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MARKET PRICE FORECASTING FOR WHEAT AND CORN

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ABSTRACT

In the course of defining a price forecasting model applicable for wheat and corn in Hungary, first the application of stepwise regression was attempted, however there was a poor fit, and the parameters were not in line with the assumptions either. In addition, an extreme multiple collinearity was found, therefore the ARMA model was tried. Considering that the results for wheat and corn did not show a constant dispersion, and taking into account that in the case of the ARMA model there is a constant conditional dispersion in time, it was necessary to introduce the GARCH process analogous to a conditionally parameterised ARCH(∞) model. Based on the results, the GARCH(1,1) model could be defined. This model has a good fit and can be used to forecast the market price of wheat in Hungary. In view of the results it was possible to set up the GARCH(0,3) model for corn. This model has a good fit and can be used to forecast the market price of corn in Hungary. Based on the aforementioned, we can declare that it is possible to define a price forecasting model predicting the price movements of wheat and corn in Hungary by applying the GARCH model.
Keywords: wheat, corn, market price, forecast

INTRODUCTION

In Hungary, a significant fluctuation in the average price of corn can be observed (*Figure 1*). Between 1990 and 2010, corn prices were changing in a range below the world and the EU market prices. Corresponding to the prices in the EU, a peak could only be observed in 2007 in Hungary.

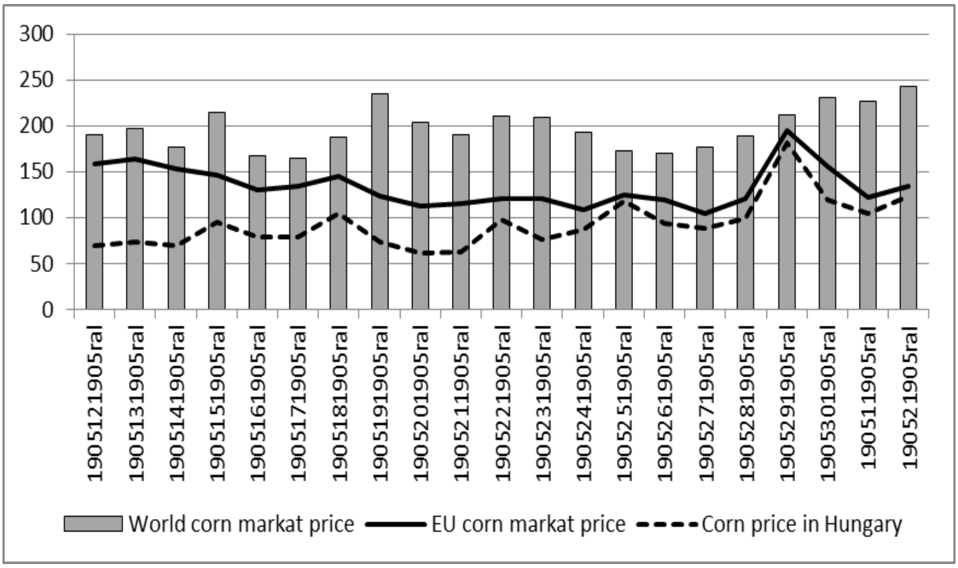
Based on the data, it is obvious that the United States has a predominant role in the world. Consequently, it is nearly apparent that the commercial prices mostly depend on them, and the various continental as well as regional prices are generated by the US prices. Prices on the world market are regulated by the internal market prices in the USA. This statement is particularly true of the current situation, when supply-based pricing is applied. Accordingly, world prices respond to any news of positive or negative changes in the weather conditions in the crop producing areas of the US (*Tömösi*, 2010).

In Hungary, a significant fluctuation of the average annual wheat price can be observed (*Figure 2*). Between 1990 and 2010, wheat prices were changing in a range below the world and the EU market prices. Corresponding to the prices in the EU, a peak could only be observed in 2007 in Hungary.

Based on the aforesaid, it is apparent that changes in the world market price of agricultural crops may result in substantial fluctuation of prices in the EU and on the internal market of Hungary, as well as in the income from agricultural exports.

Figure 1

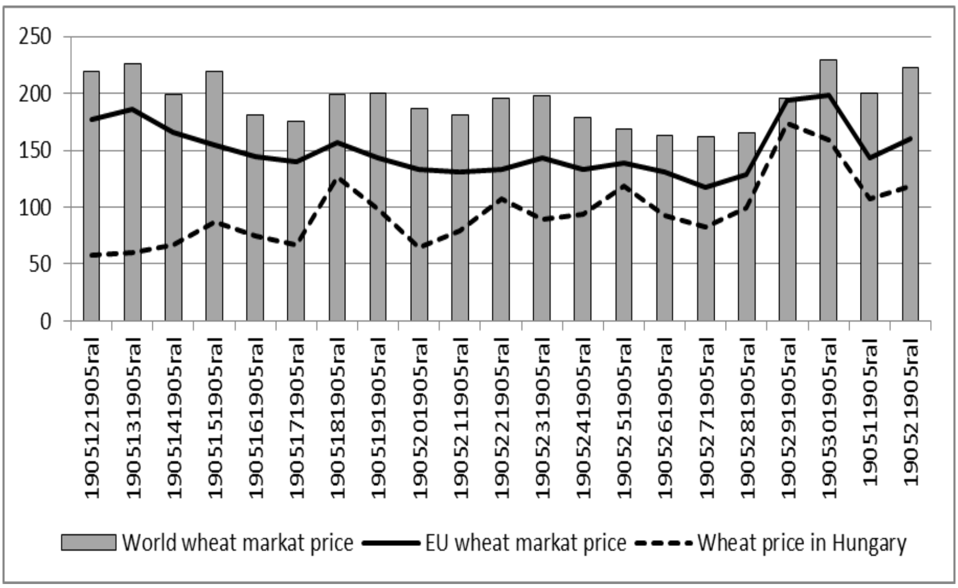
The average annual corn prices in Hungary (EUR/ton)



Source: Based on FAOSTAT and AKII data

Figure 2

The average annual wheat prices in Hungary (EUR/ton)



Source: Based on FAOSTAT and AKII data

It was observed by *Bedő et al.* (2011) that during the recent four years prices vastly increased on two occasions. First, they explained the abrupt substantial rises as a result of speculation, but at the present time, these price changes recurring within a short period of time are no longer considered to occur by chance: they are the outgrowth of continuously growing consumption.

Short-term price fluctuations are too large and frequent, thus influencing the risk management strategy of farmers. Namely, in the case of irregular price fluctuations there is an increased uncertainty. Concerning welfare aspects, the uncertainty of agricultural and rural income experienced without price stabilization is also a problem. Consequently, long-term investments are not made, farmers do not take out loans, and as a result there will be limited or no technological development, and the financing of production can also cause problems. However, price stabilization is not equivalent to stabilizing the income, as the latter is not a function of the supply and demand situation (*Fertő*, 1995).

My research tries to define a model that supports the estimation of prices in order to develop a buying and selling strategy. The objective of this model is to enable farmers to make the most appropriate estimation of the timing for selling their crops. However, it is questionable whether a model for the forecast of price movements of wheat and corn at a high level of accuracy can be developed for Hungary.

MATERIALS AND METHODS

Databases

For the development of the model data pertaining to the period of January 1998 to April 2011 were used. All prices were converted to HUF using the foreign exchange rates for each specific time range.

- *Market price:* AKII market price information system (following: PAIR) database: *https://pair.akii.hu*
- *World market price:* FOB price for the Gulf of Mexico *http://www.indexmundi.com/*; I used prices for the Gulf of Mexico as the World Market price, as most of the overall quantity of corn is loaded to vessels in the Gulf of Mexico
- *Crude oil price: http://www.oil-price.net/?gclid=CLCsuODsq6gCFVUj3wodQ0C8HQ*
- *Quantity of production:* AKII database
- *EUR/HUF exchange rate:* the exchange rate set by the ECB
- *Area payments:* ARDA database.
- Although the area payments are calculated on a per hectare basis, the amount of subsidy was also calculated by using data on the production area and the average yields. The average SAPS payment per hectare increases at a rate of 5% each year.
- *Buying-in price:* ARDA database

For the purpose of the research the net intervention prices actually paid are considered as the buying-in price. The data used pertain to the period of November 2004 - April 2011.

The method of analysis

Essentially, the model was defined in accordance with the instructions of *Ramanathan* (2003). The data were arranged in Microsoft Excel, and IBM SPSS (*Sajtos and Mitev*, 2007) Statistics and the Eviews7 programs were used for the analysis.

To set up the models, the following models/methods were used.

Examination 1

Stepwise regression: Regression-calculation is a method in which a context is analyzed through a metric, dependent and one or more independent variables. The questions of the regression and the correlation differ from each other, in that in the first case the estimated value is searched for. In the regression it is necessary to give the dependent and independent variables as well.

Regression-calculation – similarly to the correlation – works with metric variables. The basic model of the regression is the two-variable linear regression. It means that the movements of a dependent variable are tested depending on an independent variable. It is assumed that the context between the variables is linear, and this would be proved.

The set of a dependent variable is also tested in the multiple variables linear regression, but depending on more independent variables and the context between the variables is assumed to be linear also. Therefore, the multiple variables regression correlates a Y dependent variable with several independent variables (X_1, X_2, …., X_k).

The general form of a multiple variables linear regression model is the following:

$$Y_t = \beta_1 + \beta_2 X_{t2} + \ldots + \beta_k X_{tk} + u_t, \quad (1)$$

The value of the X_t1 is 1, because it is necessary to have an 'intercept'. The t subscript is concerned with the ordinal number of the monitoring and it is changed from 1 to n. The u_t deviation variable is the random component from not observation, and it is the difference of Y_t and Y conditional expected value concerning to X. It explains the presence of the u_t deviation variable: the eliminated variables; the ignorance of the non-linearity; the measurement errors; the purely random; the irregular effects. The number of the independent variables is k, so k, the unknown coefficient of the regression, needs to be estimated.

When just X_{ti} is changing, the magnitude of the change in Y_t is given from $\Delta Y_t/\Delta X_{ti} = \beta_i$.

Stepwise regression

The independent variables are aggregated or eliminated individually to the regression equatation.

Primarily those are introduced to the equation that decisively explains the Y.

Forward selection

Examination begins with no variables in the equation. The variables are introduced individually, but just in the case that it fulfils the predetermined criteria (the order is according to the power of the exposition).

Backward method
Starting with all variables in the model and deleting the variables continuously when the criteria are not met.

Stepwise method
This is the combination of the forward and backward methods: in every step the unfit variables are removed from the equation. The usage is appropriate if the sample is large enough.

Firstly regression was attempted, but the fit was not good because extreme multicollinearity is experienced and after the transformation of the data it did not suit the basic criteria of the regression.

The regression was estimated with the stepwise method, whose advantage is that in every step it verifies the p probability of the previously involved variables. In the case that p is higher than the pout, the variable is going to be dropped from the model.

The endless cycle can be avoided, because the fixed maximum needs to be lower than the pout value. The default PIN (fixed maximum)=0.05 POUT=0.10.

In the model the explanatory variables need to be uncorrelated, hence the tolerance can be $1\text{-}R^{\wedge 2}$, possibly the variance inflation factor (VIF)=$1/1\text{-}R^{\wedge 2}$, if there is a close link between the variables, its value can be really high.

The last indices for the independence is the condition index (CI)=$(\lambda_{max}/\lambda_i)^{(1/2)}$, where i=1,…,(p+1) and λ_i the X^TX are uneven, but divided with standard deviation data and formed matrix multiplication's own value.

Examination 2

Autoregressive (AR-) models: A clean autoregressive time series model, whose structure is the following:

$$Y_t=\alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + u_t, \quad (2)$$

where, Y_t is the dependent variable, which concerns the observation on the t-th occasion, after the average is subtracted; u_t is a good playing deviation variable with zero expected value and constant variance, which is not correlated with u_s, if $t \neq s$ (time series like this are called white noise). There isn't a constant term, because Y_t is described by the difference from the average. The Y_t is explained with only its own past values and not with other independent variables. These are the autoregressive or AR-models; its mark: AR (p).

Moving avarage- (MA-) models: The following model is called q ordered moving average- or MA-model; mark: MA(q), and can be written in the following way:

$$Y_t= \upsilon_t - \beta^1\upsilon_{t-1} - \beta_2\upsilon_{t-2} - \ldots - \beta_q \upsilon_{t-q}, \quad (3)$$

where υ_t is the white noise. Therefore, Y_t is the white noise, the linear combination of the variate.

ARMA-models: It is the mixture of the autoregressive and the moving avarage models.

The average form of the ARMA (p, q) model:

$$Y_t=\alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} +\ldots+ \alpha_p Y_{t-p} + \upsilon_t - \beta_1\upsilon_{t-1} - \beta_2\upsilon_{t-2} - \ldots - \beta_q \upsilon_{t-q} \quad (4)$$

Engle's ARCH test

Engle (1982) has introduced a new approach to setting up a model for heteroskedasticity for time series data. This model has been denominated as the ARCH (Autoregressive Conditional Heteroskedasticity) model. The following has been assumed as the process generating variance:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \ldots + \alpha_p u_{t-p}^2 \quad (5)$$

The process described by the aforementioned equation is called an ARCH process of degree p. The reason for using the term „autoregressive" is that the variance of the deviation variable at time t is a function of the preceding deviation variables brought to a square. The variation in t is a function of the preceding time periods (it is a requirement thereof), that is the reason for using the term heteroskedasticity (*Ramanathan*, 2003).

GARCH-test: generalization of the ARCH-test, model of volatility.

The GARCH methods (Generalised Autoregressive Conditional Heteroskedasticity, which is generalized autoregressive conditional heteroskedasticity) were lead in by *Bollerslev* (1986).

The systematic description of the models were found in *Hamilton*'s (1994) and *Franco's and Zakoian's* (2010) work, and the overview discussion were found in *Mills'* (1993) and *Shams' and Haghighi's* (2013) work.

GARCH-models

The yield observed in the course of setting up the model can be divided to two components: $r_{t+1} = \mu+\eta_{t+1}$ where μ is the anticipated value of the yield (in practice this value can be considered to be zero), and η means the "innovation" (practically: the deviation from the average). The model attempts to manage the variance of innovations (which – in the case of an anticipated value of zero corresponds with the variance of the yields). According to the ARCH model, the conditional variance is a function of the latter observed innovations. In addition, as per the GARCH model, variance is a function of the latter conditional variance as well (variance appraisals). Consequently, two equations are described by the GARCH models: one for the average of the market yield, and another one for variance (this is where the ARCH and GARCH terms are included). In my analyses, the second equation has the leading part. In fact, the equation for variance can be divided to a term autoregressive to a preceding value of variance (a GARCH term), and another term fitting moving average to a residue (an ARCH term).

In a general form, the GARCH (*p,q*) model is:

$$r_t = \mu+\eta_t \quad (6)$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 + \sum_{i=1}^{q} \alpha_i \, \eta_{t+1-i}^2 , \tag{7}$$

that is, the conditional variance on a specific day can be estimated as a function of the latest q innovation and the latest p conditional variance. In the model, coefficients α pertain to the ARCH terms, and coefficients β apply to the GARCH terms.

RESULTS AND DISCUSSION

Examination 1: Stepwise regression

To define a price forecasting model for wheat and corn applicable for Hungary, first the stepwise regression was used, but poor fitting and multicollinearity were found. The data did not meet the primary conditions of regression even after transformation.

Regression was assessed by using the stepwise model, which has the advantage of testing the probability "p" of the variables formerly included in the model after each specific step, and deleting a given variable if "p" is above the threshold.

A set of additional parameters influencing domestic market prices were incorporated into the model including the market price, the world market price, the oil price, the quantity of production, the USD/HUF exchange rate, the area-based payments (SAPS), and the intervention price.

Wheat model

Among the parameters listed above, the market price for wheat, the quantity of wheat production, and the area-based payments (SAPS) were deleted by the model. At the same time, the following parameters were included: the world market price for wheat, the USD/HUF exchange rate, the intervention price, and the oil price.

For the parameters included, four models were defined. The significance levels and the powers (R^2) were determined for all four models. Based on the results, high powers (over 85%) were found, and all models were statistically significant.

The parameters defining the *market price for wheat in Hungary* were assessed in the model. Based on the results, the equation of the regression model is:

LN_Market_price_for_wheat=
-8.358+1.095*LN_World_market_price_for_wheat
-1.047*LN_USD_HUF
+1.236 *LN_Intervention_price_for_wheat HUF/ton. (8)

Unfortunately, at this point it was apparent from the data that there was collinearity. According to the results of the collinerarity tests, the CI index was over 30. Consequently, none of these four models could be accepted for wheat.

Corn model

Among the parameters listed above, the following parameters were deleted by the model: the market price for corn, and the USD/HUF exchange rate. At the same time, the following parameters were included: the world market price and the intervention price (HUF/ton) for corn, the quantity of corn production, the oil price, and the area-based payments (SAPS).

For the parameters included, six models were defined. The significance levels and the powers (R^2) were determined for all six models. According to the results, the value of the corrected R-squared is considerably lower for these models than those found in the case of the models defined for wheat: it varies between only 23.3 and 56.8 %.

The parameters defining the *market price for corn in Hungary* were assessed in the model. Based on the results, the equation of the regression model is:

LN_Corn_market_price =
-0.486+0.598*LN_Corn_world_market_priceHUF/ton_
FOB_price_Gulf_of_Mexico
+ 0.487 * LN_Corn_intervention_price_HUF/ton
+ 0.110 * LN_Corn_Quantity_of_production _million_tons (9)

It appeared from the data that – similarly to the wheat model – there was collinearity. According to the results of the collinerarity tests, the CI index is over 30. Consequently, we could not accept any of these corn models.

Based on the above, the model found suitable for the forecast of wheat and corn prices in Hungary could not be defined by using stepwise regression and the available set of data. Therefore, it was decided to use another method.

Examination 2: the ARMA-GARCH-model

As the market prices could not be forecasted by using stepwise regression, I made and attempt to use the ARMA-model.

The ARMA(p,q) model:

$$y_t=c+\varphi_1 y_{t-1}+\ldots+\varphi_p y_{t-p}+\varepsilon_t+\varphi_1\varepsilon_{t-1}+\varphi_q\varepsilon_{t-q}, \quad (10)$$

where ε_t ~FAE $N(0,\sigma^2)$ distribution.

The relative dispersion of the market prices of wheat and corn was assessed (*Figure 3* and *Figure 4*).

Since the annual relative dispersion is not constant for wheat and corn (*Figure 3* and *Figure 4*), the GARCH process had to be introduced as well. (In the ARMA model the relative dispersion is constant in time.)

The GARCH-model corresponding to an ARCH (∞) model with parameter restriction:

$$y_t=(\ldots)+\varepsilon_t \quad (11)$$

$$\varepsilon_t=\sigma_t\eta_t \quad (12)$$

The general form of the GARCH-model:

$$\sigma^2=a_0+a_1\,\varepsilon^2(t-1)+\ldots+a_q\,\varepsilon^2(t-q)+b_1+b_1\,\sigma^2(t-1)+\ldots+b_p\,\sigma^2(t-p) \quad (13)$$

Fitting the Wheat model:

ARCH test

Considering the ARCH test, the null hypothesis is that there is no ARCH effect, namely, F-statistic ~ Obs*R^2. Although it does not apply to our case, an ARCH effect can be found (*Table 1*).

Figure 3

The annual relative dispersion of wheat prices (%)

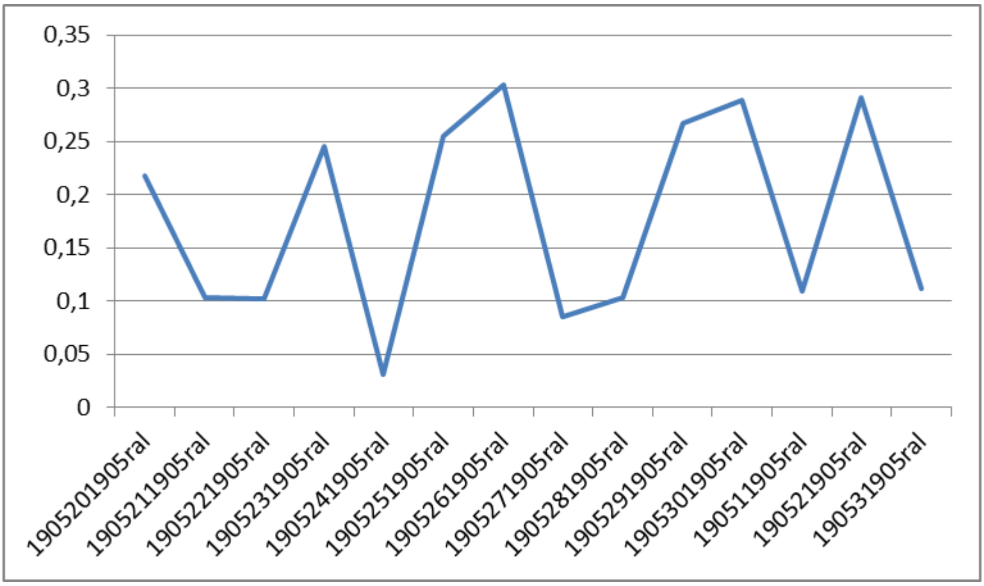
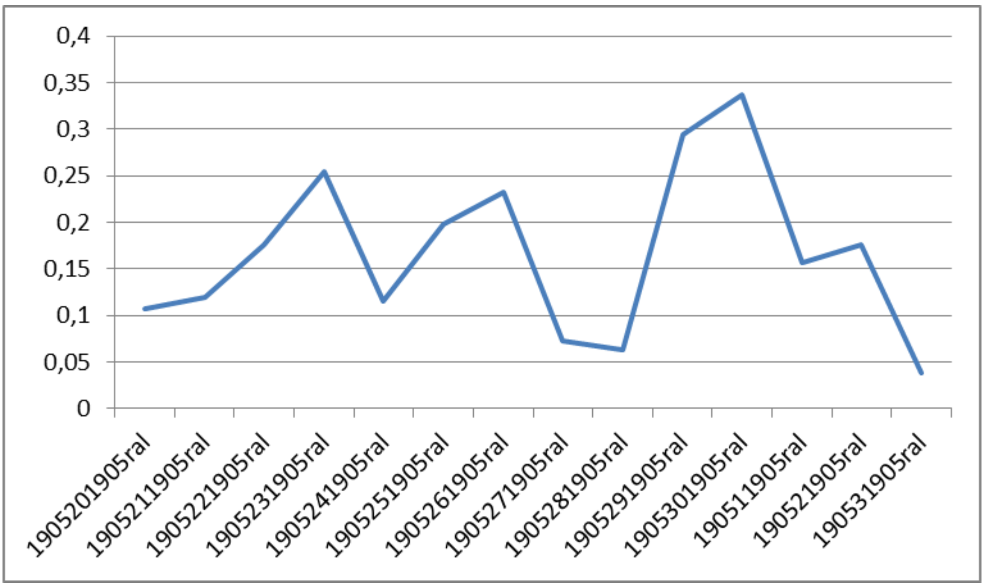


Figure 4

The annual relative dispersion of corn prices (%)



The ARMA model

I ran a self-developed computer program for the ARMA model, and as a result 121 models were defined. The appropriate models were selected by using the SIC and AIC information criteria, as well as the determinant coefficient. Based on this assessment, it was obvious to me that the ARMA(4,5) model could be chosen. After examining the significance of the individual factors, it turned out that the ARMA(4,5) model was inadequate (*Table 2*). Therefore, I decided to use the ARMA(1,1) model and I fitted an additional GARCH model to it.

The GARCH model

Based on the GARCH (1,1) model, this model has a power of 94.17%, which can be considered a very good value, and both the AR and the MA parts are significant (*Table 3*).

Accordingly, the equation for GARCH(1,1) is as follows:

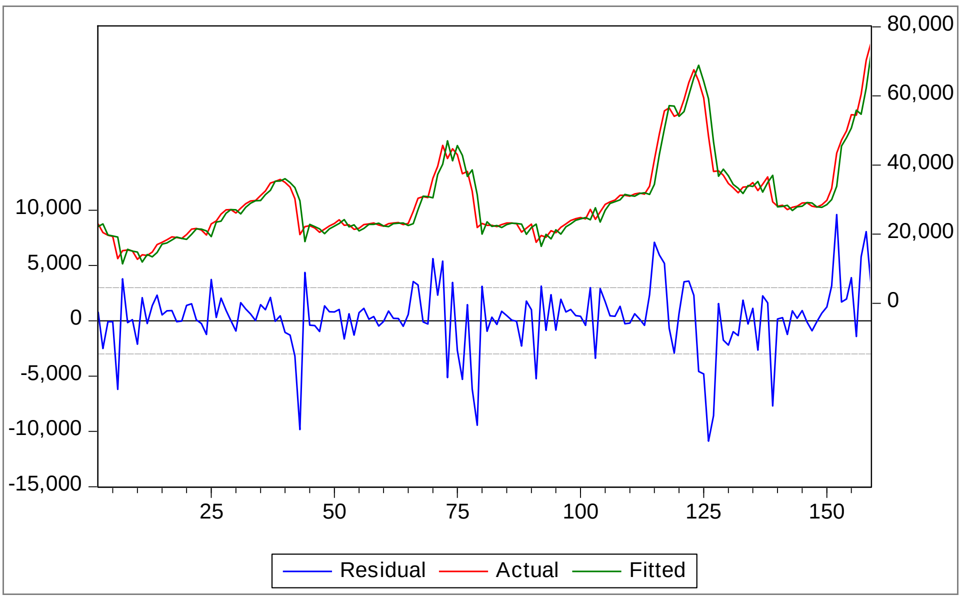
$$Yt= 30123.96+1.022517*Yt\text{-}1+\varepsilon+0.182353\varepsilon(t\text{-}1) \quad (14)$$

$$GARCH=97623902+ 0.123467*\varepsilon^2(t\text{-}1)\text{-}0.997702\sigma^2 (t\text{-}1) \quad (15)$$

Fitting and plotting the price forecasting model for wheat based on the above equation (*Figure 5*):

Figure 5

Fitting the price forecasting model for wheat



The results show that the model had a very good fit.

Fitting the Corn model:

The ARCH test

Considering the ARCH test, the null hypothesis is that there is no ARCH effect, namely F-statistic ~ Obs*R^2. Although it does not apply to our case, there is an ARCH (*Table 4*).

ARMA model

I ran a self-developed program for the ARMA model. As a result, 121 models were defined. The appropriate models were selected by using the SIC and AIC information criteria, as well as the determinant coefficient. The minimum values were determined for AIC and SIC, whereas the maximum value was established for the determinant coefficient, considering that the AIC tends to be overestimated. Based on the minimum value of AIC the ARMA(6,3) model (*Table 5*) should be selected, whereas considering the minimum value of SIC we should decide on the ARMA(3,3) model (*Table 6*). At the same time, in view of the maximum value of R^2 the ARMA(6,7) (*Table 7*) model had to be chosen. However, similarly to the situation experienced in the case of wheat, I found that the factors were not significant and decided to use the ARMA(1,1) (*Table 8*) model by applying the determinant coefficient and the information criteria.

GARCH model

Based on the GARCH (1,1) model, this model has a power of 94.17%, which is considered a very good value, and both the AR and the MA parts are significant (*Table 9*).

GARCH(p,q)

An assessment of GARCH p and q was made for models Garch(1,1) and Garch p=0 and q=0,1,2,3,4, and based on the parameters I considered Garch (0,3) the ideal model.

Accordingly, the equation for GARCH(0,3) is as follows:

$$Yt=42571.83+0.982295*Yt\text{-}1+\varepsilon+0.185554*\varepsilon(t-1) \quad (16)$$

$$GARCH=65284433-1.003803*\sigma^2(t-1)-0.983242*\sigma^2(t-2)-0.969621*\sigma^2(t-3) \quad (17)$$

Fitting and plotting the price forecasting model for wheat based on the above equation (*Figure 6*).

The results show that in case of the model defined for forecasting the market price of corn there is an outstanding fitting.

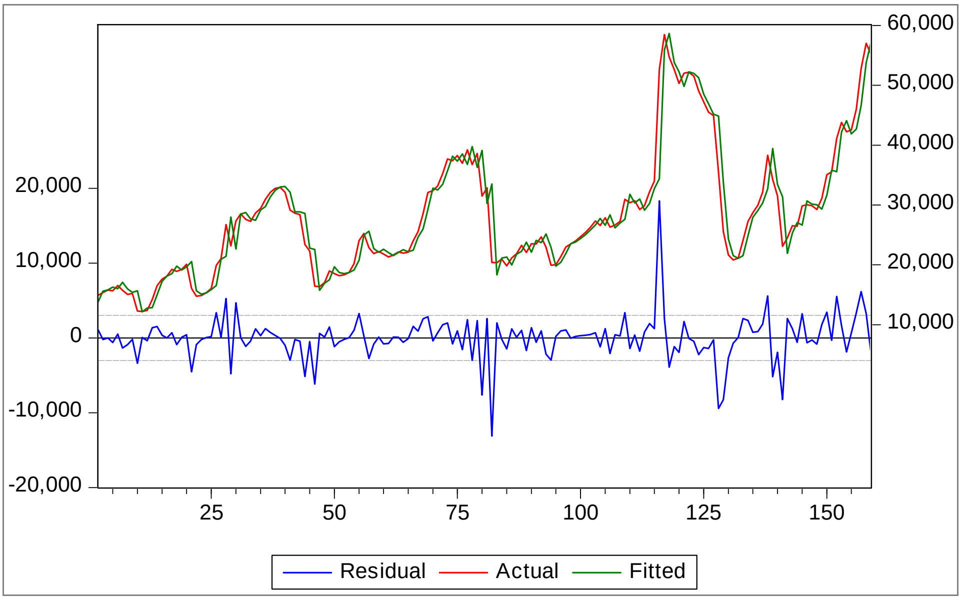
CONCLUSIONS

Examination 1: Stepwise regression

In the course of defining the price forecasting model for wheat and corn applicable for Hungary, first the stepwise regression was used, but the model did not fit well and the parameters were not in line with the assumptions either. Furthermore, extreme multiple collinearity was found, therefore other methods were attempted.

Figure 6

Fitting the price forecasting model for corn



Examination 2: ARMA-GARCH-model

As stepwise regression did not result in an efficient forecasting of market prices, I attempted to apply the ARMA model. Based on our results, a constant dispersion could not be found either in the case of wheat or corn. In view of these results and considering the fact that in the ARMA model the relative dispersion is constant in time, it was necessary to introduce the GARCH process corresponding to an ARCH(∞) model with restricted parameterization.

The results made it possible for me to define the GARCH(1,1) model, which fitted well and could be used for the forecast of the market price of wheat in Hungary:

$$Yt=30123.96+1.022517*Yt\text{-}1+\varepsilon+0.182353\varepsilon(t\text{-}1) \quad (18)$$

$$GARCH=97623902+0.123467*\varepsilon^2(t\text{-}1)\text{-}0.997702\sigma^2(t\text{-}1) \quad (19)$$

Based on the results I was able to define the GARCH(0,3) model, which fitted well and could be used to the forecast the market price of corn in Hungary:

$$Yt=42571.83+0.982295*Yt\text{-}1+\varepsilon+0.185554*\varepsilon(t\text{-}1) \quad (20)$$

$$GARCH=65284433\text{-}1.003803\sigma2*(t\text{-}1)\text{-}0.983242*\sigma2(t\text{-}2)\text{-}0.969621*\sigma2(t\text{-}3) \quad (21)$$

Based on the results we can declare that it is possible to define a price forecasting model predicting the price movements of wheat and corn in Hungary by applying the GARCH model.

The importance of defining price forecasting models is that these models can support the market players in decision making through facilitating the development of their buying and selling strategies.

REFERENCES

Bedő Z., Láng L. (2011): Wheat in 2011 and beyond. Magyar mezőgazdaság. 66. 22. p.

Bollerslev, T. (1986): Generalited Autoregressive Conditional Heteroskedasticity. Journal of Econometrics, 31. 307–327. p.

Engle, R.F. (1982): Autoregressive Conditional Heteroskedasticity With Estimates of the Variance of U.K. Inflation. Econometrica 50. 987–1008. p.

Fertő I. (1995): Issues of stabilizing agricultural prices. Közgazdasági Szemle, 3. 256-269. p.

Franco, Ch., Zakoian, J. (2010): GARCH models, structure, statistical inference and financial application. Wiley : United Kingdom

Mills, T.C. (1993): The Econometric Modelling of Financial Time Series. Cambridge University Press : Cambridge.

Ramanathan, R. (2003): An introduction to econometrics with application. Panem Könyvkiadó : Budapest; 516-549. p.

Sajtos, L., Mitev, A. (2007): A Guide to Research and Data Analysis Using SPSS. (In. Hung.), Alinea Kiadó : Budapest, ISBN 978-963-9659-08-7, 397 p.

Shams, S., Haghighi, F.K. (2013): A Copula-GARCH Model of Conditional Dependencies: Estimating Tehran Market Stock Exchange Value-at-Risk. Journal of Statistical and Econometric Methods, 2. 2. 39-50. p. ISSN: 1792-6602 (print), 1792-6939 (online)

Tömösi A. (2010): World corn trade. [online] <URL: http://www.agrararu.hu/joomla/index.php?option=com_content&view=article&id=86:a-kukorica-kereskedelme-a-vilagban&catid=41:erdekessegek&Itemid=91>

Online sources

pair.akii.hu [08-10-2011]

www.indexmundi.com/ [08-10-2011]

www.oil-price.net/?gclid=CLCsuODsq6gCFVUj3wodQ0C8HQ [08-10-2011]

www.ecb.int/ecb/html/index.hu.html [08-10-2011]

www.faostat.fao.org [08-10-2011]

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APPENDIX

Table 1

Wheat model, ARCH test

Heteroskedasticity Test: ARCH			
F-statistic	0.529209	Prob. F(1,155)	0.4680
Obs*R-squared	0.534213	Prob. Chi-Square(1)	0.4648
Test Equation:			
Dependent Variable: WGT_RESID^2			
Method: Least Squares			
Date: 10/23/11 Time: 18:43			
Sample (adjusted): 3 159			
Included observations: 157 after adjustments			

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.550991	0.107103	5.144485	0.0000
WGT_RESID^2(-1)	-0.058300	0.080141	-0.727467	0.4680

R-squared	0.003403	Mean dependent var	0.520800
Adjusted R-squared	-0.003027	S.D. dependent var	1.235284
S.E. of regression	1.237152	Akaike info criterion	3.276158
Sum squared resid	237.2345	Schwarz criterion	3.315091
Log likelihood	-255.1784	Hannan-Quinn criter.	3.291970
F-statistic	0.529209	Durbin-Watson stat	1.977664
Prob(F-statistic)	0.468037		

Table 2

Wheat, ARMA(4,5) model

Sample (adjusted): 5 159				
Included observations: 155 after adjustments				
Convergence achieved after 78 iterations				
MA Backcast: OFF (Roots of MA process too large)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	35866.80	3386.888	10.58990	0.0000
AR(1)	0.169251	0.057765	2.929979	0.0039
AR(2)	1.287280	0.110077	11.69438	0.0000
AR(3)	0.040614	0.057484	0.706534	0.4810
AR(4)	-0.608831	0.117719	-5.171916	0.0000
MA(1)	1.284472	0.121186	10.59920	0.0000
MA(2)	-0.042775	0.209487	-0.204191	0.8385
MA(3)	-0.471061	0.248567	-1.895109	0.0601
MA(4)	-0.066845	0.185096	-0.361138	0.7185
MA(5)	-0.199051	0.102804	-1.936229	0.0548
R-squared	0.958681	Mean dependent var	30328.49	
Adjusted R-squared	0.956116	S.D. dependent var	12345.45	
S.E. of regression	2586.185	Akaike info criterion	18.61610	
Sum squared resid	9.70E+08	Schwarz criterion	18.81245	
Log likelihood	-1432.747	Hannan-Quinn criter.	18.69585	
F-statistic	373.8064	Durbin-Watson stat	1.602631	
Prob(F-statistic)	0.000000			
Inverted AR Roots	0.89+0.14i	0.89-.14i	-0.80-0.33i	-0.80+0.33i
Inverted MA Roots	0.71	0.00+.50i	0.00-0.50i	-1.00+0.36i
	-1.00-.36i			
	Estimated MA process is noninvertible			

Table 3

Wheat, GARCH(1,1) model

Sample (adjusted): 2 159				
Included observations: 158 after adjustments				
Convergence achieved after 56 iterations				
MA Backcast: 1				
Pre-sample variance: backcast (parameter = 0.7)				
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	30123.96	11772.43	2.558857	0.0105
AR(1)	1.022517	0.023895	42.79170	0.0000
MA(1)	0.182353	0.052799	3.453713	0.0006
	Variance Equation			
C	97623902	22014962	4.434434	0.0000
RESID(-1)^2	0.123467	0.018349	6.728852	0.0000
GARCH(-1)	-0.997702	0.000927	-1076.418	0.0000

R-squared	0.941732	Mean dependent var	30152.41
Adjusted R-squared	0.940981	S.D. dependent var	12294.20
S.E. of regression	2986.742	Akaike info criterion	19.42597
Sum squared resid	1.38E+09	Schwarz criterion	19.54227
Log likelihood	-1528.651	Hannan-Quinn criter.	19.47320
Durbin-Watson stat	1.581303		

Inverted AR Roots	1.02
	Estimated AR process is nonstationary
Inverted MA Roots	-0.18

Table 4

Corn model, ARCH test

Heteroskedasticity Test: ARCH				
F-statistic	0.048519	Prob. F(1,155)	0.8260	
Obs*R-squared	0.049130	Prob. Chi-Square(1)	0.8246	
Test Equation:				
Dependent Variable: WGT_RESID^2				
Method: Least Squares				
Date: 10/23/11 Time: 19:58				
Sample (adjusted): 3 159				
Included observations: 157 after adjustments				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.762794	0.179724	4.244254	0.0000
WGT_RESID^2(-1)	0.017683	0.080276	0.220271	0.8260
R-squared	0.000313	Mean dependent var	0.776438	
Adjusted R-squared	-0.006137	S.D. dependent var	2.107485	
S.E. of regression	2.113942	Akaike info criterion	4.347643	
Sum squared resid	692.6561	Schwarz criterion	4.386576	
Log likelihood	-339.2899	Hannan-Quinn criter.	4.363455	
F-statistic	0.048519	Durbin-Watson stat	2.001408	
Prob(F-statistic)	0.825950			

Table 5

Corn, ARMA(6,3) model

Dependent Variable: CORN				
Method: Least Squares				
Date: 10/23/11 Time: 19:10				
Sample (adjusted): 7 159				
Included observations: 153 after adjustments				
Convergence achieved after 48 iterations				
MA Backcast: OFF (Roots of MA process too large)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	33337.88	141809.4	0.235089	0.8145
AR(1)	1.319344	0.086599	15.23502	0.0000
AR(2)	-0.270108	0.135164	-1.998367	0.0476
AR(3)	0.686835	0.111926	6.136516	0.0000
AR(4)	-0.945510	0.113556	-8.326343	0.0000
AR(5)	0.093279	0.137153	0.680113	0.4975
AR(6)	0.115614	0.085855	1.346624	0.1802
MA(1)	-0.146116	0.059841	-2.441734	0.0158
MA(2)	0.026384	0.055635	0.474227	0.6361
MA(3)	-1.086533	0.060650	-17.91471	0.0000

R-squared	0.934538	Mean dependent var	28386.53
Adjusted R-squared	0.930418	S.D. dependent var	10389.14
S.E. of regression	2740.479	Akaike info criterion	18.73278
Sum squared resid	1.07E+09	Schwarz criterion	18.93085
Log likelihood	-1423.058	Hannan-Quinn criter.	18.81324
F-statistic	226.8320	Durbin-Watson stat	2.088224
Prob(F-statistic)	0.000000		

Inverted AR Roots	1.00	0.84	0.60	-0.28
	-0.42+.81i	-0.42-0.81i		
Inverted MA Roots	1.07	-0.46+0.90i	-0.46-0.90i	
	Estimated MA process is noninvertible			

Table 6

Corn, ARMA(3,3) model

Dependent Variable: CORN				
Method: Least Squares				
Date: 10/23/11 Time: 19:10				
Sample (adjusted): 4 159				
Included observations: 156 after adjustments				
Convergence achieved after 51 iterations				
WARNING: Singular covariance - coefficients are not unique				
MA Backcast: OFF (Roots of MA process too large)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	35133.64	NA	NA	NA
AR(1)	1.893955	NA	NA	NA
AR(2)	-0.911396	NA	NA	NA
AR(3)	0.017087	NA	NA	NA
MA(1)	-0.738683	NA	NA	NA
MA(2)	-0.057645	NA	NA	NA
MA(3)	-0.315207	NA	NA	NA

R-squared	0.930659	Mean dependent var	28148.32
Adjusted R-squared	0.927867	S.D. dependent var	10428.84
S.E. of regression	2800.934	Akaike info criterion	18.75713
Sum squared resid	1.17E+09	Schwarz criterion	18.89398
Log likelihood	-1456.056	Hannan-Quinn criter.	18.81271
F-statistic	333.3013	Durbin-Watson stat	2.109991
Prob(F-statistic)	0.000000		

Table 7

Corn, ARMA(6,7) model

Dependent Variable: CORN				
Method: Least Squares				
Date: 10/23/11 Time: 19:10				
Sample (adjusted): 7 159				
Included observations: 153 after adjustments				
Convergence achieved after 83 iterations				
MA Backcast: OFF (Roots of MA process too large)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	29726.13	4244.420	7.003578	0.0000
AR(1)	1.756556	0.421671	4.165703	0.0001
AR(2)	-1.052255	0.822224	-1.279767	0.2028
AR(3)	-0.492761	0.687594	-0.716645	0.4748
AR(4)	1.486490	0.393679	3.775895	0.0002
AR(5)	-1.006084	0.451538	-2.228125	0.0275
AR(6)	0.238734	0.289419	0.824875	0.4109
MA(1)	-0.567719	0.437924	-1.296387	0.1970
MA(2)	0.493576	0.414120	1.191867	0.2353
MA(3)	0.667835	0.352652	1.893751	0.0603
MA(4)	-0.613897	0.328966	-1.866144	0.0641
MA(5)	0.255380	0.367693	0.694547	0.4885
MA(6)	-0.068712	0.128831	-0.533348	0.5946
MA(7)	0.202336	0.121497	1.665361	0.0981

R-squared	0.937126	Mean dependent var	28386.53
Adjusted R-squared	0.931246	S.D. dependent var	10389.14
S.E. of regression	2724.137	Akaike info criterion	18.74473
Sum squared resid	1.03E+09	Schwarz criterion	19.02203
Log likelihood	-1419.972	Hannan-Quinn criter.	18.85738
F-statistic	159.3674	Durbin-Watson stat	2.091451
Prob(F-statistic)	0.000000		

Table 8

Corn, ARMA(1,1) model

Dependent Variable: CORN				
Method: Least Squares				
Date: 10/23/11 Time: 19:10				
Sample (adjusted): 2 159				
Included observations: 158 after adjustments				
Convergence achieved after 16 iterations				
MA Backcast: 1				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	33457.58	7225.956	4.630194	0.0000
AR(1)	0.954067	0.028900	33.01298	0.0000
MA(1)	0.205279	0.082303	2.494172	0.0137
R-squared	0.918713	Mean dependent var	27983.59	
Adjusted R-squared	0.917664	S.D. dependent var	10464.50	
S.E. of regression	3002.713	Akaike info criterion	18.87122	
Sum squared resid	1.40E+09	Schwarz criterion	18.92938	
Log likelihood	-1487.827	Hannan-Quinn criter.	18.89484	
F-statistic	875.9091	Durbin-Watson stat	1.905378	
Prob(F-statistic)	0.000000			
Inverted AR Roots	0.95			
Inverted MA Roots	-0.21			

Table 9

Corn, GARCH model

Sample (adjusted): 2 159				
Included observations: 158 after adjustments				
Convergence achieved after 55 iterations				
MA Backcast: 1				
Presample variance: backcast (parameter = 0.7)				
GARCH = C(4) + C(5)*GARCH(-1) + C(6)*GARCH(-2) + C(7)*GARCH(-3)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	42571.83	25695.06	1.656810	0.0976
AR(1)	0.982295	0.018476	53.16707	0.0000
MA(1)	0.185554	0.043496	4.266043	0.0000
	Variance Equation			
C	65284433	8145898	8.014393	0.0000
GARCH(-1)	-1.003803	0.000980	-1024.440	0.0000
GARCH(-2)	-0.983242	0.004082	-240.8922	0.0000
GARCH(-3)	-0.969621	0.004209	-230.3573	0.0000

R-squared	0.918180	Mean dependent var	27983.59
Adjusted R-squared	0.917125	S.D. dependent var	10464.50
S.E. of regression	3012.531	Akaike info criterion	18.62994
Sum squared resid	1.41E+09	Schwarz criterion	18.76562
Log likelihood	-1464.765	Hannan-Quinn criter.	18.68504
Durbin-Watson stat	1.899356		
Inverted AR Roots	0.98		
Inverted MA Roots	-0.19		