The Optimal Wheat Futures Hedge at the Euronext Paris from a Farmer's Perspective

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Abstract

Futures contracts are extensively used by commercial market participants to hedge commodities against the risk of adverse price fluctuations. But although farmers have faced increased volatility in commodity prices in recent years, only very few of them actively use hedging as a risk management instrument. In this article we analyze the hedging potential of the Euronext milling wheat futures market for German farmers based on the estimation of optimal static as well as optimal dynamic hedge ratios. We find that both hedging approximately one year and half a year before harvesting leads to a reduction in the variance of returns compared with unhedged portfolios. But this risk minimization is achieved at the cost of lower returns on average. In addition we find that margin calls might be one of the reasons why so few farmers hedge since they cause liquidity problems especially in marketing years with unanticipated price shocks.

Key Words

hedge ratio; GARCH; futures; margin calls; wheat

1 Introduction

In recent years, agricultural commodity futures markets have been characterized by steadily rising trading activities and an increasing importance for decision making for a variety of market participants. They offer different opportunities for use as they enable price discovery (VOLLMER and CRAMON-TAUBADEL, 2017; YANG et al., 2001; ADÄMMER et al., 2016), or provide commodities as a financial asset for investors to speculate with (GILBERT, 2010). But one of the main potential uses of futures markets is hedging (EDERINGTON, 1979).

Hedging means in general the combination of investments in spot and futures markets to control or reduce the risk of adverse price fluctuations in a portfolio value (CHOU et al., 1996). Thereby, hedges can be short or long. A short hedge is entered by investors who want to fix the price for selling physical assets on the spot market in the future to hedge against decreasing prices. This concerns, for example, farmers who take a short position in commodity futures contracts before harvesting. In case of a long hedge traders plan to buy physical assets on the spot market in the future. They therefore try to hedge against a price increase by taking a long position in the respective futures contracts. Usually traders close their position by entering counter positions to receive the resulting profit in addition to trading the physical asset on the spot market (JOHNSON, 1960).

As a risk management tool, hedging is used extensively by commercial market participants to transfer price risk. But farmers are often reluctant to get involved in commodity futures markets (ANASTASSIADIS et al., 2014). During the past decades, numerous studies have analysed the factors that influence farmers' decisions to participate in futures markets. SHAPIRO and BRORSEN (1988), for example, show that farmers with high debt loads are more likely to hedge than producers with a solid financial position. PENNINGS and LEUTHOLD (2000) find that hedging decisions are influenced by the opinions of family members. ANASTASSIADIS et al. (2014) show that farmers with available storage capacities are less willing to use hedging as a risk management instrument. Other factors influencing the adoption of hedging are farm size, crop intensity, input intensity, and the farmers' level of education and knowledge of futures markets (GOODWIN and SCHROEDER, 1994) as well as the farmers' respective risk attitude and risk perception (PENNINGS and GARCIA, 2004). Furthermore, while most studies consider hedging as a risk management instrument, PANNELL et al. (2008) find, that farmers are most likely to hedge in situations in which they expect to realize speculative profits and that risk reduction only plays a secondary role.

Although only a few farmers hedge their products on commodity futures markets, several studies determine that hedging can be worth it. LEE (2009) investigates the hedging potential of corn, oats, wheat and cocoa futures markets in the United States (US) and shows that a significant variance reduction in returns can be achieved through hedging. These finding are in line with BAILLIE and MYERS (1991) who analyze the hedging potential of US futures markets for six different commodities. DAWSON et al. (2000) estimate hedge ratios for European wheat and barley futures and show their risk minimizing potential. ZUPPIROLI and GIHA (2016) compare the hedging potential of European and US wheat futures markets. They show that hedging with US futures leads to a higher reduction in the price variability than hedging with European wheat futures. In addition a better performance of hedges with longer time intervals compared to hedges with shorter time intervals is observable when looking at four different hedging intervals between one week and three months.

But these previous studies only focus on the reduction in the variance of returns from hedging and disregard effects on the level or returns. SALHOFER and ZOLL (2005) analyze profits and losses for farmers who hedge German pork futures and show that the risk reduction from hedging is accompanied by lower average returns. To do so, they must address one of the main theoretical problems related to hedging, which is the determination of the optimal hedge ratio. This ratio describes the optimal amount of futures contracts the hedger must buy or sell for each unit of the spot commodity on which price risk is borne (CHANG et al., 2011). The determination of the optimal hedge ratio depends on the objective function to be optimized and in particular the hedger's risk aversion. To sidestep this issue, SALHOFER and ZOLL (2005) apply a static hedge ratio, which means that potential changes in the riskiness of the assets are ignored.

Our objective in this paper is to analyze the hedging potential of commodity futures for farmers with static as well as with dynamic hedge ratios. We define the optimal hedge ratios by estimating ordinary least squares regressions (OLS), error correction models (ECM) and vector error correction models that allow for error terms with generalised autoregressive conditional heteroscedasticity (VECM-GARCH). In order to compare hedge ratios based on these different objective functions we estimate a hedging efficiency index (HE). In addition we analyze the hedging potential from a farmer's perspective by estimating the monetary profits or losses that result from hedging the optimal proportion of his/her expected harvest. In this context, potential margin calls are of particular interest since they not only result in costs (interest charges) but might lead to liquidity problems.

Our empirical analysis is based on German spot market prices for wheat and the Euronext Paris wheat futures price. The Euronext Paris is the EU's major futures exchange for agricultural soft commodities, and Germany is the second largest wheat producer in the EU with a share of nearly 18% of total EU wheat production (EUROPEAN COMMISSION, 2017a). We analyze the hedging potential of the wheat market for the time period from 2002 to 2016, which includes episodes of high and low price volatility. Hence, we are able to test whether the profitability of hedging for farmers depends on this volatility.

The study is organized as follows: in Section 2, the methodological approach is introduced and in Section 3, we describe the data we use. In Section 4, we present and discuss our empirical results. Section 5 concludes and makes suggestions for future research.

2 Methodological Approach

The empirical analysis is structured as follows: we first estimate the optimal hedge ratio based on the conventional approach using an OLS regression. We compare these results with the optimal hedge ratio based on ECM estimation, with and without allowance for GARCH structures in the residuals. Finally, the hedging efficiency of these three different approaches is analysed and compared.

The estimation of hedge ratios based on these approaches follows the minimum variance (MV) strategy of the hedged portfolio. The MV hedge ratios are the most widely-used hedge ratios.

2.1 Conventional Approach

The conventional approach of estimating the MV hedge ratio is based on the regression of changes in a logarithmised spot price ($\Delta\ln(p_{S,t})$) on changes in a logarithmised futures price ($\Delta\ln(p_{F,t})$) by using the OLS technique with the following formula:

$$\Delta\ln(p_{S,t}) = \beta_0 + \beta_1\Delta\ln(p_{F,t}) + \varepsilon_t, \qquad (1)$$

where β_0 is a constant parameter and ε_t is a white noise error term. The estimate of the optimal hedge ratio is then given by $OHR^{OLS} = \beta_1$ (EDERINGTON, 1979; HILL and SCHNEEWEIS, 1982).

2.2 Error Correction Method

Although the OLS technique is commonly used to estimate optimal hedge ratios it might lead to biased results. As KRONER and SULTAN (1993) point out, regression (1) is misspecified if both price time series are cointegrated because it ignores the error correction term as well as possible short-run dynamics. An alternative way of obtaining optimal hedge ratios is the estimation of an ECM.

To this end, the time series are first tested for unit roots using Augmented Dickey Fuller tests (ADF tests) (DICKEY and FULLER, 1979) and KPSS tests (KWIATKOWSKI et al., 1992). Johansen trace tests are adopted in the following to find out whether the time series are cointegrated and share a common long-term equilibrium relationship (JOHANSEN and JUSELIUS, 1990). If the price time series are found to be cointegrated the optimal hedge ratio can be estimated in two steps. First the cointegrating relationship is estimated with the following regression:

$$\ln(p_{S,t}) = \gamma_0 + \gamma_1 \ln\left(p_{F,t}\right) + u_t, \tag{2}$$

where γ_0 is the constant. γ_1 is the slope parameter and u_t is the residual series. In a second step the following ECM is estimated:

$$\Delta ln(p_{S,t}) = \alpha_1 u_{t-1} + \beta_1 \Delta ln(p_{F,t}) + \sum_{i=1}^{k} \theta_i \Delta ln(p_{F,t-i}) + \sum_{j=1}^{l} \Phi_j \Delta ln(p_{S,t-j}) + \varepsilon_t, \tag{3}$$

where u_t is the residual time series from equation (2) that displays the long run equilibrium relationship. α_1 is the adjustment parameter that determines the speed of adjustment back to the long run equilibrium after exogenous price shocks, and ε_t is a white noise error term. θ_i and Φ_j represent the coefficients of the lagged price changes in $p_{F,t}$ and $p_{S,t}$ with k and l as the number of lags that are defined by the Akaike Information Criterion (AIC). The optimal hedge ratio is then given by $OHR^{ECM} = \beta_1$ (CHOU et al., 1996; GHOSH, 1993).

2.3 GARCH Models

Both the OLS and the ECM approaches outlined above produce static hedge ratios based on the implicit assumption that the risk in spot and futures markets is constant over time. This assumption is not realistic because the riskiness of each of the assets changes whenever new information is received by the market (KRONER and SULTAN, 1993). To generate time-varying hedge ratios we estimate two-step VECM with three different GARCH error term specifications: CCC, DCC, and BEKK. The first of these models is the following VECM-CCC-GARCH(1, 1), where CCC stands for constant conditional correlation.

$$\begin{bmatrix} \Delta ln(p_{S,t}) \\ \Delta ln(p_{F,t}) \end{bmatrix} = \begin{bmatrix} \alpha^S \\ \alpha^F \end{bmatrix} \left(\begin{bmatrix} 1 & -\gamma_1 \end{bmatrix} \begin{bmatrix} \Delta ln(p_{S,t-1}) \\ \Delta ln(p_{F,t-1}) \end{bmatrix} - \gamma_0 \right) + \sum_{i=1}^{k} \Theta_i \begin{bmatrix} \Delta ln(p_{S,t-i}) \\ \Delta ln(p_{F,t-i}) \end{bmatrix} + \begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{bmatrix}, \tag{4}$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, H_t).$$

In equation (4), in addition to the notations defined above, the Θ_i are *2 x 2* matrices of short-run coefficients, and the α are adjustment parameters that determine the speeds with which the logarithmised prices $ln(p_F)$ and $ln(p_S)$ adjust to correct transient deviations from their long-run equilibrium relationship. The ε_t are the residual time series that are normally distributed with zero mean and a conditional variance-covariance matrix H_t. Ω_{t-1} is the information set at time *t-1*. For the case of constant conditional correlation between the variances of the residuals BOLLERSLEV (1990) assumes the following structure of H_t:

$$H_t = D_t R D_t = \begin{pmatrix} h_{S,t}^{1/2} & 0 \\ 0 & h_{F,t}^{1/2} \end{pmatrix} \begin{pmatrix} 1 & \rho_{SF} \\ \rho_{SF} & 1 \end{pmatrix} \begin{pmatrix} h_{S,t}^{1/2} & 0 \\ 0 & h_{F,t}^{1/2} \end{pmatrix}, \tag{5}$$

where H_t is a matrix of conditional variances of ε_t at time t and R is a constant conditional correlation matrix of ε_t. D_t is a diagonal matrix of conditional standard deviations of ε_t at time t that are univariate GARCH(1, 1) models:

$$h_{S,t} = c_S + a_S \varepsilon_{S,t-1}^2 + b_S h_{S,t-1} \tag{6}$$

$$h_{F,t} = c_F + a_F \varepsilon_{F,t-1}^2 + b_F h_{F,t-1}$$

$$i = S, F;\ c_i > 0;\ a_i, b_i \geq 0;\ a_i + b_i < 1\,,$$

where c_i is a constant parameter, a_i measures the influence of random deviations in the previous period (own past shocks, ARCH effect) and b_i reflects the part of the randomized variance in the previous period that is carried over into the current period (volatility, GARCH effects).

The second model is a VECM-DCC-GARCH(1, 1), where DCC stands for dynamic conditional correlation between the variances of the residuals. ENGLE (2002) suggests the following structure of H_t, where R_t is a conditional correlation matrix of ε_t at time *t*:

$$H_t = D_t R_t D_t \tag{7}$$

$$= \begin{pmatrix} h_{S,t}^{\frac{1}{2}} & 0 \\ 0 & h_{F,t}^{\frac{1}{2}} \end{pmatrix} \begin{pmatrix} 1 & \rho_{SF,t} \\ \rho_{SF,t} & 1 \end{pmatrix} \begin{pmatrix} h_{S,t}^{\frac{1}{2}} & 0 \\ 0 & h_{F,t}^{\frac{1}{2}} \end{pmatrix}$$

$$\rho_{SF,t} = (1-\kappa_1-\kappa_2)\overline{\rho_{SF,}} + \kappa_1\rho_{SF,t-1} + \kappa_2\varrho_{t-1},$$

where ρ_t is the conditional correlation coefficient and ϱ_{t-1} is the unconditional correlation coefficient between the residuals at time *t-1*.

The third multivariate GARCH model is the BEKK specification introduced by ENGLE and KRONER (1995). In case of a VECM-BEKK-GARCH(1, 1, 1) the following structure of H_t is assumed:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B\ , \tag{8}$$

where C is a *2x2* upper triangular matrix covering the intercepts. A and B are *2 x 2* parameter matrices representing the ARCH and GARCH effects, respectively. k determines the generality of the process. Mostly k equals one since there is not only a single parameterization that can obtain the same representation of the model in case of $k > 1$.

2.4 Hedge Ratios and Hedging Efficiency

In the bivariate case the conditional variance-covariance matrix of the error terms of the three different GARCH approaches is given by $H_t = \begin{pmatrix} h_{SS,t} & h_{SF,t} \\ h_{SF,t} & h_{FF,t} \end{pmatrix}$ and the time-varying optimal hedge ratio can be estimated as follows:

$$OHR_t^{GARCH} = \frac{h_{SF,t}}{h_{FF,t}}, \tag{9}$$

(BAILLIE and MYERS, 1991; CECCHETTI et al., 1988). To compare the performance of optimal hedge ratios obtained from the different models we follow KU et al. (2007) and estimate a hedging efficiency index (HE) given as:

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \tag{10}$$

$$= \frac{var(R_{S,t}) - var(R_{H,t})}{var(R_{S,t})}$$

$$R_{H,t} = R_{S,t} - OHR_t^{GARCH} * R_{F,t},$$

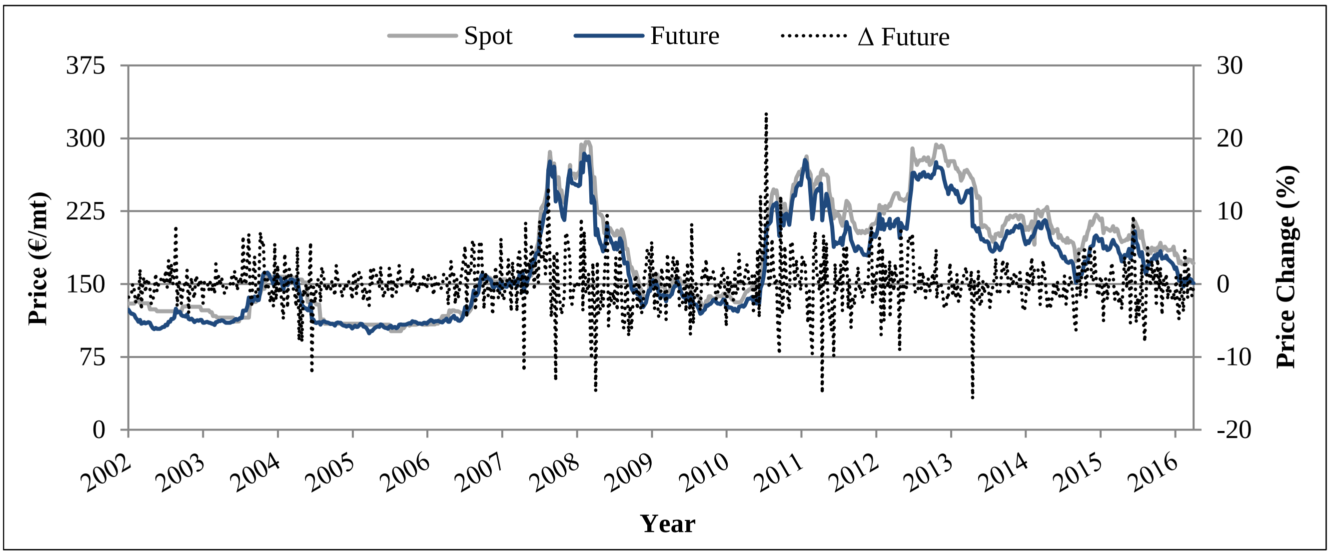
where $R_{S,t}$ is the logarithmic difference of the spot prices, and $R_{F,t}$ is the logarithmic difference of the futures prices. A higher HE indicates higher hedging effectiveness and larger risk reduction and the hedging method with the highest HE can be regarded as the superior hedging strategy.

3 Data

To analyse the optimal futures hedge for wheat in the EU we use logarithms of weekly wheat prices from September 2001 until April 2016 obtained from Thomson Reuters Datastream. As an indicator of the German spot market price $(ln(p_t^S))$ we use milling wheat prices fob Rostock on the Baltic Sea, which is one of the biggest German ports where grain and oilseeds are tendered. For the corresponding futures market price $(ln(p_t^F))$ we use the milling wheat futures contract no. 2 which is traded at the Euronext Paris, Europe's major exchange for agricultural commodities. Accounting for changes in the expiry dates of the Euronext Paris wheat contract over the sample period, we consider the contract months January (2002-2015), March and May (2002-2016), July (2002-2005), August (2008-2012), September (2002-2007, 2015), November (2001-2014) and December (2015).

To analyse the hedging potential of the Euronext wheat futures contract we look at two different scenarios. In the first scenario, a farmer goes short in futures contracts directly after seeding winter wheat when he/she has first expectation regarding the harvest volume. The farmer closes this position after the harvest in the following year and therefore, the time horizon of one round turn is approximately 12 months. In the second scenario, the farmer goes short in futures contracts in the spring and closes the position after the harvest in the same year. Farmers might wait until spring to hedge because at this time they know how the crop has emerged from the winter and

Figure 1. European spot and nearby futures prices for wheat between 2002 and 2016



Source: own diagram

therefore have a better idea of how much wheat they will harvest later in the summer. In this case, the time horizon of one round turn is approximately 6 months. Therefore, we construct three different futures time series: i) a nearby futures time series ($ln(p_t^F)$), ii) a time series with quotations of futures contracts that expire approximately in 12 months ($ln(p_t^{F\text{-}12})$), and iii) a time series with quotations of futures contracts that expire approximately in 6 months ($ln(p_t^{F\text{-}6})$). Furthermore, as it is common in the literature (YANG et al., 2001; LIU and AN, 2011; GILBERT, 2010), on the first day of its maturity month we roll over from the current contract month to the following one. Although the Euronext wheat contracts expire on the 10th of the month, rolling over somewhat earlier ensures that we work with the most liquid contracts.

The resulting spot and nearby futures prices are presented in Figure 1 (left axis). It appears that both prices co-move and exhibit common price increases in 2003/04, 2007/08 and again from mid-2010 through 2013. Figure 1 also presents the volatility of the nearby futures prices (right axis), which increases between August 2003 and July 2004, between May 2007 and April 2008, and later again between August 2010 and May 2013.

Additionally, Table 1 provides the descriptive statistics of the spot price series, the nearby futures price series, and the two price series with quotations of futures contracts that expire approximately in 12 and 6 months, respectively. The values without parentheses are the descriptive statistics of the price time series in €/mt and the values written in parentheses are the descriptive statistics of the price time series in logarithms that are used later on for the analyses.

Between 2002 and 2016 the spot price averaged 177.75€/mt which is more than 11€ higher than the average nearby futures price (p_t^F). The spot (nearby futures) price ranges between 101.50€/mt (99.25€/mt) and 296.25€/mt (284.25€/mt). Furthermore, the maximum and mean values for the futures time series decrease with an increased temporal distance to the expiry, whereas the minimum values increase. Thereby, the price series with quotations of futures contracts that expire approximately in 12 months has the lowest standard deviation (39.88€/mt).

Table 1. Descriptive statistics of the spot and futures time series in levels and in logarithms

Price	Minimum	Maximum	Mean	Median	Standard deviation
p_t^S - spot (€/mt)	101.50 (4.62)	296.25 (5.69)	177.75 (5.13)	162.50 (5.09)	53.98 (0.31)
p_t^F - futures (€/mt)	99.25 (4.60)	284.25 (5.65)	166.47 (5.07)	156.25 (5.05)	48.89 (0.29)
$p_t^{F\text{-}6}$ - futures (€/mt)	103.75 (4.64)	277.00 (5.62)	164.50 (5.07)	161.00 (5.08)	44.37 (0.27)
$p_t^{F\text{-}12}$ - futures (€/mt)	105.75 (4.66)	264.00 (5.58)	162.51 (5.06)	162.75 (5.09)	39.88 (0.25)

Note: the values without brackets are the descriptive statistics of the price time series in levels and the values in brackets are the descriptive statistics of the price time series in logarithms.
Source: own calculations

4 Results and Discussion

We first estimate optimal hedge ratios based on the conventional approach using OLS regression (Table 2). For a hedge round turn of 12 months the optimal hedge ratio is OHR_{12}^{OLS} = 45.5%. For a time horizon of 6 months the optimal hedge ratio of OHR_{6}^{OLS} = 37.5% is considerably lower.

We next use ADF tests (DICKEY and FULLER, 1979) and KPSS tests (KWIATKOWSKI et al., 1992) to test the price series for unit roots (Table 3).

We first apply the ADF tests without a constant or a trend. The results show that the null hypothesis of a unit root cannot be rejected for either of the two futures price series with contracts that expire in 12 months ($p_t^{F\text{-}12}$) or in 6 months ($p_t^{F\text{-}6}$), nor for the spot price (p_t^S). Re-running the tests including a constant or a constant and a trend lead to similar results. Hence, regardless of which variant of the ADF test is most appropriate, we conclude the time series are I(1). The results of the KPSS tests in Table 3 confirm these findings; the null hypothesis of stationarity can be rejected for all of the price series in levels but not for the first differences of the price series, regardless of whether the test is carried out with a constant or with a trend. The number of lags included in the different ADF tests and KPSS tests is selected according to the AIC.

Next we apply the Johansen trace test for cointegration (JOHANSEN and JUSELIUS, 1990) to determine whether the spot and one of the futures prices are cointegrated. Table 4 reports the results of the Johansen trace test which suggests that the spot prices are cointegrated with both the futures time series with contracts that expire in one year and the futures time series with contracts that expire in 6 months.

Table 3. Results of the ADF tests and KPSS tests

Test	Price	Lags	Test-statistic [a)]
ADF test (no constant, no trend)	$\ln(p_t^S)$ - spot	3	0.1797
	$\ln(p_t^{F\text{-}12})$ - futures	11	0.6074
	$\ln(p_t^{F\text{-}6})$ - futures	6	0.3393
	$\Delta\ln(p_t^S)$ - spot	2	-11.5981
	$\Delta\ln(p_t^{F\text{-}12})$ - futures	10	-9.8787
	$\Delta\ln(p_t^{F\text{-}6})$ - futures	5	-9.8216
ADF test (constant)	$\ln(p_t^S)$ - spot	3	-1.9096
	$\ln(p_t^{F\text{-}12})$ - futures	11	-1.4664
	$\ln(p_t^{F\text{-}6})$ - futures	6	-2.1711
	$\Delta\ln(p_t^S)$ - spot	2	-11.5952
	$\Delta\ln(p_t^{F\text{-}12})$ - futures	10	-9.8991
	$\Delta\ln(p_t^{F\text{-}6})$ - futures	5	-9.8237
ADF test (constant and trend)	$\ln(p_t^S)$ - spot	3	-2.1367
	$\ln(p_t^{F\text{-}12})$ - futures	11	-1.6819
	$\ln(p_t^{F\text{-}6})$ - futures	6	-2.6170
	$\Delta\ln(p_t^S)$ - spot	2	-11.6030
	$\Delta\ln(p_t^{F\text{-}12})$ - futures	10	-9.9195
	$\Delta\ln(p_t^{F\text{-}6})$ - futures	5	-9.8325
KPSS test (constant)	$\ln(p_t^S)$ – spot	3	10.2506
	$\ln(p_t^{F\text{-}12})$ – futures	11	4.4335
	$\ln(p_t^{F\text{-}6})$ – futures	6	6.2560
	$\Delta\ln(p_t^S)$ – spot	2	0.1268
	$\Delta\ln(p_t^{F\text{-}12})$ – futures	10	0.0740
	$\Delta\ln(p_t^{F\text{-}6})$ – futures	5	0.0642
KPSS test (trend)	$\ln(p_t^S)$ - spot	3	0.8632
	$\ln(p_t^{F\text{-}12})$ - futures	11	0.3633
	$\ln(p_t^{F\text{-}6})$ - futures	6	0.5069
	$\Delta\ln(p_t^S)$ - spot	2	0.0966
	$\Delta\ln(p_t^{F\text{-}12})$ - futures	10	0.0576
	$\Delta\ln(p_t^{F\text{-}6})$ - futures	5	0.0486

[a)] Critical values: ADF test (no constant, no trend): -2.58 (1%), -1.95 (5%), -1.62 (10%); ADF test (constant): -3.43 (1%), -2.86 (5%), -2.57 (10%); ADF test (constant and trend): -3.96 (1%), -3.41 (5%), -3.12 (10%); KPSS test (constant): 0.74 (1%), 0.46 (5%), 0.35 (10%); KPSS test (trend): 0.22 (1%), 0.15 (5%), 0.12 (10%)
Source: own calculations

Table 2. Results of the OLS regression

Dependent variable	Time horizon	Independent variable	Estimate	Std. error	t-value	p-value
$\Delta\ln(p_t^S)$ - spot	~ 12 months	Constant	<0.001	0.001	0.182	0.856
		$\Delta\ln(p_t^{F\text{-}12})$ - futures	0.455	0.035	12.815	<0.001
$\Delta\ln(p_t^S)$ - spot	~ 6 months	Constant	<0.001	0.001	0.234	0.815
		$\Delta\ln(p_t^{F\text{-}6})$ - futures	0.375	0.028	13.395	<0.001

Source: own calculations

Table 4. Results of the Johansen trace tests for cointegration

Prices	Lags [a)]	Rank	Test-statistic [b), c)]
$\ln(p_t^S)$, $\ln(p_t^{F\text{-}12})$	3	0	26.38
		1	2.71
$\ln(p_t^S)$, $\ln(p_t^{F\text{-}6})$	3	0	48.84
		1	3.45

[a)] number of lags chosen by AIC
[b)] critical values for trace-test-statistic for rank 0: 24.60 (1%), 19.96 (5%), 17.85 (10%)
[c)] critical values for trace-test-statistic for rank 1: 12.97 (1%), 9.24 (5%), 7.52 (10%)
Source: own calculations

time for both time horizons. Between 2004 and 2005 the hedge ratios are negative which means that long hedges instead of short hedges are recommended for both time horizons. The values for hedging over a 6-month horizon are, as above, lower on average than those for a 12-month horizon.

The optimal hedge ratios estimated with a VECM-BEKK-GARCH (1, 1, 1) are displayed in Figure 4. Here we can see strong variations for a 12-month hedge over the whole time period with a slightly positive trend. The hedge ratios for a 6-month time horizon also show a slightly positive trend but they fluctuate less.

We next estimate an ECM based on changes in the logarithmised spot price and changes in the logarithmised futures prices with contracts that expire in 12 months. Table 5 presents the results of the ECM parameters and we can see that the optimal hedge ratio for a time horizon of 12 months is OHR_{12}^{ECM} = 45.6% which differs only slightly from the hedge ratio estimated with an OLS regression.

Table 5. Results of the ECM parameters (~12 months)

Dependent variable	Independent variables	Estimate	Std. error	t-value	p-value
$\Delta\ln(p_t^S)$	α	-0.049	0.012	-4.072	<0.001
	$\Delta\ln(p_t^{F\text{-}12})$	0.456	0.034	13.339	<0.001
	$\Delta\ln(p_{t-1}^S)$	-0.091	0.036	-2.494	0.013
	$\Delta\ln(p_{t-1}^{F\text{-}12})$	0.157	0.038	4.076	<0.001
	$\Delta\ln(p_{t-2}^S)$	0.044	0.036	1.217	0.224
	$\Delta\ln(p_{t-2}^{F\text{-}12})$	0.045	0.039	1.152	0.250
	$\Delta\ln(p_{t-3}^S)$	0.156	0.036	4.399	<0.001
	$\Delta\ln(p_{t-3}^{F\text{-}12})$	0.062	0.039	1.489	0.112

Source: own calculations

Table 6 presents the results of an ECM based on changes in the logarithmised spot price and changes in the logarithmised futures prices with contracts that expire in 6 months. The optimal hedge ratio of OHR_6^{ECM} = 36.8% also only slightly differs from the hedge ratio estimated via OLS.

Table 6. Results of the ECM parameters (~ 6 months)

Dependent variable	Independent variables	Estimate	Std. error	t-value	p-value
$\Delta\ln(p_t^S)$	α	-0.076	0.013	-5.699	<0.001
	$\Delta\ln(p_t^{F\text{-}6})$	0.368	0.026	14.029	<0.001
	$\Delta\ln(p_{t-1}^S)$	-0.099	0.036	-2.777	0.006
	$\Delta\ln(p_{t-1}^{F\text{-}6})$	0.142	0.031	4.572	<0.001
	$\Delta\ln(p_{t-2}^S)$	0.022	0.036	0.631	0.528
	$\Delta\ln(p_{t-2}^{F\text{-}6})$	0.048	0.031	1.542	0.124
	$\Delta\ln(p_{t-3}^S)$	0.105	0.035	3.022	0.003
	$\Delta\ln(p_{t-3}^{F\text{-}6})$	0.060	0.031	1.936	0.053

Source: own calculations

Next, we estimate VECM-GARCH models[1] to obtain time-varying optimal hedge ratios. Figure 2 displays the optimal hedge ratios estimated with a VECM-CCC-GARCH (1, 1). We can see that the hedging rates for a 12-month time horizon fluctuate mainly around 40% with stronger fluctuations between 2003 and 2005 and later again between 2013 and 2015. The optimal hedge ratios for a 6-month time horizon follow a similar course but are slightly lower on average.

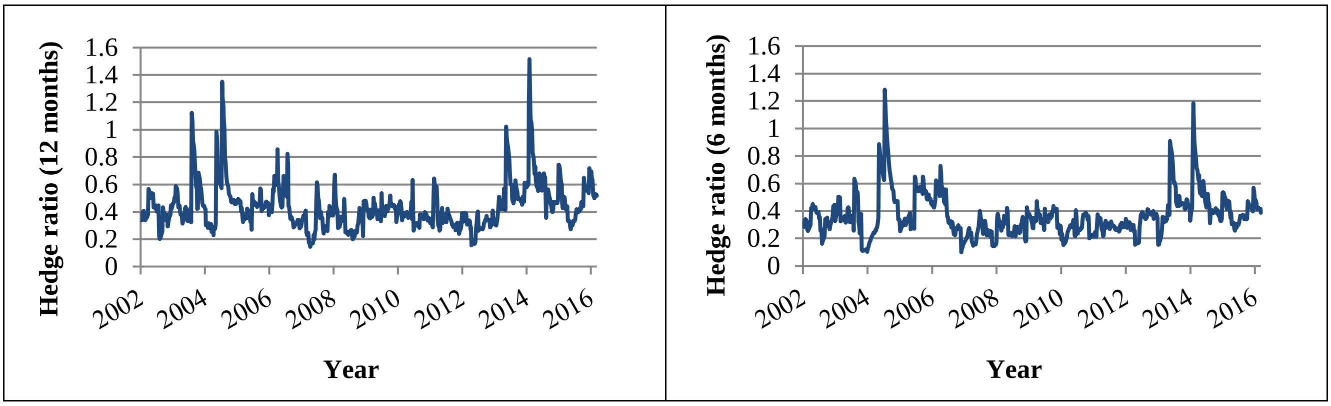
Figure 3 displays hedge ratios estimated with a VECM-DCC-GARCH (1, 1). Compared with the CCC-GARCH model, we can see that the hedge ratios fluctuate less but seem to follow a positive trend over

To compare the performance of the different optimal hedge ratios we estimate the HE index as well as the variance of the unhedged and the hedged portfolios based on the optimal hedge ratios over time. For comparison, we also consider a scenario in which the whole position is hedged (OHR^{total} = 100%). The results are presented in Table 7. In case of a round turn of 12 months, the two static (OLS, ECM) as well as the three dynamic hedging strategies (CCC, DCC BEKK) lead to a reduction in the portfolio variance

1 The parameter estimates are presented in the Appendix (Table A1 – Table A4).

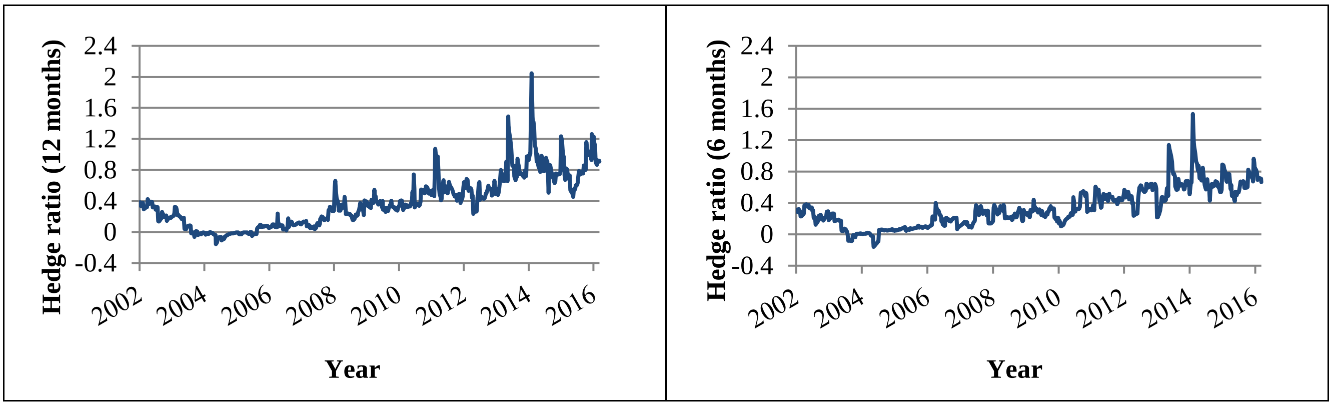
compared with the unhedged portfolio. The time-varying optimal hedge ratios estimated with the VECM-BEKK-GARCH (1, 1, 1) lead to the highest HE index of 30.2% and can be regarded as the superior hedging strategy. A hedge ratio of 100% increases the variance of the portfolio compared with an unhedged portfolio which leads to a negative HE index. This means that it would be better not to hedge instead of hedging the whole portfolio. For a hedging period of 6 months, the results are similar. The optimal hedge ratios estimated with the five different models are on average lower than the ratios estimated for a hedging period of 12 months, but they also all lead to a variance reduction compared with the unhedged portfolio. The VECM-BEKK-GARCH (1, 1, 1) is again the superior model because the optimal hedge ratios lead to the highest HE index of 33.3% which is even higher than the HE index for a 12-month horizon. A hedge

Figure 2. Time-varying optimal hedge ratios estimated with VECM-CCC-GARCH (1, 1)



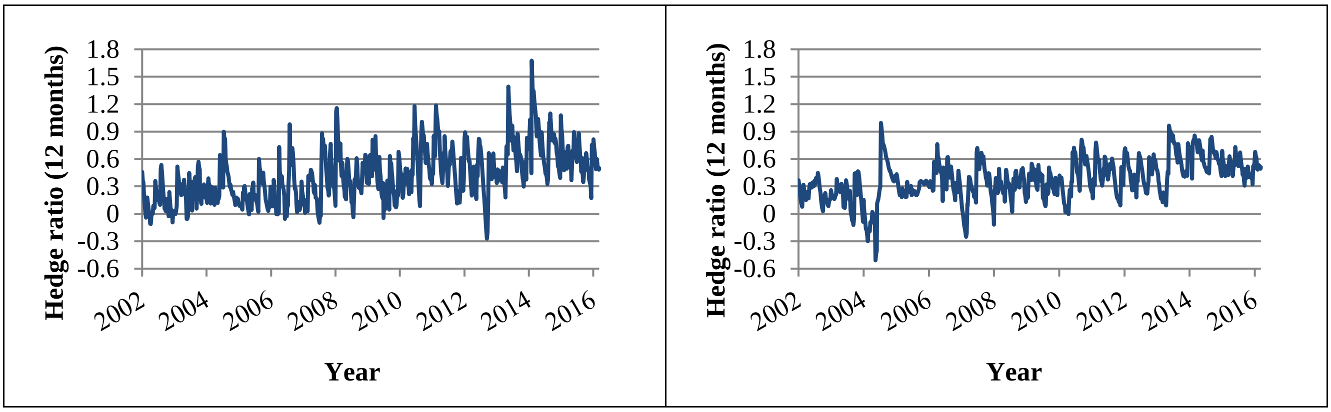
Source: own diagrams

Figure 3. Time-varying optimal hedge ratios estimated with VECM-DCC-GARCH (1, 1)



Source: own diagrams

Figure 4. Time-varying optimal hedge ratios estimated with VECM-BEKK-GARCH (1, 1, 1)



Source: own diagrams

Table 7. Comparison of the different hedging strategies between 2002 and 2016

Time horizon	Hedge ratio according to	Ø OHR (%)	Variance of portfolios	HE
~ 12 months	Total	100.0	0.00085	-0.080
	OLS	45.5	0.00064	0.181
	ECM	45.6	0.00064	0.181
	CCC	43.6	0.00064	0.187
	DCC	38.1	0.00058	0.266
	BEKK	41.8	0.00056	0.302
~ 6 months	Total	100.0	0.00106	-0.345
	OLS	37.5	0.00063	0.195
	ECM	36.8	0.00063	0.195
	CCC	36.6	0.00060	0.241
	DCC	33.4	0.00054	0.319
	BEKK	38.6	0.00054	0.333
	unhedged	0	0.00079	0

Source: own calculations

ratio of 100% leads to a negative HE index again so that a hedge ratio of 0% would be better than a hedge ratio of 100%.

In a next step we evaluate the actual profits or losses for a farmer who decides to hedge a 12-month time horizon around the 1st of October each year, or a 6-month time horizon around the 1st of March. Around the 1st of October the farmer goes short in futures contracts with expiry in November[2] of the following year at price $p^F_{t,open}$. We assume that the farmer uses the optimal hedge ratios estimated with the VECM-BEKK-GARCH (1, 1, 1), which has the highest HE index value. The optimal hedge ratio for each round turn is estimated as the average of the time-varying hedge ratios estimated with the VECM-BEKK-GARCH(1, 1, 1) of all observations previous to opening the futures position. The cost per round turn (C_t) are composed of the trading cost to open and close a futures position of 1 €/t and the sum of interest charges for the margin calls over time, which vary between 0.03€/t and 1.45€/t. The position is closed after the end of harvest around the 1st September in the following year at price $p^F_{t,close}$ and the physical wheat is sold on the spot market at price p^S_t. The overall revenue after hedging (R_t) is defined as follows:

$$R_t = p^S_t + \left(p^F_{t,open} - p^F_{t,close}\right) * \emptyset OHR^{BEKK} - C_t. \quad (11)$$

[2] Since the contract months July (2002-2005), August (2008-2012) and September (2002-2007) were extremely illiquid we use the November contracts in each trading year.

Furthermore, we compare the overall revenue after hedging (R_t) with a pure sale on the spot market without any hedging (Hedging vs. no hedging). The results are presented in Table 8.

As we can see in Table 8, the average spot price after the grain harvest (185.58€/t) was remarkably higher than the average futures price at the same time (177.33€/t). Taking into account the cost per round turn and the prices at which the futures contracts were sold approximately 12 months earlier the farmer loses on average 6.34€/t from hedging the average optimal ratio of the previous years of his/her wheat harvest. Looking at the results for the single years separately we can see that this loss is caused by years with unanticipated price spikes (2003, 2006-2007, 2010, 2012). But this also means, that farmers who decide to hedge benefit in years with sharp price decreases (2008-2009, 2013). Nevertheless, comparing the variance of the spot prices (unhedged portfolio) and the variance of the overall revenue from hedging (hedged portfolio) we can see that hedging leads to a variance reduction of 26%.

Next, we estimate potential profits or losses from hedging a time interval of 6 months (Table 9). The farmer goes short in futures contracts with expiry in November around the 1st of March at price $p^F_{t,open}$, and closes the position after harvest around the 1st of September at price $p^F_{t,close}$. We assume again that the farmer uses the according to the VECM-BEKK-GARCH(1, 1, 1) optimal hedge ratio because it displays the highest HE index. This optimal ratio is calculated as the average of the time-varying hedge ratios of all observations previous to opening the futures position. For a time horizon of approximately 6 months, the cost per round turn (C_t) varies between 1.02€/t and 1.76€/t. The results show that the farmer loses on average 4.93€/t from hedging 6 months before harvesting (-1.92%). This loss is 1.41€/t lower than the loss calculated for hedging 12 months before harvesting. Hedging the according to the VECM-BEKK-GARCH(1, 1, 1) average optimal ratio of the previous years 6 months before harvesting leads to a variance reduction of 19% of the hedged portfolio compared with the unhedged portfolio. This reduction in the variance caused by a hedging period of 6 months is lower than the reduction caused by a hedging period of 12 months.

Based on these average reduction in revenues of 6.34€/t for a hedging period of 12 months, and 4.93€/t for a hedging period of 6 months, we calculate the

Table 8. Costs and benefits from hedging a 12-month time horizon

t (seeding/ 12 months)	$p^F_{t,open}$ (€/t)	C_t (€/t)	t (harvest)	p^S_t (€/t)	$p^F_{t,close}$ (€/t)	$\varnothing OHR^{BEKK}$ (%)	R_t (€/t)	Hedging vs. no hedging (€/t)	Hedging vs. no hedging (%)
01/10/2002	121.00	1.03	01/09/2003	115.50	136.25	16.91	111.89	-3.61	-3.12
01/10/2003	120.00	1.62	31/08/2004	113.50	111.75	16.69	113.26	-0.24	-0.21
01/10/2004	109.75	1.15	29/08/2005	101.50	108.25	22.54	100.69	-0.81	-0.80
03/10/2005	111.00	1.23	04/09/2006	138.00	143.25	21.55	129.82	-8.18	-5.93
02/10/2006	134.50	1.89	03/09/2007	265.80	266.75	22.23	234.51	-31.29	-11.77
01/10/2007	199.75	2.19	01/09/2008	203.75	182.00	22.93	205.63	1.88	0.92
01/10/2008	168.50	1.00	31/08/2009	137.50	127.00	26.30	147.41	9.91	7.21
01/10/2009	136.00	1.50	30/08/2010	242.50	227.50	28.10	215.29	-27.21	-11.22
01/10/2010	176.25	2.45	29/08/2011	235.50	214.00	29.66	221.85	-13.65	-5.80
01/10/2011	184.25	1.41	03/09/2012	277.50	264.50	33.45	249.24	-28.26	-10.18
03/10/2012	229.00	1.25	02/09/2013	201.50	190.00	34.61	213.75	12.25	6.08
01/10/2013	187.00	1.26	01/09/2014	193.50	173.75	36.16	197.03	3.53	1.83
01/10/2014	171.50	1.19	31/08/2015	186.50	160.25	39.23	189.73	3.23	1.73
Mean	157.58	1.47		185.58	177.33	26.95	179.24	-6.34	-2.41

Source: own calculations

Table 9. Costs and benefits from hedging a 6-month time horizon

t (spring/ 6 months)	$p^F_{t,open}$ (€/t)	C_t (€/t)	t (harvest)	p^S_t (€/t)	$p^F_{t,close}$ (€/t)	$\varnothing OHR^{BEKK}$ (%)	R_t (€/t)	Hedging vs. no hedging (€/t)	Hedging vs. no hedging (%)
28/02/2003	111.50	1.13	01/09/2003	115.50	136.25	23.07	108.66	-6.84	-5.92
01/03/2004	125.75	1.04	31/08/2004	113.50	111.75	21.27	115.44	1.94	1.71
01/03/2005	108.75	1.02	29/08/2005	101.50	108.25	22.81	100.59	-0.91	-0.90
01/03/2006	114.00	1.14	04/09/2006	138.00	143.25	23.88	129.88	-8.12	-5.89
01/03/2007	136.25	1.76	03/09/2007	265.80	266.75	26.45	229.53	-36.27	-13.65
29/02/2008	238.25	1.13	01/09/2008	203.75	182.00	27.16	217.89	14.14	6.94
02/03/2009	143.00	1.23	31/08/2009	137.50	127.00	27.76	140.71	3.21	2.33
01/03/2010	132.00	1.37	30/08/2010	242.50	227.50	28.59	213.83	-28.26	-11.82
01/03/2011	218.50	1.33	29/08/2011	235.50	214.00	29.80	235.51	0.01	0.00
01/03/2012	196.75	1.25	03/09/2012	277.50	264.50	31.38	254.99	-22.51	-8.11
01/03/2013	214.00	1.03	02/09/2013	201.50	190.00	32.53	208.27	6.77	3.36
01/03/2014	193.25	1.12	01/09/2014	193.50	173.75	34.19	199.05	5.55	2.87
02/03/2015	184.00	1.03	31/08/2015	186.50	160.25	36.44	194.13	7.63	4.09
Mean	162.77	1.20		185.58	177.33	28.10	180.65	-4.93	-1.92

Source: own calculations

potential monetary consequences for different farm sizes. The results are presented in Table 10.

Varying the wheat acreage between 50ha and 1,000ha and assuming the long-term average wheat yield in Germany of 7.85t/ha (BUNDESMINISTERIUM FÜR ERNÄHRUNG UND LANDWIRTSCHAFT, 2018), the farmer can expect to harvest between 393t and 7,850t. Hedging on average 26.95% of the expected harvest for a round-turn of 12 months, the farmer has to short-sell 2 futures contracts when planting 50ha wheat. This would lead to a reduction in returns of 671€ compared with an unhedged portfolio. With a 6-month time horizon the farmer would have to accept 544€ lower returns by hedging on average 28.10% of the expected harvest to reduce the price uncertainty. Assuming that the farmer plants 1,000ha wheat and hedges 42 lots (44 lots) for a hedging period of 12 months (6 months), the reduction would increase up to 13,413€ (10,875€) to reduce the price risk.

Table 10. Average reduction in revenues for different farm sizes

Wheat acreage (ha)	Wheat yield (t)	12-month time horizon		6-month time horizon	
		Con-tracts	Reduction in revenues (€)	Con-tracts	Reduction in revenues (€)
50	393	2	671	2	544
100	785	4	1341	4	1087
200	1570	8	2683	9	2175
500	3925	21	6706	22	5437
800	6280	34	10730	35	8700
1000	7850	42	13413	44	10875

Source: own calculations

In summary, both scenarios, a hedging period of 12 months or 6 months, lead to lower revenues but they also reduce the variances and therefor the uncertainty. Whether one of the two strategies benefits a farmer depends on his/her individual risk attitude. The loss in revenues can be regarded as an insurance fee for the reduced variances in both cases, and the farmer then has to decide whether he/she is willing to pay 6.34€/t for a 26% lower variance or 4.93€/t for a 19% lower variance compared with an unhedged portfolio. Furthermore, the farmer faces the highest reduction in revenues in years with unanticipated price spikes but benefits in years with sharp price decreases. Therefore, it can be assumed that hedging is especially costly for commodities with prices changes characterized by the rockets and feathers phenomenon. This asymmetry in price changes can be found for storable as well as for non-storable goods (BECK, 2001; DEATON and LAROQUE, 1992) and makes hedging less profitable, since the farmer cannot benefit from price increases and has less opportunity to increase his or her revenues due to price decreases.

The variance reduction of 19% or 26% of the hedged portfolio compared with the unhedged portfolio seems to be quite low compared to previous studies. ZUPPIROLI and GIHA (2016), for example, find a variance reduction of 34% to 77 % for hedging wheat at the Euronext Paris for different hedging intervals between 5 and 66 days. BAILLIE and MYERS (1991) show that hedging soybeans reduces the price risk by up to 57 %. In contrast, DAWSON et al. (2000) only find an average reduction in the variance of returns of less than 4% for hedging wheat and barley. SALHOFER and ZOLL (2005) analyze profits and losses for farmers who short-sell German pork futures and show that the price risk reduction of 10 % is accompanied by a 2 % lower average yield. Compared with our results, a similar reduction in the returns in their application leads to even lower risk reduction. These findings show that lower revenues and a decreased variance are not only caused by hedging storable goods, but also by non-storable goods. However, it should be noted that the comparability of our results with previous applications is limited. Since previous studies work with different hedge ratios, commodities or futures markets, their findings may not be directly comparable to ours.

However, the reduced average revenue compared with an unhedged portfolio is not the only possible disadvantage of hedging. The calculation of costs above does account for interest charges for the margin calls over time. But margin calls do not only cause costs in terms of interest charges but can also cause liquidity problems for the farmer. Table 11 presents the sum of margin calls per hedge for the two different scenarios, a hedge round-turn of 12 months and of 6 months. A farmer who hedges 12 months before harvesting faces margin calls of 40.91€/t on average, and margin calls of 32.75€/t on average if he/she hedges 6 months before harvesting. This is equivalent to 2045.50€/lot (12 months) and 1637.50€/lot (6 months), if the farmer hedges one 50t lot. In Table 11 we see that the highest margin calls occurred in 2007. Here the farmer had to pay margin calls of 6125€/lot in total for a 12-months hedge and 6037.50€/lot for a 6-months hedge because of the steadily rising wheat prices between 2006 and 2007 at the beginning of the so-called food price crisis in 2007/08. For a farmer who hedges not 50t but 500t, for example, margin calls of over 60,000€ result. The resulting liquidity or financing problems might also explain why most farmers do not hedge their crops.

Besides these potential liquidity problems the farmer might face further risks associated with hedging, such as production risk. Choosing a 6-months hedge instead of a 12-months hedge already leads to a lower production uncertainty because in spring the farmer knows how the crop has emerged from the winter period which gives him a better idea of the quantity of wheat he or she will harvest later in the summer. However, unexpected weather conditions after short-selling the wheat before harvest, for example, can lead to different yields than expected, making a perfect hedge nearly implausible. Furthermore, quality specifications and the size of standardized futures contracts limit the flexibility of the farmers and may not always fit their needs when choosing the optimal hedge ratio.

Table 11. Sum of margin calls per hedge

t (seeding/ 12 months)	$p^F_{t,open}$ (€/t)	Margin calls (€/t)	t (spring/ 6 months)	$p^F_{t,open}$ (€/t)	Margin calls (€/t)	t (harvest)	$p^F_{t,close}$ (€/t)
01/10/2001	120.75	4.75	01/03/2002	114.75	4.75	02/09/02	115.25
01/10/2002	121.00	14.00	28/02/2003	111.50	23.50	01/09/03	136.25
01/10/2003	120.00	17.00	01/03/2004	125.75	2.50	31/08/04	111.75
01/10/2004	109.75	4.50	01/03/2005	108.75	2.00	29/08/05	108.25
03/10/2005	111.00	32.50	01/03/2006	114.00	29.50	04/09/06	143.25
02/10/2006	134.50	122.50	01/03/2007	136.25	120.75	03/09/07	266.75
01/10/2007	199.75	47.25	29/02/2008	238.25	7.50	01/09/08	182.00
01/10/2008	168.50	0.00	02/03/2009	143.00	22.00	31/08/09	127.00
01/10/2009	136.00	91.75	01/03/2010	132.00	95.75	30/08/10	227.50
01/10/2010	176.25	76.50	01/03/2011	218.50	34.25	29/08/11	214.00
01/10/2011	184.25	85.50	01/03/2012	196.75	73.00	03/09/12	264.50
03/10/2012	229.00	20.25	01/03/2013	214.00	5.50	02/09/13	190.00
01/10/2013	187.00	22.75	01/03/2014	193.25	16.50	01/09/14	173.75
01/10/2014	171.50	33.50	02/03/2015	184.00	21.00	31/08/15	160.25
Mean	154.95	40.91		159.34	32.75		172.89

Source: own calculations

Our findings regarding the hedging potential of the Euronext wheat futures contract for German farmers might contribute to the ongoing debate about public and private risk management. Currently, the Common Agricultural Policy (CAP) tries to limit the consequences of high price volatility for farmers by providing income support and stabilization via direct payments. Additionally, the CAP encourages farmers, for example in the so-called “milk-package”, to use hedging as a risk management instrument to avoid adverse price developments and to accompany management decisions (EUROPEAN COMMISSION, 2017b). Our findings for the wheat sector support the assumption that hedging reduces the price risk and may provide an interesting risk management tool for German farmers. But the transferability of our results to other agricultural commodities is limited. In Europe, grain and oilseed futures contracts are much more liquid than most futures contracts for non-storable goods such as milk or pork. Illiquid futures market may not price in all relevant market information, and prices generated on such futures markets may even be not cointegrated with the respective spot prices. Furthermore, on illiquid futures markets a farmer may not always find a trading partner to open and close his or her futures position. To overcome these problems farmers might focus on forward contracts instead of futures contracts. Forward transactions offer a greater flexibility in terms of contract specifications and the farmer needs less technical knowledge and information. Furthermore, farmers may profit indirectly from risk management on futures markets without hedging themselves since the trading and processing firms that they deal with often use futures to hedge their forward positions.

5 Conclusions

Rising trading activities on commodity exchanges and increasing price volatilities in the last years strengthened the interest in futures markets as a risk management tool. However, hedging is commonly used by commercial market participants, but only very few farmers hedge their crops against adverse price fluctuations. Using OLS, ECM and VECM-GARCH approaches to determine the optimal hedge ratio we analyze the hedging potential of the Euronext milling wheat futures contract for German farmers. To evaluate hedging from a farmer’s perspective we estimate potential profits and losses for hedging the optimal ratio of the expected harvest. Thereby we differentiate between hedging directly after seeding with a time horizon of approximately 12 months, and hedging in spring with a time horizon of approximately 6 months.

For hedging German milling wheat at the Euronext Paris our results suggest that estimating time-varying optimal hedge ratios with the VECM-BEKK-GARCH approach leads to the highest risk reduction for time horizons of 12 and 6 months, respectively. Furthermore, we find that on average farmers face lower returns in exchange a reduced variability in prices through hedging. But for a time horizon of 12 months both the income reduction and the decrease in the price variability through hedging are higher than for a time horizon of only 6 months. Which one of the two points in time would be preferable depends on the farmer's individual risk attitude. In addition we show that margin calls should not be underestimated because they can cause liquidity problems, especially in years with unanticipated price spikes.

Since we only focus on hedging crops before harvesting our study offers potential for future research. Further studies could focus on hedging storage as well as on finding the optimal moment in time to hedge. In addition, the reduction in returns farmers are willing to accept for a risk reduction could be looked upon more in detail.

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Appendix

Table A1. Results of the VECM parameters (12 months)

Dependent variable	Independent variable	Estimate	Standard error	t-value	p-value
$\Delta\ln(p_t^S)$	α_S	-0.062	0.040	-1.562	0.118
	$\Delta\ln(p_{t-1}^S)$	-0.008	0.068	-0.117	0.906
	$\Delta\ln(p_{t-1}^{F\_6})$	0.108	0.052	2.079	0.038
	$\Delta\ln(p_{t-2}^S)$	0.199	0.059	3.377	<0.001
	$\Delta\ln(p_{t-2}^{F\_6})$	0.172	0.062	2.764	0.006
	$\Delta\ln(p_{t-3}^S)$	0.071	0.048	1.476	0.140
	$\Delta\ln(p_{t-3}^{F\_6})$	0.024	0.049	0.493	0.622
$\Delta\ln(p_t^F)$	α_F	0.021	0.009	2.470	0.014
	$\Delta\ln(p_{t-1}^S)$	0.042	0.033	1.262	0.207
	$\Delta\ln(p_{t-1}^{F\_6})$	0.064	0.034	1.852	0.064
	$\Delta\ln(p_{t-2}^S)$	-0.014	0.031	-0.452	0.651
	$\Delta\ln(p_{t-2}^{F\_6})$	0.064	0.041	1.543	0.123
	$\Delta\ln(p_{t-3}^S)$	0.014	0.040	0.350	0.726
	$\Delta\ln(p_{t-3}^{F\_6})$	-0.060	0.041	-1.460	0.144

Source: own calculations

Table A2. Results of the VECM parameters (6 months)

Dependent variable	Independent variable	Estimate	Standard error	t-value	p-value
$\Delta\ln(p_t^S)$	α_S	-0.090	0.029	-3.061	0.002
	$\Delta\ln(p_{t-1}^S)$	-0.007	0.058	-0.128	0.899
	$\Delta\ln(p_{t-1}^{F\_6})$	0.090	0.047	1.925	0.054
	$\Delta\ln(p_{t-2}^S)$	0.153	0.053	2.912	0.004
	$\Delta\ln(p_{t-2}^{F\_6})$	0.101	0.051	1.971	0.049
	$\Delta\ln(p_{t-3}^S)$	0.037	0.041	0.911	0.362
	$\Delta\ln(p_{t-3}^{F\_6})$	0.026	0.041	0.645	0.519
$\Delta\ln(p_t^F)$	α_F	0.015	0.013	1.105	0.269
	$\Delta\ln(p_{t-1}^S)$	0.004	0.036	0.110	0.913
	$\Delta\ln(p_{t-1}^{F\_6})$	0.062	0.038	1.641	0.101
	$\Delta\ln(p_{t-2}^S)$	0.036	0.030	1.204	0.229
	$\Delta\ln(p_{t-2}^{F\_6})$	0.020	0.052	0.379	0.705
	$\Delta\ln(p_{t-3}^S)$	-0.036	0.048	-0.759	0.448
	$\Delta\ln(p_{t-3}^{F\_6})$	0.011	0.049	0.222	0.824

Source: own calculations

Table A3. Results of the CCC-GARCH (1,1) and DCC-GARCH (1,1) parameters

Time horizon	Coefficient	Estimate	Standard error	t-value	p-value
12 months	c_1	<0.001	<0.001	1.241	0.214
	a_1	0.199	0.124	1.604	0.109
	b_1	0.761	0.060	12.684	<0.001
	c_2	<0.001	<0.001	1.902	0.057
	a_2	0.166	0.049	3.366	0.001
	b_2	0.816	0.050	16.455	<0.001
6 months	c_1	<0.001	<0.001	1.426	0.154
	a_1	0.189	0.089	2.124	0.034
	b_1	0.777	0.072	10.775	<0.001
	c_2	<0.001	<0.001	1.480	0.139
	a_2	0.175	0.040	4.334	<0.001
	b_2	0.824	0.043	19.207	<0.001

Source: own calculations

Table A4. Results of the BEKK-GARCH (1,1,1) parameters

Coefficient	Estimates	
	12 months	6 months
C_{11}	0.022	<0.001
C_{12}	0.000	<0.001
C_{22}	0.005	0.324
A_{11}	-0.114	<0.001
A_{12}	0.634	<0.001
A_{21}	0.036	< -0.001
A_{22}	0.539	<0.001
B_{11}	0.107	<0.001
B_{12}	0.160	<0.001
B_{21}	0.390	< -0.001
B_{22}	0.576	< -0.001

Source: own calculations