Volume IX Number 4, 2017

Price Volatility Modelling – Wheat: GARCH Model Application

Michal Čermák, Karel Malec, Mansoor Maitah

Faculty of Economics and Management, Czech University of Life Sciences Prague, Czech Republic

Abstract

This paper is focused on the modelling of volatility in the agricultural commodity market, specifically on wheat. The aim of this study is to develop an applicable and relevant model of conditional heteroscedasticity from the GARCH family for wheat futures prices. The GARCH (1,1) model has the ability to capture the main characteristics of the commodity market, specifically leptokurtic distribution and volatility clustering. The results show that the forecasted volatility of wheat has a tendency towards standard error reversion in the long-run and the position of price distribution is closed to the normal distribution. The wheat production can be hedged against the price variability with long-term contracts. The price of wheat was influenced during the years of 2005 to 2015 by different events, in particular; financial crisis, increasing grain demand and cross-sectional price variability. The results suggest that agricultural producers should focus on short-term structural events the wheat market, rather than long-term variability.

Keywords

Price volatility, forecasting, GARCH, wheat price, CME, futures contracts.

Čermák, M., Malec, K. and Maitah, M. (2017) "Price Volatility Modelling – Wheat: GARCH Model Application", *AGRIS on-line Papers in Economics and Informatics*, Vol. 9, No. 4, pp. 15-24. ISSN 1804-1930. DOI 10.7160/aol.2017.090402.

Introduction

In today's market, commodities are frequently characterized by an increasing trend in the long term. There were significant fluctuations of commodity prices during the period of 2006 to 2009, followed by decreasing prices in the commodity markets due to the financial crisis (Bourdon-Huchet, 2011). In general, high volatility is now evident in every financial market, especially in the case of the commodities market. Examples of this can be found in the problems of storability, seasonality (agricultural products) and price shocks during periods of high volatility. These events are important in the modelling of the chosen commodity.

Volatility modelling is of great interest to many financial analysts and practitioners, in particular, Reider (2009), Zhang (2015), Huang Poon (2005). The origin of the evaluation of price fluctuation is based on price movements and dynamics. Markowitz (1952) firstly focuses on the concept of uncertainty of the asset price. The problem of price variability modelling is primarily due to the difficulties with visibility and the analysis of patterns or other structures of simulated data, see Zhang et al. (2015) The structure of price trajectory has changed over last decade because of the availability of high-frequency data (Maneesoonthorn, 2015). These movements are often brought on by news announcements or trading activity by institutions. Due to this price variability and volatility, there is an obvious effect on commodity market returns. The ability to accurately and unambiguously forecast and predict volatility in any market has multiple applications. Firstly, there is asset allocation in regards to risk management. There are other utilizations, however the most significant effect of volatility measurement for commodity and equities traders can be felt in the field of portfolio management consisting of assets and derivatives (Hull, 1987). According to a study by Fama (1965), the prices of commodities are characterized with volatile periods changing over time.

There are multiple reasons why to study the price volatility of agricultural commodities. Firstly, the variability of prices is influenced by external shocks or weather. Secondly, we can predict price fluctuation in regards to confidence levels. The volatility is also influenced by the supply of commodities.

The main approach of characteristics of financial time series exhibits the volatility clustering. The papers of Mandelbrot (1963) and Black (1973) documented this evidence in detail about leptokurtosis and clustering among financial time series. In the last fifteen years, many economists and researchers have begun estimating time series variation by utilizing higher levels of lagged variables. The recent studies of Najand (2002) and Lee, Faff (2009) handle aspects of both volatility clustering and fat-tailed time series. The approach of modern financial volatility modelling was developed by Engle (1982). This paper deals with changing variance using the Autoregressive Conditional Heteroscedasticity (ARCH) model. Later, Bollerslev (1986) introduced the extended version of the ARCH model e.g. with the generalized version – GARCH model. The assumption of this model is that the returns have time-varying conditional variances. According to Val, Pinto and Klotze (2014) the family of GARCH models has significant predictive power when using intra-day data. We assume that the ARCH – family models have a tendency to capture the conditional variance using lags. The conclusion of modelling price volatility is based on the stochastic process. It assumes a financial time series can be defined as a result of a collection of random elements (Douc et al., 2014).

Wheat as a commodity belongs to the family of basic food commodities. The main reason for using wheat is directly connected with nutrition. Wheat has a large impact on mostly agricultural producers, but it influences processors as well.

This paper principally addresses modelling and forecasting the volatility of wheat prices using Generalized Autoregressive Conditional Heteroscedasticity (GARCH). For the purpose of this paper we have selected the time series of wheat futures prices traded on the Chicago Mercantile Exchange (CME). The primary objective of this study is to design an appropriate model of conditional heteroscedasticity from the GARCH family for wheat futures prices based on variance analysis and data. With that in mind, the paper specifically addresses the following research questions:

i. What are the prediction capabilities of GARCH (1,1) for the CME wheat market?

ii. Is it possible to use the output of the GARCH model application for the hedging of risks by wheat producers?

Literature review

Kroner, Kneafsey, Claessenes (1995) studied the long-term forecasting of commodity price volatility. They divided the commodities into different types of forecasts.

In the study by Yang, Haigh, Leatham (2010) there is a GARCH model application under conditions of agricultural liberalization policy. They discovered that the price liberalization caused an increase in the commodity price volatility in the case of several popular commodities – wheat, corn and soybeans. The results included an observation from the 1990s.

Authors Onour, Sergi (2012) employed the competing models with Student t- distribution in the period of 1984 – 2009. The forecast captured the existence of short-term memory behaviour. The paper from Musunuru (2014) focuses on the relationship between wheat and corn in modelling price volatility with the use of the multivariate GARCH model. The results of the paper show that agricultural commodity returns can change significantly over time. Franses, Van Dijk (1996) argue that there are some models, which are not recommended for forecasting such as the Glosten, Jagannathan, and Runkle (GJR) model. The model that is best suited for forecasting non-linear or seasonal time series comes from the GARCH model family. Also, authors such as Tulley and Lucey (2007) have estimated the predictive power of the GARCH model. Baur (2011) employed stochastic volatility models to predict the asymmetry of the volatility of gold. Chkili, Hammoudeh and Nguyen (2014) explored the determinants of change in volatility and forecasting in the example of gas, oil, gold and silver. In a book by Knight and Satchell (2007) there is an evaluation of crucial determinants of commodities, for instance the distribution of contracts, volatility clustering or leverage.

Hansen and Lunde (2005) compare ARCH – type models in the context of describing their conditional variance using exchange rates. According to the authors, the model GARCH (1,1) is unbiased. In addition, Chong (1999) works with modifications of the GARCH model in the stock exchange.

Authors Wei, Wang and Huang (2010) use the non-linear models of the GARCH family to forecast the price of crude oil with the capability to capture the long-term memory over long time periods. Olowe (2009) assumes and advises that the best model for forecasting and evaluating the volatility is GARCH (1,1).

The structure of the paper follows: The next chapter is focused on used methods and data basement. The chapter results and discussion describes results with discussed problems. The last chapter Conclusion summarizes the overall topic according to research questions.

Materials and methods

The data set consists of 2770 observations. The time series represents the period of 2005 to 2015. The frequency is daily and represents the closing prices of wheat CME Futures. The stationarity is tested using the ADF test (Dickey et al., 1979).

We address the problem of time-variant residual variance by using the ARCH and GARCH models, respectively. The GARCH model is an extended version of the ARCH model that allows for the inclusion of lags of conditional variance.

The ARCH model is extended with the possibility of using the lags of conditional variance. The volatility is dependent on previous observations. Thus the volatility model Generalized Autoregressive Conditional Heteroscedasticity (GARCH) is used (Bollerslev, 1986).

The general form of GARCH(p,q) is:

$$h_t = \alpha_0 + \alpha_1 Y^2_{t-1} + \alpha_2 Y^2_{t-2} + \ldots + \alpha_p Y^2_{t-p} + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \ldots + \beta_q h_{t-q} + u_t \quad (1)$$

where $p > 0$; $q \geq 0$; $\alpha_0 > 0$; $\alpha_i \geq 0$ for i =1; 2 ... p; $\beta_y \geq 0$ for y = 1; 2 …. q (2)

and u_t is the an error term.

The value of "p" represents the lags of residual returns and "q" is a lag of variances.

In our application, the lag length choice is based on Akaike Information Criterion. The verification of the model includes the test data for heteroscedasticity and residual autocorrelation. Heteroscedasticity is tested using the ARCH model, i.e. Langrange multiplier for testing to assess the significance of ARCH effects.

ARCH LM test, can be specified as:

$$u_t^2 = \gamma_0 + \sum_{i=1}^{q} \gamma_1 u_{t-1}^2 + v_t \quad (3)$$

With the null hypothesis about the constant conditional variance, i. e. H_0: $\gamma_i = 0$ for i = 1.. q, and v_t is the error term.

The serial correlation is tested by using the Breusch-Godfrey test. This test is based on a null hypothesis there is no autocorrelation of order p.

The Breusch-Godfrey test is based on the following regression.

$$\hat{u}_t = \mu_0 + \mu X_{t,1} + \rho_1 \hat{u}_{t-1} + \cdots + \rho_p \hat{u}_{t-p} + \varepsilon_t \quad (4)$$

where X is a matrix of regressors, and ε_t is an error term.

Then the null hypothesis H_0 is $\rho_1 = \ldots . \rho_p = 0$

Results and discussion

Table 1 provides the results of the Augmented Dickey-Fuller test to detect the unit root in time series. The results suggest that the null hypothesis about the unit root in time series cannot be rejected with a 10% significance level. That is, the time series needs to be transformed.

Test statistic with constant	-2.5364`
Test statistic with constant and trend	-2.3395`

Note: ` Akaike Information Criterion was used for lag length selection

Source: Own calculation in EViews based on CME data, 2016

Table 1: Augmented Dickey-Fuller test statistic.

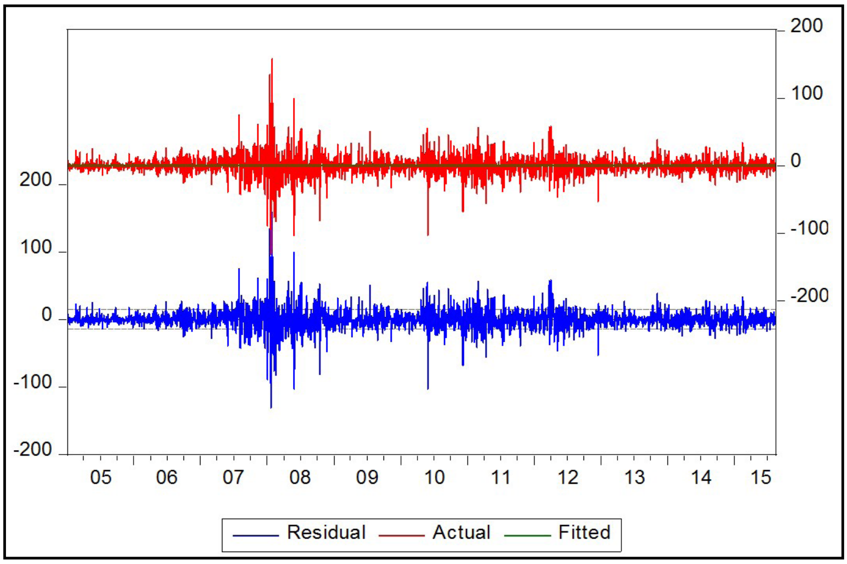
First, the daily closing prices of wheat traded at the CME were transformed using the first differences. Table 2 shows residuals from OLS regression. The table demonstrates that the intercept is not significant with a significance level of 0.05.

Figure 1 displays the residuals from OLS regression and the returns on wheat prices, both actual and fitted ones. The chart captures the volatility clustering and the period with high volatility in 2008 related to the shocks on financial markets. The volatility clustering can be captured by GARCH (p,q). The volatility clustering is based on the assumption

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.059567	0.279947	0.212779	0.8315
R-squared	0.000000	Mean dependent var		0.059567
Adjusted R-squared	0.000000	S.D. dependent var		14.73383
S.E. of regression	14.73383	Akaike info criterion		8.218530
Sum squared resid	601110.2	Schwarz criterion		8.220670
Log likelihood	-11381.66	Hannan-Quinn criter.		8.219303
Durbin-Watson stat	1.889717			

Source: Own calculation in STATA 13 based on CME data, 2016

Table 2: OLS regression.



Source: Own calculation in STATA 13 based on CME data, 2016

Figure 1: Residuals.

that the large values of conditional variance are followed by large values of volatility during the given period.

Figure 1 shows the period with higher volatility during the years from 2005 to 2015. The trend correction occurred at the beginning of 2005, but it did not affect the volatility of residuals. The correction was caused by the growth in grain production, which increased the supply in the market. The period of higher volatility started in 2006. In this case, the grain market paralleled increasing prices of stocks and crude oil (farmdoc, 2006). At the same time, the demand for bio-fuels was increasing as well (Babock and Fabiosa, 2011; Zilberman et al., 2013). The volatility reached its maximum height between 2007 and 2008. The period of 2008 to 2009 can be characterized by financial crisis in the markets and the period of high volatility continued during this time. In this case, the commodities shadowed the stock market with a delay of approximately half of year (CRB, 2013). The recovery of financial and commodity markets occurred in second half of 2009. We can observe the decrease in volatility during this period. At the same time, quantitative easing started in United States and other countries (FRED, 2016; Klotz et al., 2014). Financial markets and the crude-oil market were affected by the so called "Arab spring" in 2013, when the price of crude-oil suddenly increased (Krane, 2015). The other commodities including grains followed this trend, but with a moderate course, so there was not an obvious impact on volatility.

Table 3 and Table 4 contain the parameter estimates of GARCH (1,1) and GARCH (1,0) model, respectively. Both estimated models can be compared according to Akaike information criterion and Schwarz criterion. These criteria indicate how much information has been lost by using the given form of model. Both criteria prefer the use of the GARCH (1,1) model that will be used further.

Then the model is defined as:

$$h_t = 1.106458 + 0.066772 * Y^2_{t-1} + 0.928826 * h_{t-1} + u_t \tag{5}$$

The serial correlation in GARCH (1,1) model has been tested by using the Breusch-Godfrey Serial Correlation LM test. Table 4 shows that the null hypothesis about no autocorrelation in data can be rejected.

The ARCH LM test has been run to test for heteroscedasticity in the estimated GARCH (1,1) model. The results in Table 5 suggest that the hypothesis about homoscedasticity cannot be rejected, not even at the level of significance $\alpha = 0.01$.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.081645	0.172681	-0.472808	0.6364
Variance Equation				
C	1.106458	0.153129	7.225650	0.0000
RESID(-1)^2	0.066772	0.005021	13.29797	0.0000
GARCH(-1)	0.928826	0.00506	183.5767	0.0000
R-squared	-0.000092	Mean dependent var		0.059567
Adjusted R-squared	-0.000092	S.D. dependent var		14.73383
S.E. of regression	14.7345	Akaike info criterion		7.704837
Sum squared resid	601165.4	Schwarz criterion		7.713395
Log likelihood	-10667.2	Hannan-Quinn criter.		7.707928
Durbin-Watson stat	1.889544			

Source: Own calculation in STATA 13 based on CME data, 2016

Table 3: - GARCH (1,1).

F-statistic	8.423408	Prob. F(2,2767)		0.0002
Obs*R-squared	16.76302	Prob. Chi-Square(2)		0.0002
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-6.13E-05	0.279199	-0.00022	0.9998
RESID(-1)	0.058111	0.018983	3.061281	0.0022
R-squared	0.006052	Mean dependent var		-7.55E-15
Adjusted R-squared	0.005333	S.D. dependent var		14.73383
S.E. of regression	14.69449	Akaike info criterion		8.213904
Sum squared resid	597472.5	Schwarz criterion		8.220323
Log likelihood	-11373.26	Hannan-Quinn criter.		8.216222
F-statistic	8.423408	Durbin-Watson stat		2.001479
Prob(F-statistic)	0.000225			

Source: Own calculation in STATA 13 based on CME data, 2016

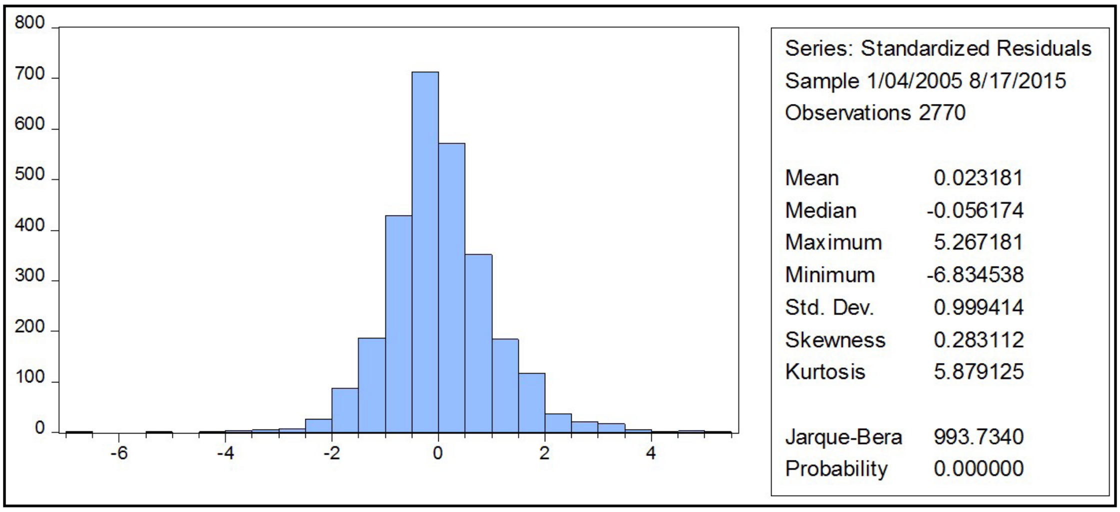
Table 4: Breusch-Godfrey Serial Correlation LM Test.

F-statistic	1.727948	Prob. F(2,2767)		0.1888
Obs*R-squared	1.728118	Prob. Chi-Square(2)		0.1887
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.973908	0.046132	21.11134	0
RESID(-1)	0.024982	0.019005	1.314514	0.1888
R-squared	0.000624	Mean dependent var		0.998866
Adjusted R-squared	0.000263	S.D. dependent var		2.212689
S.E. of regression	2.212399	Akaike info criterion		4.426754
Sum squared resid	13543.66	Schwarz criterion		4.431034
Log likelihood	-6126.84	Hannan-Quinn criter.		4.4283
F-statistic	1.727948	Durbin-Watson stat		2.000289
Prob(F-statistic)	0.188782			

Source: Own calculation in STATA 13 based on CME data, 2016

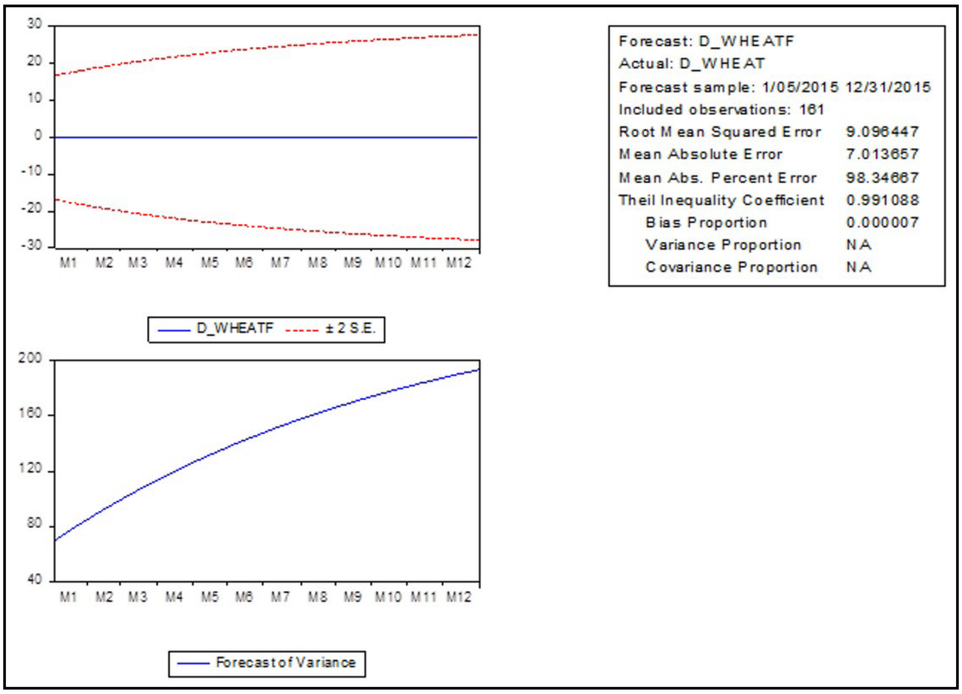
Table 5: - ARCH LM TEST.

Figure 2 provides the residuals distribution. It suggests that the residuals are not distributed normally. In particular, the visual representation of data shows that the residuals are skewed towards lower values. It can be seen that there is still no normality. The skewness of data is characterized by the value 0.28. Moreover, the data is characterized by fatter tails with a long peak in the mean. This evidence we can call leptokurtosis.



Source: Own calculation in STATA 13 based on CME data, 2016

Figure 2: Residuals Distribution.



Source: Own calculation in STATA 13 based on CME data, 2016

Figure 3: GARCH (1,1) 2016 static forecast.

Similar results were achieved by the work of Bai et al. (2003). The authors applied the GARCH model, which detected the leptokurtosis within commodity financial time series. On the other hand, there is a study of Zuppiroli, Giha (2015) showing the use of the GARCH model in application to wheat futures prices. The results support the time-varying process of time series similar to volatility behaviour in something like streamflow trajectory. Authors Alberg et al. (2008) recommend that the characteristics of the GARCH model in fat-tailed densities are evidence of forecasting utilization and accuracy. As a result of the research of the paper by Fang (2008), the GARCH model, which has leptokurtosis, disappeared after introducing the break into the variance equation. There are many studies working with conditional variance that ignore the problem of leptokurtosis and fat-tailed density.

After the verification of the estimated model the prediction for one year has been done. The results are represented in Figure 3. The forecast was made for the year 2016 and included 161 observations. There is a need to take into account that the forecast is based on daily data for wheat futures contracts traded at the CME.

The results of the static forecast for 2016 suggest that the daily basis of data is more appropriate for short-term predictive purposes. For long-term forecasting, it would be better to use weekly or monthly data. These findings have an implication for agricultural producers in different fields. First, the producers of wheat can hedge their production with short-term futures contracts, due to the ability of a fitted model to predict price fluctuations in short run. Next, the wheat price has a trend to revert to its mean.

The economic implication of wheat volatility modelling has considerable influence on producers and processing decision making. That is, the production cycle is predominantly dependent on external factors. There are also financial participants for instance investors. They are holding large contracts in basic agricultural commodity, as it is case of wheat.

Conclusion

The aim of this paper was to determine and forecast the volatility of CME daily closing prices of wheat by using stochastic models of conditional heteroscedasticity. The observed data is characterized by the clustering of volatility. This fact is best demonstrated by Figure 1 which shows that the performance of wheat prices recorded the period with high volatility in year 2008. The tests of the fitted model for heteroscedasticity shows that the data's variance was changing over the observed period.

According to Hansen and Lunde (2005) the model GARCH is best utilized when implemented for the purpose of forecasting time series in the financial markets, which are specified by non-constant variance and volatility clustering. Based on that, the authors proposed a GARCH model in order to forecast short-term periods for the daily data of wheat commodity prices traded on the Chicago Mercantile Exchange.

The testing of the fitted model for heteroscedasticity shows that the data has non-constant variance. According to the verification, the GARCH (1,1) model can be used as an appropriate model for wheat futures prices volatility modelling. Based on this model and the static prediction of volatility, it is possible to see the convergence of predicted values to the conditional variance in long-term. Thus the GARCH (1,1) is more suitable for short-term predictions. Some other forms of GARCH family models can be considered for long-term volatility of wheat daily closing price prediction. For instance the non-linear models of GARCH family can be tested to predict the volatility with higher statistical significance.

The fitted GARCH model is suitable in the short-term as a tool for risk management when the prediction capability of the model can be used by wheat producers. In the beginning of 2005, there was a trend correction which didn't affect the observed volatility. After that, the increasing grain production on the supply side influenced the level of volatility. During the years 2008 to 2009, wheat prices reached a significant peak in volatility degree. The other reaction in higher wheat price variability was caused by quantitative easing in the United States.

From the economic point of view, the results have wide implications for wheat processing, especially for earnings and agricultural producers. First, the price fluctuation of wheat is more persistent in the short term. That means the fitted model used in this paper is accurate for predictions. The outputs in agriculture are variable all the time, such as natural shocks or weather. Second, there is a problem on the supply side. It means, that the producers cannot respond to the changes of the wheat price in the short term.

The paper also has implications for agricultural producers in hedging techniques. In particular, the wheat producers can sell contracts with longer maturity to protect the price of wheat. This concept can be extended by focusing on the Granger analysis of fundamental events.

Acknowledgements

This paper was supported by the Internal grant agency (IGA) of the Faculty of Economics and Management, Czech University of Life Sciences Prague, grant no. 20161031 "Application of GARCH volatility models in the agricultural market with asymmetry aspect" (Czech: Aplikace modelů volatility GARCH na trhu zemědělských komodit s aspektem asymetrie).

Corresponding author:
Ing. Michal Čermák
Department of Economics, Faculty of Economics and Management,
Czech University of Life Sciences Prague, Kamýcká 129, 165 00, Prague 6, Czech Republic
Phone: +420 224382089, e-mail: cermak@pef.czu.cz

References

[1] Alberg, D., Shalit, H., a Yosef, R., (2008) "Estimating stock market volatility using asymmetric GARCH models: A Clarification", *Applied Financial Economics*, Vol. 18, No. 15, pp. 1201-1208. ISSN 0960-3107. DOI 10.1080/09603100701604225.

[2] Babcock, B. A. and Fabiosa, J. F. (2011) "The Impact of Ethanol and Ethanol Subsidies on Corn Prices: Revisiting History", CARD Policy Briefs, Center for Agricultural and Rural Development, Vol. 11, No. 5. [Online]. Available: https://www.card.iastate.edu/products/publications/synopsis/?p=1155 [Accessed: 25 April 2017].

[3] Bai, X., Jeffrey, R. R. and Tiao, G. C. (2003) "Kurtosis of GARCH and stochastic volatility models with non-normal innovations: A Clarification", *Journal of Econometrics*, Vol. 114, No. 2, pp. 349-360. ISSN 03044076. DOI 10.1016/S0304-4076(03)00088-5.

[4] Baur, D. G. (2011) "Explanatory mining for gold: Contrasting evidence from simple and multiple regressions", *Resources Policy*, Vol. 36, No. 3, pp. 265-275.

[5] Benavides, G. (2004) "Price Volatility Forecasts for Agricultural Commodities: An Application of Historical Volatility Models, Option Implied and Composite Approaches for Futures Prices of Corn and Wheat", SSRN, 38 p. [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=611062 [Accessed: 25 April 2017]. DOI 10.2139/ssrn.611062.

[6] Black, F. and Cox, J. C. (1973) "Valuing Corporate Securities: Some Effects of Bond Indenture Provisions", *Journal of Political Economy*, Vol. 81, No. 3, pp. 637-654.

[7] Bliemel, F. (1973) "Theil's Forecast Accuracy Coefficient: A Clarification", *Journal of Marketing Research*, Vol. 10, No. 4, pp. 444-446. ISSN 00222437. DOI 10.2307/3149394.

[8] Bollerslev, T. (1986) "Generalized Autoregressive Conditional Heteroskedasticity". *Journal of Econometrics*, Vol. 31, No. 3, pp. 307-327. ISSN 0304-4076. DOI 10.1016/0304-4076(86)90063-1.

[9] Bouchet-Hourdon (2011) "*Agricultural Commodity Price Volatility: An Overwiev*", OECD Food, Agriculture and Fisheries Working Papers, OECD Publishing.

[10] Chkili, W., Hammoudeh, S. and Nguyen, D. K. (2014) "Volatility forecasting and risk management for commodity markets in the presence of asymmetry and long memory", *Energy Economics*, Vol. 41, pp. 1-18. ISSN 0140-9883. DOI 10.1016/j.eneco.2013.10.011.

[11] Chong, C. W., Ahmad, M. I. and Abdullah, M. Y. (1999) "Performance of GARCH models inforecasting stock market volatility", *Journal of Forecast*, Vol. 18, pp. 333–343.

[12] CRB Commodity Yearbook (2013) "*CRB Commodity Yearbook*", 1. Chicago: Commodity Research Bureau, 384p. ISBN 9780910418928.

[13] Dickey, D. A., Fuller, W. A. and Huang D. (1979) "Distribution of the Estimators for Autoregressive Time Series With a Unit Root: Further evidence using GARCH-class models", *Journal of the American Statistical Association*, Vol. 74, No. 366, pp. 427-431. ISSN 01621459.

[14] Douc, R., Moulines, E., and Stoffer, D. S. (2014) "Nonlinear Time Series-Theory, Methods and Applications with R Examples", CRC Press, UK, 551 p. ISBN 9781466502253 - CAT# K14426.

[15] Engle, R. F. and Yoo, B. S. (1987) "Forecasting and Testing in Co-Integrated Systems", *Journal of Econometrics*, Vol. 35 (May), pp. 143-159. ISSN 0304-4076.

[16] Fama, E. F. (1965) "The Behavior of Stock-Market Prices", *The Journal of Business*, Vol. 38, No. 1, pp. 34-105. JSTOR, [Online]. Available: https://www.jstor.org/stable/2350752. [Accessed: 5 April 2017].

[17] Fang, W., Miller, S. M. and Lee, Ch. (2008) "Cross-Country Evidence on Output Growth Volatility: Nonstationary Variance and Garch Models", *Scottish Journal of Political Economy*, Vol. 55, No. 4, pp. 509-541. ISSN 00369292. DOI 10.1111/j.1467-9485.2008.00464.x.

[18] FARMDOC (2015) University of Illnois at Utbana, Chamapaign, College of Agricultural, Consumer and Environmental Sciences: Illinois, US, Dec. 2015 [Online]. Available at: http://www.farmdoc.illinois.edu/ [Accessed: 10 May 2017].

[19] Franses, P. H. and Van Dijk, D. (1996) "Forecasting stock market volatility using (non-linear) Garchmodels", *Journal of Forecast*, Vol. 15, pp. 229-235.

[20] FRED (2016) Federal Reserve Bank of St. Louis, St. Louis: Economic Research, Feb. 2016 [Online]. Available at: https://research.stlouisfed.org/fred2/ [Accessed: 25 Jun. 2017].

[21] Hansen, P. R. and Lunde, A. (2005) "A forecast comparison of volatility models: does anything beat a GARCH(1,1)?", *Journal of Applied Economics*, Vol. 20, pp. 873–889. ISSN 1514-0326. DOI 10.1002/jae.800.

[22] Hull, J. (2003) "*Options, futures*", 5th ed. Upper Saddle River: Prentice Hall, c. Prentice Hall finance series. 822 p. ISBN 01-300-9056-5.

[23] Iqbal, F., Mukherjee, K., Baah, M., E. and Nortey, N. N. E. (2010). "M-estimators of some GARCH-type models; computation and application: an autoregressive conditional heteroscedastic (ARCH) models", *Statistics and Computing,* Vol. 20, No. 4, pp. 435-445. E-ISSN 1573-1375, ISSN 0960-3174. DOI 10.1007/s11222-009-9135-x.

[24] Javed, F. and Mantalos, P. (2013) "GARCH-Type models and the performance of information criteria", *Communications in Statistics: Simulation and Computation*, Vol. 42, No. 8, pp.1917-1933. ISSN 0361-0918.

[25] Klotz, P., Lin, T. C., Hsu, S.-H. (2014) "Global commodity prices, economic activity and monetary policy: The relevance of China", *Resources Policy*, Vol. 42, pp. 1-9. ISSN 0301-4207. DOI: 10.1016/j.resourpol.2014.08.001.

[26] Knight, J. L. and Satchel, S. (2007) "*Forecasting volatility in the financial markets*", 3rd ed. Boston: Butterworth-Heinemann. 432 p. ISBN 978-0-7506-6942-9.

[27] Krane, J. (2015) "A refined approach: Saudi Arabia moves beyond crude", *Energy Policy*, Vol. 82, No. 1, pp. 99-104. ISSN 0301-4215. DOI 10.1016/j.enpol.2015.03.008.

[28] Kroner, K. F., Kneafsey, K. P. and Claessens, S. (1995) "Forecasting volatility in commodity markets. *Journal of Forecasting*, Vol. 14, No. 2, pp. 77–95. E-ISSN 1099-131X. DOI 10.1002/for.3980140202.

[29] Lee, D. D. and Faff, R. W. (2009) "Corporate Sustainability Performance and Idiosyncratic Risk: A Global Perspective", *Financial Review*, Vol. 44, No. 2, pp. 213-237. ISSN 07328516. DOI 10.1111/j.1540-6288.2009.00216.x.

[30] Mandelbrot, B. (1963) "The Variation of Certain Speculative Prices", *The Journal of Business,* Vol. 36, No. 4, pp. 394-419. ISSN 0021-9398. DOI 10.1086/294632.

[31] Maneesoonthorn, O. W. (2015) "High-Frequency Financial Econometrics, by Yacine Aït-Sahalia and Jean Jacod (Princeton University Press, Princeton, NJ, 2014), pp. xxiv + 659", *Economic Record*, Vol. 91, pp. 542–544. ISSN 00130249. DOI: 10.1111/1475-4932.12228.

[32] Musunuru, N. S. (2014) "Modeling Price Volatility Linkages between Corn and Wheat: A Multivariate GARCH Estimation", *International Advances in Economic Research,* Vol. 20, No. 3, pp. 269-280. ISSN 1083-0898. DOI 10.1007/s11294-014-9477-9.

[33] Najand, M. (2002) "Forecasting Stock Index Futures Price Volatility: Linear vs. Nonlinear Models", *The Financial Review,* Vol. 37, No. 1, pp. 93-104. ISSN 0732-8516. DOI 10.1111/1540-6288.00006.

[34] Olowe, R. A. (2009) "Modelling Naira/Dollar Exchange Rate Volatility: Application of GARCH and Asymmetric Models, *International Review of Business Research Paper*, Vol. 5, pp. 377 - 398. E-ISSN 1832-9543, ISSN 1837-5685.

[35] Onour, I. A. and Sergi, B. S. (2012) “Modeling and Forecasting Volatility in the Global Food Commodity Prices” (Modelování a Prognózování Volatility Globálních cen Potravinářských Komodit, In Czech), *Agricultural Economics - Czech*, Vol. 57, No. 3, pp. 132–139. E-ISSN ISSN 1805-9295, ISSN ISSN 0139-570X.

[36] Quaicoe,T. M., Twenefour, F. B., Baah, E. M. and Nortey, E. N. (2015) "Modeling variations in the cedi/dollar exchange rate in Ghana: an autoregressive conditional heteroscedastic (ARCH) models", *SpringerPlus,* Vol. 4, No. 1. ISSN 2193-1801. DOI 10.1186/s40064-015-1118-0.

[37] Poon, S.-H. (2005) "A practical guide for forecasting financial market volatility", Hoboken, NJ: Wiley. ISBN 978-0-470-85613-0.

[38] Reider R. (2009) "Volatility forecasting I: GARCH models“, New York: Courant Institute of Mathematical Sciences, New York University. [Online]. Available at: https://cims.nyu.edu/~almgren/timeseries/Vol_Forecast1.pdf [Accessed: 14 January 2014].

[39] Tulley, E. and Lucey, B. M. (2007) "A power GARCH examination of the gold market", *Research in International Business and Finance, Vol.* 21, No. 2., pp. 316-325. ISSN 0275-5319. DOI 10.1016/j.ribaf.2006.07.001.

[40] Val, F., Pinto, A., C., F. and Klotzle, M., C. (2014) “Volatilidade e Previsão de Retorno com Modelos de Alta Frequência e GARCH: Evidências para o Mercado Brasileiro”, *Revista Contabilidade,* Vol. 25, No. 65, pp. 189-201. ISSN 1808-057x. DOI 10.1590/S1519-70772014000200008.

[41] Wang, Y. C., Yoshitani, J. and Fukami, K. (2005) "Stochastic multiobjective optimization of reservoirs in parallel: A Clarification", *Hydrological Processes*, Vol. 19, No. 18, pp. 3551-3567. ISSN 0885-6087. DOI: 10.1002/hyp.5845.

[42] Wei, Y, Yudong, W. and Huang, D. (2010) "Forecasting crude oil market volatility: Further evidence using GARCH-class models“, *Energy Economics*, Vol. 32, No. 6, pp. 1477-1484. ISSN 01409883. DOI 10.1016/j.eneco.2010.07.009.

[43] Yang, J., Haigh, M. S. and Leatham, D. J. (2001) “Agricultural liberalization policy and commodity price volatility: a GARCH application”, *Applied Economics Letters*. Vol. 8, No. 9, pp. 593-598. ISSN 1350-4851. DOI 10.1080/13504850010018734.

[44] Zhang, Y., Yao, T. and He, L. (2015) "Forecasting crude oil market volatility: can the Regime Switching GARCH model beat the single-regime GARCH models?," Papers 1512.01676, arXiv.org, [Online]. Available at: http://arxiv.org/pdf/1512.01676. [Accessed: 10 May 2017].

[45] Zilberman, D., Hochman, G., Rajagopal, D., Sexton, S. and Timilsina, G. (2013) "The impact of biofuels on commodity food prices: Assessment of findings", *American Journal of Agricultural Economics*, Vol. 95, No. 2, pp. 275-281. DOI 10.1093/ajae/aas037.

[46] Zivot, E. (2009) “Practical Issues in the Analysis of Univariate GARCH models“, In: Andersen, T. G., Davis, R. A., Kreiss, J.-P., Mikosch, Th. V. "*Handbook of Financial Time Series"*, Springer, New York, 113 - 155. ISBN 978-3-540-71296-1.

[47] Zuppiroli, M. and Giha, C. R. (2016) "Hedging effectiveness of European wheat futures markets: an application of multivariate GARCH models", *International Journal of Applied Management Science,* Vol. 8, No. 2, 132-158. E-ISSN 1755-8913, ISSN 1755-8913. DOI 10.1504/IJAMS.2016.077006.