) found that the static OLS hedge ratio performed better than the time-varying one for the electricity market. Park and Jei (2010) showed that the bivariate GARCH models cannot guarantee an improvement of the effectiveness compared to the OLS model. Also, when hedge ratios are too volatile, the hedging performance measured by the variance reduction, value at risk or expected shortfall become worse. Juhl *et al.* (2012) emphasized that the OLS and ECM yield similar results when the spot and futures prices are cointegrated. Chen et al. (2004) found that the hedge ratio estimated through ARDL model performs better than the one estimated through OLS regression.

A small number of studies analyse the impact of hedging horizons' length on the OHR and hedging effectiveness (Geppert, 1995; Chen *et al.*, 2004; Dewally and Mariott, 2008; Juhl *et al.*, 2012). They found that both OHR and hedging effectiveness increase with hedging horizon, converging to the unit value for longer tenors.

Our paper contributes to the literature by providing an in-sample comparison between the hedging effectiveness of the OLS, ECM and ARDL hedge ratios for the most important agricultural market. Also, there is analysed the greatest number of hedging horizons and is provided an original approach regarding the relationship between hedging horizons' length and OHR, respectively hedging effectiveness.

III. Methodology

In order to estimate the OHR, we consider the case of a producer that has a long position in the agricultural market. Hedging involves in this case taking a short position in the futures market. The return on the hedge portfolio is given by:

$$r_{H_t} = s_t - hf_t \tag{1}$$

Where s_t and f_t are the log returns of the spot and futures markets at time *t* and *h* is the hedge ratio between the quantity traded on the futures market and the quantity expressing the spot exposure.

$$h = Q_F/Q_S \tag{2}$$

The risk of the portfolio can be assessed by its variance and is given by:

$$Var(r_{H_t}) = Var(s_t - hf_t) \tag{3.1}$$

$$Var(r_{H_t}) = Var(s_t) + h^2 Var(f_t) - 2hCov(s_t, f_t) \tag{3.2}$$

The optimal hedge ratio (OHR) that minimizes the variance of the hedge portfolio is given by:

$$h^* = \frac{Cov(s_t, f_t)}{Var(f_t)} \tag{4}$$

In practice, the OHR has to be estimated. For the selection of the model used to estimate the OHR one has to account for several aspects. Juhl *et al.* (2012) show that the proper specification of the model depends on the involved time series behavior. Thus, in the case that the series do not contain unit roots, a simple regression on levels or price changes can be applied. If the price series contain unit roots, but are not cointegrated, a regression on price changes can be appropriate. Finally, when price series contain unit roots and are cointegrated, there can be included an error-correction term.

In order to test for stationarity, we apply the augmented Dickey-Fuller (ADF) and for testing cointegration the Johansen test was performed.

The Dickey-Fuller test is carried out by estimating the following regression:

$$\Delta S_t = \alpha_1 + \alpha_2 t + \delta S_{t-1} + u_t \tag{5}$$

Where S_t is the logarithm of the price at time *t*, Δ is the difference operator, α_1 is the intercept, t is the trend or time variable and u_t is the error.

If the error term u_t is autocorrelated, then the above regression is modified and the ADF test is applied.

$$\Delta S_t = \alpha_1 + \alpha_2 t + \delta S_{t-1} + \beta_i \sum_{i=1}^{p} \Delta S_{t-i} + \varepsilon_t \qquad (6)$$

The number of lagged difference terms to include is determined empirically, so that the error term in the equation (6) becomes serially independent.

The null and alternative hypotheses are written as:

$H_0 : \delta = 0$

$H_1 : \delta < 0$

And are evaluated using the conventional *t*-test for δ:

$$t_\delta = \frac{\hat{\delta}}{SE(\hat{\delta})}$$

Where $\hat{\delta}$ is the estimate of δ, and $SE(\hat{\delta})$ is the coefficient standard error.

The failure in rejecting the null hypotheses drives to the conclusion that the series are non-stationary.

After testing for stationarity and cointegration, we estimate the OHR using three methods: the OLS regression, error-correction model (ECM) and auto-regressive distributed lag (ARDL) model.

The OLS method sets the following:

$$s_t = \alpha + \beta f_t + \varepsilon_t \qquad (7)$$

Where β represents the estimated OHR and ε_t is the error term.

The second model used to estimate the optimal hedging ratio is the ECM. The long-run relation between spot and futures price is represented by the following equation:

$$S_t = a + b\mathrm{F}_t + \varepsilon_t \qquad (8)$$

Where S_t and F_t are the logarithm of the spot, respective futures prices at time *t* and ε_t is the error term.

The ECM regression that sets the OHR is:

$$s_t = \alpha + \lambda\hat{\varepsilon}_{t-1} + \beta f_t + \mathrm{e}_t \qquad (9)$$

Where $\hat{\varepsilon}_{t-1} = S_{t-1} - (\hat{a} + \hat{b}\mathrm{F}_{t-1})$, represents the lagged error term from the long-run relationship and e_t is the error term. The coefficient β is the OHR estimated using the ECM.

Chen *et al.* (2004) proposed a version of the error-correction models, based on the simultaneous equations models considered by Hsiao (1997) and Pesaran (1997), obtaining a joint estimation of the short-run and long-run hedging ratio. This is the ARDL cointegration model.

$$s_t = \alpha_1 + \alpha_2 S_{t-1} + \alpha_3 F_{t-1} + \beta f_t + \varepsilon_t \qquad (10)$$

The model incorporates both short and long-run relationships and the short-run hedge ratio is given by β, while the long-run hedge ratio is given by $-\alpha_3/\alpha_2$.

In order to assess the hedging effectiveness of the each model, we computed the adjusted R^2. The R^2 statistic measures the proportion of the total variation in the endogenous variable explained by the regression model and in the same time shows how much variance is eliminated through hedging and is given by:

$$R^2 = \frac{\sum_{i=1}^{T}(\hat{s}_i - \bar{s})^2}{\sum_{i=1}^{T}(s_i - \bar{s})^2} \qquad (11)$$

The adjusted R^2 penalizes the models with more exogenous variables and has the following form:

$$Adjusted\ R^2 = 1 - (1 - R^2)\frac{T-1}{T-k} \qquad (12)$$

Where T denotes the number of sample observations and k is the number of regressors.

We decided to choose the adjusted R^2 statistic for comparing the models especially for its characteristic of penalizing the R^2 for the addition of regressors that do not contribute to the explanatory power of the model.

After comparing the three models based on their hedging effectiveness, we focused on analyzing the impact of the hedging horizons' length on the OHR and hedging effectiveness. In order to choose the proper relationship between the length of the hedging horizon and OHR, respective hedging effectiveness, we tested different regression specifications: the linear, the logarithmic and the polynomial form. The proper specification was chosen based on the adjusted R^2 and Akaike Information Criterion (AIC). Based on these criteria, it is found that the relationship between the hedging horizon and OHR is best described by the linear logarithmic form, while the relationship between the hedging horizon and hedging effectiveness is best described by the order 3 polynomial logarithmic form. More specifically, the relationships found are:

$$\beta_i = a + b\log(T_i) + e_i \qquad (13)$$

$$Adjusted\ R^2{}_i = a + b_1\log(T_i) + b_2\log(T_i)^2 + b_3\log(T_i)^3 + e_i \qquad (14)$$

where T_i is the hedging horizon, expressed in weeks and e_i is the error term.

The database used consists in daily spot and futures prices of wheat, corn, soybeans and soybean oil traded on CBOT. The futures price is represented by the nearest-to-maturity contract price. The periods covered are: for wheat from 01.07.1996 to 20.11.2012 (4047 daily observations); for corn from 02.01.1996 to 20.11.2012 (4152 daily observations); for soybeans from 02.01.1992 to 20.11.2012 (5160 daily observations) and for soybean oil from 03.01.1984 to 20.11.2012 (7207 daily observations).

Also, in order to compute the OHR for different hedging horizons we matched the data frequency with the hedging horizon. For example, in order to compute the 1 week hedging ratio we used weekly data and for computing the 1 day hedging ratio we used daily data. By applying this methodology we avoid the problems associated with data overlapping, like the existence of autocorrelated error terms in the regression. A detailed description of this issue can be found in Chen et al. (2004). The sample size of our study allowed us to use non-overlapped data in order to compute the hedging ratio for 12 different hedging horizons, from 1 day to 25 weeks. Specifically, the hedging horizons are: 1 day, 1, 2, 3, 4, 6, 8, 10, 12, 16, 20 and 25 weeks. This is the greatest number of hedging horizons used in the existing literature. In order to compute a hedging ratio for one agricultural type and for one hedging horizon length a specific regression using was estimated. Having 4 agricultural types and 12 hedging horizons, for each analyzed model were estimated 48 hedge ratios.

IV. Results

The objectives of the paper are: a) to derive the short run and the long run OHR by applying the models described in the methodology section for the agricultural market on the analyzed period; b) to compare in-sample the three models based on the hedging effectiveness and c) to quantify the impact of the hedging horizons' length on the OHR and on the hedging effectiveness.

Using non-stationary data can lead to spurious regressions and invalidate in this way the estimation of the OHR (Cotter and Hanly, 2006). For testing the unit root hypothesis was applied the augmented Dickey-Fuller (ADF) test and for testing the cointegration was used the Johansen test.

The ADF test results show that all the log prices of the four analyzed agricultural are unit root processes and are integrated of order 1. The Johansen test provides evidence that cash prices and futures prices series are co-integrated for each case. These results suggest that regressions should be applied on differences between the log prices (the log returns) and that models that account for cointegration should be well specified and perform better.

Table 1

ADF unit root test

		Spot		Futures	
		t-stat	p-value	t-stat	p-value
Wheat	Level	-1.3553	0.6056	-1.1529	0.6967
	First Diff	-65.6534	0.0001	-63.9837	0.0001
Corn	Level	-0.8266	0.8110	-0.8652	0.7996
	First Diff	-65.1345	0.0001	-61.5879	0.0001
Soybeans	Level	-1.0566	0.7348	-1.1462	0.6995
	First Diff	-71.2688	0.0001	-69.4447	0.0001
Soybean oil	Level	-1.5863	0.4896	-1.4927	0.5375
	First Diff	-83.5824	0.0001	-81.8107	0.0001

Source: Authors calculations

Table 2

Johansen cointegration test

No cointegrating vector	At most one
15.4823	1.4190
45.9351	0.6446
158.0416	1.1802
41.7491	2.4591
Critical values: None: 1%: 20.04; 5%: 15.41; At most one: 1%: 6.65; 5%: 3.76	

Source: Authors calculations

The results of the OLS estimation are depicted in Table 3. The OHR tends to increase with the hedging horizons' length. For the cases of three out of four commodities studied, the OHR is significantly less than the unit value for the very short tenors (1 day and 1 week). The exception is made by wheat, its estimated OHR exceeding 1 starting with the shortest hedging horizon. Actually, for wheat we also find the highest value of the OHR: 1.1269 for the 25 weeks tenor and the greatest average value of the OHR (1.0476), significantly higher than the naive hedge ratio. Also, for all hedging horizons the wheat's OHR is higher than 1. For the cases of corn, soybeans and soybean oil we find that the average OHR is not significantly different from 1. However, for tenors starting with 8 weeks, the OHR becomes greater than the naive hedge ratio for these commodities also. For corn, the OHR is smaller than 1 for all horizons up to 6 weeks, when it reaches 0.9561. Thus, in the case of corn we can find a clear delimitation: for short hedging horizons (up to 6 weeks), the OHR is smaller than 1, while for longer tenors (starting with 8 weeks) the OHR exceeds the unit value.

Regarding the hedging effectiveness, like in the case of the OHR, it can be noticed a positive relationship with the hedging horizon length. While for the case of the 1 day hedging horizon, all 4 values of the adjusted R^2 statistic are smaller than 0.8, starting with the next tenor the hedging effectiveness improves significantly, exceeding the threshold of 80%. This level is important because both US GAAP and IFRS accounting rules require a hedging effectiveness of minimum 80% in order to apply special hedge accounting treatment (Juhl *et al.*, 2012). One can also notice that the hedging effectiveness converges to 1 for the corn, soybeans and soybean oil in the case of longer hedging horizons. For wheat, the convergence is achieved slowly, the maximum value being reached at 0.9306. Also, the average hedging effectiveness for wheat and corn is around 85-86%, while for soybeans and soybean oil the hedging effectiveness is higher: 94.69%, respective 92.68%. Thus, it can be concluded that a soybeans or soybean oil producer can hedge more effectively than a producer of wheat and corn.

Table 3

Results of the OLS regression

Hedging horizon		Wheat	Corn	Soybeans	Soybean oil
1D	Hedge ratio	1.0188	0.8682	0.8761	0.9379
	Adjusted R^2	0.7952	0.6654	0.7973	0.7753
1W	Hedge ratio	1.0357	0.9391	0.9319	0.9796
	Adjusted R^2	0.8478	0.8255	0.8973	0.8651
2W	Hedge ratio	1.0479	0.9122	0.9408	1.0151
	Adjusted R^2	0.8361	0.8094	0.9184	0.9010
3W	Hedge ratio	1.0070	0.9419	0.9889	1.0057
	Adjusted R^2	0.8484	0.8317	0.9602	0.9103
4W	Hedge ratio	1.0098	0.9476	0.9971	1.0204
	Adjusted R^2	0.8509	0.8148	0.9494	0.9190
6W	Hedge ratio	1.0412	0.9561	1.0206	1.0198
	Adjusted R^2	0.8543	0.8421	0.9715	0.9475
8W	Hedge ratio	1.0382	1.0224	1.0363	1.0240
	Adjusted R^2	0.8683	0.8651	0.9700	0.9574
10W	Hedge ratio	1.0532	1.0236	1.0256	1.0470
	Adjusted R^2	0.9015	0.8893	0.9743	0.9655
12W	Hedge ratio	1.0440	1.0714	1.0515	1.0174
	Adjusted R^2	0.8675	0.9113	0.9772	0.9558

16W	Hedge ratio	1.0721	1.0518	1.0454	1.0430
	Adjusted R^2	0.8627	0.9073	0.9818	0.9754
20W	Hedge ratio	1.0762	1.0703	1.0142	1.0282
	Adjusted R^2	0.8989	0.9419	0.9826	0.9756
25W	Hedge ratio	1.1269	1.0516	0.9874	1.0671
	Adjusted R^2	0.9306	0.9758	0.9830	0.9740

Source: Authors calculations

In Table 4 are synthetized the results of the estimation of the OHR through ECM. Generally, the results regarding tendencies are similar with those of the OLS model. Compared with the OHR estimated with the OLS model, the ECM OHR is slightly smaller, on average with 0.0073. Just in 19 cases out of 48, the ECM OHR is higher, especially for wheat. Because of the decrease, in the case of corn the OHR becomes higher than the unit value starting with the 12 weeks hedging horizon.

Regarding the hedging effectiveness, all the adjusted R^2 statistics are higher than those of the OLS model, proving the superiority of the ECM OHR compared to the one estimated through the simple OLS regression.

Table 4

Results of the ECM

Hedging horizon		Wheat	Corn	Soybeans	Soybean oil
1D	Hedge ratio	1.0194	0.8698	0.8803	0.9395
	Adjusted R^2	0.7961	0.6706	0.8047	0.7831
1W	Hedge ratio	1.0372	0.9384	0.9368	0.9772
	Adjusted R^2	0.8502	0.8333	0.9086	0.8683
2W	Hedge ratio	1.0525	0.9131	0.9518	1.0104
	Adjusted R^2	0.8422	0.8280	0.9327	0.9043
3W	Hedge ratio	1.0117	0.9415	0.9903	0.9997
	Adjusted R^2	0.8550	0.8526	0.9662	0.9142
4W	Hedge ratio	1.0151	0.9416	0.9901	1.0134
	Adjusted R^2	0.8595	0.8444	0.9596	0.9236
6W	Hedge ratio	1.0449	0.9445	1.0194	1.0126
	Adjusted R^2	0.8673	0.8798	0.9773	0.9500
8W	Hedge ratio	1.0389	0.9984	1.0232	1.0168
	Adjusted R^2	0.8818	0.8960	0.9768	0.9598
10W	Hedge ratio	1.0599	0.9842	1.0130	1.0380
	Adjusted R^2	0.9125	0.9151	0.9810	0.9674
12W	Hedge ratio	1.0490	1.0401	1.0352	1.0076

	Adjusted R^2	0.8867	0.9370	0.9841	0.9590
16W	Hedge ratio	1.0822	1.0032	1.0243	1.0345
	Adjusted R^2	0.8926	0.9362	0.9872	0.9772
20W	Hedge ratio	1.0770	1.0217	0.9961	1.0177
	Adjusted R^2	0.9192	0.9583	0.9873	0.9775
25W	Hedge ratio	1.1260	1.0241	0.9882	1.0481
	Adjusted R^2	0.9498	0.9788	0.9883	0.9766

Source: Authors calculations

Table 5 provides the results of the ARDL model estimation. In respect with the short-run OHR, the results are very similar with those obtained through OLS and ECM. The ARDL OHR is, on average, smaller that the OLS OHR with 0.0070, its value being very close to the value of the ECM OHR. The long-run OHR is not significantly different form the unit value. Wheat makes again an interesting case, having all estimated short-run OHR higher than the unit value and all long-run OHR smaller than 1 (although very near this value). This finding can suggest that the wheat short-run OHR can revert in time to the unit value, but this hypothesis should be carefully addressed in a future research.

Regarding the hedging effectiveness, the results are very similar with those obtained by the ECM, but in all cases, although the difference is very small the ARDL adjusted R^2 statistics are smaller than those of the ECM.

Table 5

Results of the ARDL model

Hedging horizon	Wheat			Corn		
	β	$-\alpha_3/\alpha_2$	AdjR^2	β	$-\alpha_3/\alpha_2$	AdjR^2
1D	1.0194	0.9793	0.7960	0.8699	1.0167	0.6704
1W	1.0370	0.9764	0.8496	0.9387	1.0220	0.8326
2W	1.0519	0.9713	0.8409	0.9137	1.0208	0.8267
3W	1.0113	0.9795	0.8532	0.9421	1.0220	0.8509
4W	1.0147	0.9889	0.8571	0.9424	1.0217	0.8419
6W	1.0440	0.9812	0.8639	0.9461	1.0193	0.8770
8W	1.0387	0.9949	0.8776	0.9994	1.0222	0.8925
10W	1.0583	0.9752	0.9088	0.9864	1.0343	0.9119
12W	1.0476	0.9965	0.8807	1.0402	1.0124	0.9336
16W	1.0789	0.9656	0.8851	1.0052	1.0258	0.9317
20W	1.0751	0.9766	0.9118	1.0230	1.0239	0.9545
25W	1.1209	0.9711	0.9449	1.0299	1.0322	0.9767
Hedging	Soybeans			Soybean oil		

horizon	β	$-\alpha_3/\alpha_2$	AdjR^2	β	$-\alpha_3/\alpha_2$	AdjR^2
1D	0.8804	1.0049	0.8045	0.9395	1.0080	0.7829
1W	0.9369	1.0057	0.9082	0.9774	1.0110	0.8679
2W	0.9519	1.0057	0.9322	1.0107	1.0145	0.9036
3W	0.9904	1.0058	0.9658	1.0002	1.0133	0.9133
4W	0.9904	1.0056	0.9590	1.0139	1.0124	0.9225
6W	1.0193	1.0048	0.9767	1.0135	1.0186	0.9490
8W	1.0234	1.0036	0.9760	1.0178	1.0168	0.9586
10W	1.0134	1.0112	0.9802	1.0392	1.0235	0.9662
12W	1.0349	1.0030	0.9833	1.0090	1.0186	0.9571
16W	1.0242	1.0006	0.9864	1.0350	1.0035	0.9757
20W	0.9971	1.0166	0.9864	1.0202	1.0272	0.9758
25W	0.9889	0.9949	0.9870	1.0497	1.0047	0.9742

Source: Authors calculations

The comparison between the three models shows that the OHR estimated taking into consideration the cointegration relationship between the spot and futures prices obtain higher in-sample hedging effectiveness. Also, we find that the ECM performs slightly better than the ARDL model.

In the existing literature there is also analyzed the relation between hedging horizon and hedging ratio, respective the determination coefficient. In order to choose the proper relationship between the length of the hedging horizon and OHR, respective hedging effectiveness, we tested different regression specifications: the linear, the logarithmic and the polynomial form. We chose the proper specification based on the adjusted R^2 and Akaike Information Criterion (AIC). Based on these criteria, we find that the relationship between the hedging horizon and OHR is best described by the linear logarithmic form, while the relationship between the hedging horizon and hedging effectiveness is best described by the order 3 polynomial logarithmic form. More specifically, the estimated relationships found are:

$$\underset{}{\mathrm{OHR}_i} = \underset{(0.0048)}{0.9656} + \underset{(0.0023)}{0.0257}\log(T_i) + e_i$$

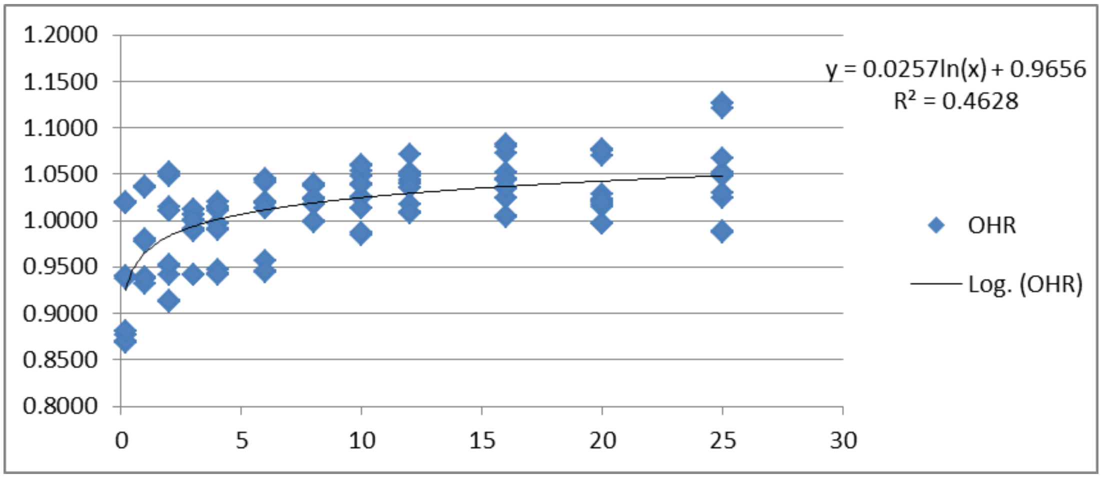
$$Adjusted\ R^2{}_i = \underset{(0.0093)}{0.8559} + \underset{(0.0056)}{0.0391}\log(T_i) - \underset{(0.0042)}{0.0082}\log(T_i)^2 + \underset{(0.0015)}{0.0021}\log(T_i)^3 + e_i$$

where T_i is the hedging horizon, expressed in weeks and the standard errors of the parameters are given into brackets.

The results show that the relationship between hedging horizons' length and OHR is positive and strongly significant. The same finding characterizes the case of the relationship between hedging horizon and hedging effectiveness.

These relationships are better illustrated in Figures 1 and 2.

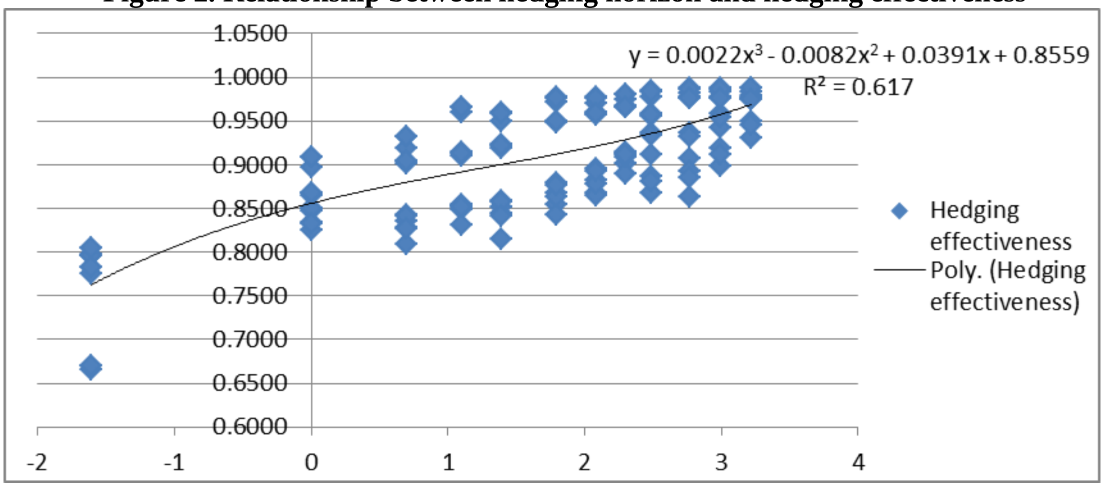
Figure 1. Relationship between hedging horizon and OHR



Source: Authors calculations

Figure 1 shows that OHR is an increasing function of hedging effectiveness. Although in the literature it is generally found that the OHR converges to 1 for longer tenors, we find that in the case of the agricultural studied the OHR usually exceeds this value starting with hedging horizons longer than 6 weeks.

Figure 2. Relationship between hedging horizon and hedging effectiveness



Source: Authors calculations

It is also found that there is a stronger relationship between hedging horizon and hedging effectiveness that it is between hedging horizon and OHR. The fact is proved by the coefficient of determination. Also, we find that hedging effectiveness converges to 1 for longer tenors.

V. Conclusions

Risk management represents one of the most important financial activities of a company. The main objective of hedging is to reduce the variations in the value of a spot position by combining it with a contrary position on a futures contract or on a different highly correlated asset.

We estimate the OHR for the case of the agricultural traded on the Chicago Board of Trade (CBOT) exchange using three methods: the simple OLS regression, the error-correction model (ECM) and the auto regressive distributed lag model (ARDL). The commodities included in our analysis are: wheat, corn, soybeans and soybean oil.

Based on the in-sample hedging effectiveness (measured by the adjusted R^2 statistic) we compare the three models. The comparison between the three models shows that the OHR estimated taking into consideration the cointegration relationship between the spot and futures prices obtain higher in-sample hedging effectiveness. Also, we find that the ECM performs slightly better than the ARDL model.

The results show that the OHR is increasing with hedging horizon length, becoming higher than the unit value for longer tenors. Although in the literature it is generally found that the OHR converges to 1 for longer tenors, we find that in the case of the agricultural studied the OHR usually exceeds this value starting with hedging horizons longer than 6 weeks.

Hedging effectiveness also increases with the length of the hedging horizon, converging to 1 for longer term hedges. Also, the correlation among the two variables is stronger than the correlation between OHR and hedging horizon.

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