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NONLINEAR STOCHASTIC MODELLING DYNAMIC OF THE AGRICULTURAL PRODUCTS EXCHANGE RATES

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Summary

The aim of this paper is to research some of the most important financial-stochastic models which enable the description of the dynamics of agricultural exchange rates. This dynamics is usually characterized by the properties of nonlinearity, hence the so-called conditional heteroskedastic models are used as the basic models for precise description of its behavior. The basic stochastic properties of these models, as well as the procedures to estimate their parameters, are also studied here. Finally, the conditional heteroskedastic models are applied in fitting of the empirical data: the nominal average cereals exchange rate indexes between the U.S. and the other countries.

Key words: *time series, stochastic modeling, agricultural exchange rates.*

JEL: *Q13, Q14, Q18, M31*

Introduction

For success in the business of market entities, it is very important to determine a certain degree of legality in the market, based on the current fluctuations (evolution) of the prices and other financial indexes of some products, as well as predict their future trends. To this aim, all relevant, available information that can be of significance for the movement of these indexes should be collected and also described by the appropriate mathematical model. The time and dynamics are usually taken into account as the basic categories, hence the determination of basic market laws can be made using the theory of probability. More precisely, the time series analysis can be made with the stochastic models, on the basis of which the uncertainty that occurs on the market is interpreted.

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The aim of this paper is to research the most important financial-stochastic models that can describe various elements of the market of agricultural products, mainly the dynamics of their exchange rates. For this purpose, the new possibilities of the dynamics analysis, primarily related to the stochastic analysis of the financial index dynamics and formation of the appropriate theoretical model, are highlighted (Chavas, Cox, 1997). Apart from the standard methods in agricultural time-series analysis special emphasis is given to their practical application (Hill, Donald, 2003).

Many empirical results confirm the pronounced non-linearity of the financial index dynamics, which is also transmitted to the corresponding financial-stochastic modelling. In this sense, the base of formation of the appropriate models should be looked for in the well-known *Autoregressive conditional heteroskedasticity* (*ARCH*) *models*. These models have made radical changes in the stochastic analysis of financial indexes. The ARCH model as the basic mechanism in the analysis of financial indexes was introduced by Robert Engle (Engle, 1982), giving the very successful analysis of inflationary dynamics in Great Britain in 1982. Later, in 1986, Tim Bollerslev (Bollerslev, 1986) defined the so-called Generalized Autoregressive Conditional Heteroskedastic models (GARCH models) with the ARCH models as a conceptual basis. These models have been further modified and are still in use today (Balakrishnan et al., 2013).

The two mentioned kinds of models were able to explain a number of the properties of financial indexes, primarily, the changes in their volatility (Barndorff, Shephard, 2002). The basic stochastic features of these models are described in this paper. Furthermore, their application in modelling and studying the volatility of monthly data for the average exchange rate of some cereals, such as corn, rice, wheat and soybeans, between the U.S. and 79 other countries, plus the European Union (EU), is also given.

Theoretical background and methodology

As we already mentioned, many results based on the analysis of empirical data indicate the pronounced nonlinearity in the financial index dynamics, which is also transmitted to the corresponding financial-stochastic models. Without going into more detail on different concepts and ways of formally defining the market itself, from a stochastic point of view, the uncertainty which occurs on the market can be described by the probability model in which the dynamics of a financial index is represented by a stochastic process (Franses, Dijk, 2000):

$$S = (S_n)_{n \geq 0}$$

which represents the family of random variables that depend on a discrete time parameter *n*. The assumption that the time moments *n* are discrete, is based on the fact that in specific (e.g. stock-exchange) situations, the index *S* is registered at separate time intervals and, as such, is described in the form of the above-mentioned stochastic time series (Figure 1.). Additionally, we assume that the problem of uncertainty that occurs in each financial market can be described by the so-called *filtration* $F = (F_n)_{n \geq 0}$, for which the following is valid:

$$F_m \subseteq F_n \subseteq F, \quad \forall m \leq n.$$

In the basic interpretation, filtration F represents a set of information on the market that is available to each participant, concluding with the moment of time n. Such a market concept corresponds to the model of the financial index in the following form:

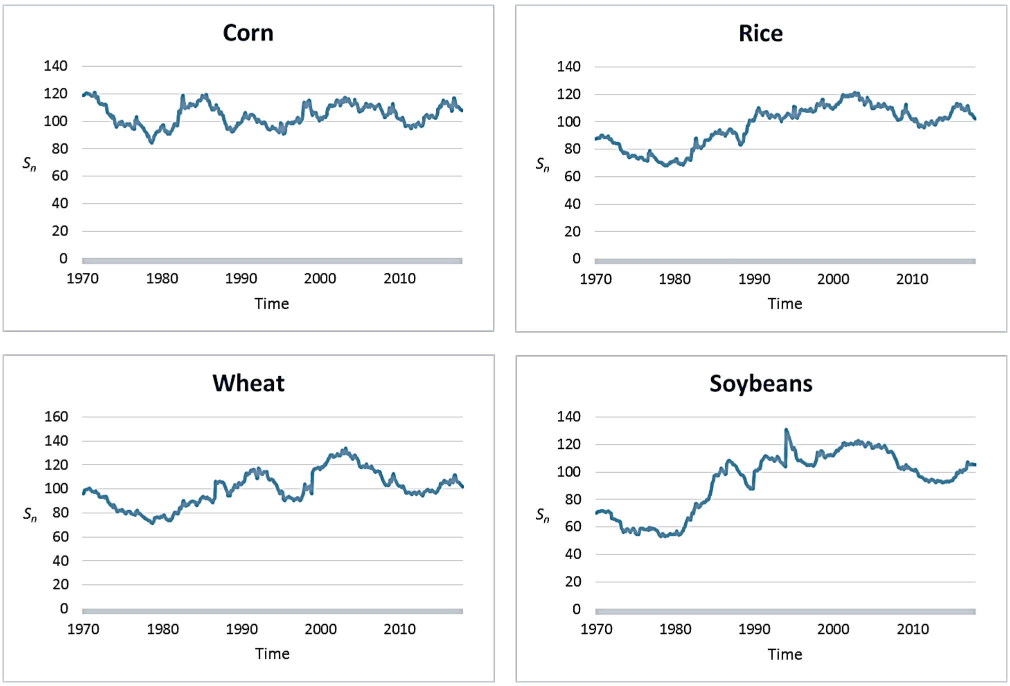
$$S_n = S_o e^{H_n}, \tag{1}$$

where $H_n = \sum_{k=0}^{p} h_k$, $h_0 = 0$, and (h_n) is a sequence of the random variables named *the logarithms of incomes* or, simply, *the log-returns*. This is motivated by the fact that, according to the previous equalities, it follows that $S_n = S_{n-1}e^{h_n}$, i.e.

$$h_n = \ln\frac{S_n}{S_{n-1}} = \ln\left(1+\frac{\Delta S_n}{S_{n-1}}\right), \quad \Delta S_n = S_n - S_{n-1} \tag{2}$$

It is obvious that $h_n > 0 \Leftrightarrow \Delta S_n > 0$ holds, so that any change of the index S (i.e. the series S_n) can be explained by the corresponding change of the log-returns h_n.

Figure 1. The dynamics of the nominal monthly average exchange rate of cereals in the U.S. trade market, compared to other countries, in the period 1970-2017.



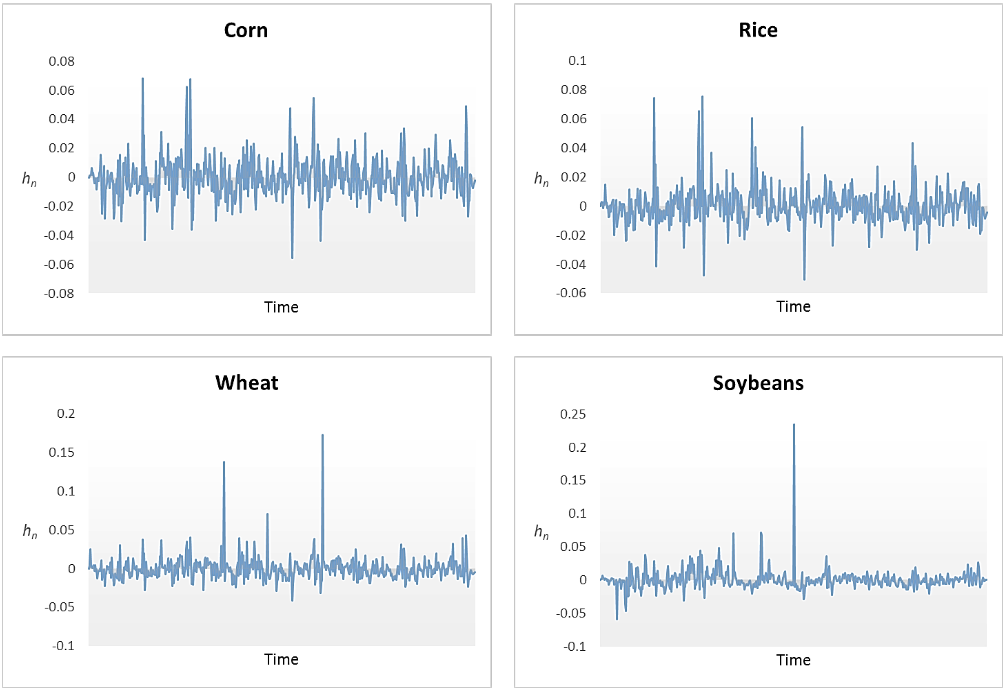
Source: Economic Research Service of the United States Department of Agriculture;
Note: Authors' computation in Excel, 2017.

Thus, the main problem here is to find an adequate model that could describe the distribution of the series (h_n) and, therefore completely describes the behaviour and dynamics of the financial index S. For that purpose, we assume that the series (h_n) has *the conditionally-Gaussian distributional form* (Mikosch, 2001):

$$h_n = \sigma_n \varepsilon_n , \quad n \geq 1 \tag{3}$$

where (σ_n) is $F_{n\text{-}1}$-adaptive series which presents *the total volatility*, i.e. variability in the dynamics of the series itself. Since each market participant takes into account the values of index S as well as the degree of risk with which it enters into a particular investment, volatility is the basis for calculating this risk. By the Eq. (3), volatility is also defined as a series of random variables and, in that way, expressing its variability in time. On the other hand, (ε_n) presents a series of F_n-adaptive independent identically distributed (i.i.d.) random variables with the standard Gaussian N(0.1) distribution, popularly called "white noise". Thus, this series defines fluctuations of the series (h_n) that cannot be described by the volatility itself.

Figure 2. The monthly log-returns of the nominal average exchange rate of cereals (U.S. trade market vs. other countries) in the period 1970-2017.



Source: Economic Research Service of the United States Department of Agriculture;

Note: Authors' computation in Excel, 2017.

The series (h_n) represents the sequence of uncorrelated random variables with a mathematical expectation:

$$E(h_n | F_{n\text{-}1}) = \sigma_n E(\varepsilon_n | F_{n\text{-}1}) = 0\,, \tag{4}$$

and dispersion:

$$D(h_n | F_{n\text{-}1}) = E(h_n^2 | F_{n\text{-}1}) = \sigma_n^2 E(\varepsilon_n^2 | F_{n\text{-}1}) = \sigma_n^2\,.. \tag{5}$$

Thus, it is often used as a stochastic model of the dynamics of empirical financial data (Figure 2). In addition, the observation of the squared series (h_n^2) is often needed, which, according to the previous equations, presents an optimal unbiased estimate of the volatile series (σ_n^2).

In order to express the volatility of financial series in the form of time series of discrete time parameter, (Engle, 1982) introduces, today already historically known, autoregressive models of conditional heteroscedasticity (ARCH models). The base of the ARCH model interpretation defines the Eq. (3) as well as the recurrence relation for determining the volatility series:

$$\sigma_n^2 = \alpha_0 + \sum_{k=1}^{p} \alpha_k h_{n\text{-}k}^2\,, \qquad \alpha_0 > 0,\ \ \alpha_k \geq 0\,. \tag{6}$$

In this way, volatility depends on the previous, known values (h_n) and can be explicitly expressed on the basis of them. The ARCH model described by Eqs. (3)-(6) has a unique stationary solution if and only if the characteristic polynomial:

$$P(x) = x^p - \sum_{j=1}^{p} \alpha_j x^{p-j}$$

has the roots $r_1, r_2, \ldots, r_p$ which satisfy the condition $| r_j | < 1, j = 1, \ldots, p$ or, equivalently, $\sum_{j=1}^{p} \alpha_j < 1$. This fact is an important prerequisite for the successful implementation of the ARCH model based primarily on the estimation of unknown coefficients $\acute{a}_1, \ldots, \acute{a}_p$. In accordance, the ARCH model can be formed over the corresponding set of real, empirical data, as will be explained in detail in the next section.

The successful applications of the ARCH model led to the creation of new, more complex models that enabled the description of the different effects of the behaviour of financial markets. As a consequence, beside standard ARCH models, today exist many of its general modifications, which are based, more or less, on similar ideas and assumptions. Historically, the first generalization of the ARCH model was introduced by Tim Bollerslev (Bollerslev, 1986), who defined the so-called *General ARCH (GARCH) model*, with two parameters $p, q > 0$. In that model, usually labelled as *GARCH* (p,q), equality is taken (3), but the volatility (σ_n) is described by a relation:

$$\sigma_n^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i h_{n-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{n-j}^2 \qquad (7)$$
,

where $\alpha_0 > 0, \alpha_j, \beta_j \geq 0$. Similarly to the ARCH models, the necessary and sufficient stationarity conditions of the GARCH models can be shown.

The basic difference between these two models consists in different values of parameter *p* in statistical processing of data (and their modelling). Namely, the GARCH models give satisfactory estimates and adaptivity to real data, even for small values of *p* and *q*. In contrary, the ARCH models require the relative large value of the parameter *p*. Further generalization of the (G)ARCH type of model has resulted in creation of new models (EGARCH, TGARCH, HARCH, etc.) which, to a greater or lesser degree, complement the deficiencies of the basic models of the ARCH / GARCH type (see, for instance (Fornari, Mele, 1997), (Francq et al. 2001), (Popović, Stojanović, 2005), (Zakoian, 1994).

Results and discussion

In this section we present the basic facts about the procedures for estimating unknown parameters. The practical application of the model of conditional heteroskedasticity in nonlinear modelling of the exchange rates of some agricultural series has also been presented. The basic assumptions of these estimation methods are based on the works (Popović, Stojanović, 2003), (Stojanović, Popović, 2004), where a detailed overview of the below mentioned procedures was given.

Estimation in ARCH models

In the first step, we consider estimation procedure and application of the ARCH models, based on empirical data, i.e. the sample $h_1, \ldots, h_n$, which represent log-returns of the aforementioned series of the nominal exchange rates of agricultural products. For that purpose, the estimation of the coefficients $\alpha_0, \ldots, \alpha_p$ of the ARCH model, given by Eq. (4), is necessary. The most commonly used technique is the so-called *Quasy Maximum Likelihood* (*QML*) method, based on the assumption of the conditional Gaussian distributed series (h_n). In this case, the likelihood function has the form:

$$L(\theta) = -\frac{n}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{n}\left(\ln \sigma_t^2 + \frac{h_t^2}{\sigma_t^2}\right)$$

and the QML-estimates of the coefficients $\alpha_0, \ldots, \alpha_p$ are obtained as solutions of the system of equations $\partial L(\theta) / \partial a_j = 0$, $j = 0,1,\ldots,p$ which, after some computation, becomes:

$$\begin{cases} \sum_{t=p}^{n} \sigma_t^2 = \sum_{t=p}^{n} h_t^2 \\ \sum_{t=p}^{n} \sigma_t^2 h_{t-j}^2 = \sum_{t=p}^{n} h_t^2 h_{t-j}^2 \ , \ \ j=\overline{1,p} \end{cases} . \tag{8}$$

Notice that in this way the obtained QML-estimates represent also the regression estimates of the series (h_n^2), observed in relation to its previous realizations $h_{n-1}^2, \ldots, h_{n-p}^2$.

Estimation in GARCH models

The procedure related to the ARCH model parameters estimation can be generalized and applied in the case of the GARCH type models. Thus, for example, the QML estimation of an unknown parameters $\theta = (\alpha_0, \alpha_1, ..., \alpha_p, \beta_1, ..., \beta_q)^T$ is based on the same likelihood function, with this difference that the volatility series $(\acute{o}_n^2)$ is here described by Eq. (5), i.e. it depends on its previous values $\sigma_{n-1}^2, \ldots, \sigma_{n-q}^2$. Therefore, the system of Eqs. (6) cannot be explicitly solved on θ, so in practice, it is usually used by some of the iterative methods for approximate finding of the estimated values. The basic idea of these methods is the forming of a recurrence sequence $\left(\hat{\theta}_n\right)$ that converges to the optimal parameter values $\hat{\theta}$, for which the likelihood function $L(\theta)$ attains its maximum. The best known method of the numerical determining the parameters estimates is *the Newton-Raphson iterative method*, based on the following assumptions:

Let θ_0 be the initial value of an unknown parameter θ, and notice the gradient vector of the likelihood function:

$$g(\theta_0) = \frac{\partial L(\theta)}{\partial \theta}\Big|_{\theta=\theta_0} \tag{9}$$

as well as the so-called Hessian:

$$H(\theta_0) = -\frac{\partial^2 L(\theta)}{\partial \theta \partial \theta^T}\Big|_{\theta=\theta_0} \tag{10}$$

which represents matrix with the second order partial derivatives of the likelihood function $L(\theta)$. If $\hat{\theta}$ is the estimated value of the parameter θ, for which the function $L(\theta)$ attains the maximum, it will be $\frac{\partial L(\hat{\theta})}{\partial \theta} = 0$, i.e.

$$\hat{\theta} \approx \theta_0 + H(\theta_0)^{-1} g(\theta_0). \tag{9}$$

The last equality clearly suggests the following iterative method for finding the parameters estimates:

$$\hat{\theta}_k = \hat{\theta}_{k-1} + H\left(\hat{\theta}_{k-1}\right)^{-1} g\left(\hat{\theta}_{k-1}\right), \quad k = 1,2,\ldots \tag{10}$$

for which, under certain conditions, convergence can be shown (detailed proof can be found in [19]). Using the iterative method (10), with certain accuracy, UMV estimates of the GARCH-coefficients are easily obtained. A particular problem here is the selection of the initial values that should allow the beginning of a convergent iteration, which will be furthermore more elaborated.

The application of the models

The described method of the parameters estimation in the ARCH models can be relatively easily applied in practical analysis of the agricultural time series. The following Table 1 shows the estimation results of the log-returns of cereals nominal monthly average exchange rates. Actual data series were observed in the period from 1970 to the first quarter of 2017, based on the data from the Economic Research Service of the United States Department of Agriculture. The sample sizes of these series is $N = 576$ and the summary statistics of the all of them are presented in the Table 1.

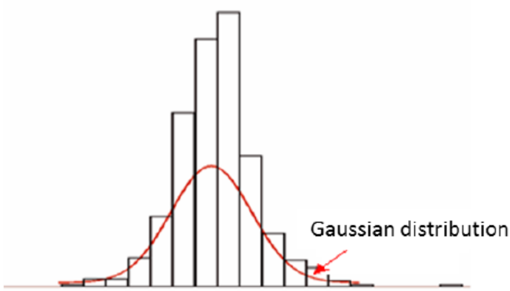
Table 1. The summary statistics of the monthly log-returns (and their squares) of the cereals nominal exchange rate.

Products	**Corn**		**Rice**		**Wheat**		**Soybeans**	
Statistics	h_n	h_n^2	h_n	h_n^2	h_n	h_n^2	h_n	h_n^2
Mean	-1.67E-4	1.81E-4	2.77E-4	1.49E-4	1.05E-4	2.22E-4	7.07E-4	2.37E-4
Stand. Error	5.61E-4	1.85E-5	5.08E-4	2.00E-5	6.21E-4	6.26E-5	6.41E-4	9.69E-5
Median	-5.99E-4	5.34E-5	-2.84E-4	3.82E-5	-1.12E-3	4.53E-5	-6.89E-4	2.80E-5
Stand. Deviat.	1.35E-2	4.44E-4	0.0122	4.81E-4	0.0149	1.50E-3	1.54E-2	2.32E-3
Variance	1.82E-4	1.97E-7	1.49E-4	2.31E-7	2.22E-4	2.26E-6	2.36E-4	5.40E-6
Kurtosis	4.0654	49.553	8.4465	75.785	44.225	308.61	94.393	533.816
Range	0.1237	4.62E-3	0.1260	5.68E-3	0.2144	0.0299	0.2932	0.0549
Min.	-0.0558	0.0000	-0.0506	0.0000	-0.0413	0.0000	-0.0589	0.0000
Max.	0.0679	4.62E-3	0.0754	5.68E-3	0.17131	0.0299	0.2343	0.0549
ACF(1)	0.018	0.145	0.015	0.192	0.004	0.148	0.005	0.192
ACF(2)	-0.063	0.110	-0.028	0.131	-0.001	0.120	-0.005	0.080
ACF(3)	0.011	0.101	-0.042	0.051	0.013	0.092	-0.004	0.050

Source: Authors' computation in Excel, 2017.

A simple comparison of the shown values can give the explanation why these series can be fitted by the models of ARCH/GARCH type. First of all, these series can be interpreted as martingale differences, because their means and autocorrelations $ACF(k)$ for non-zero lags (k = 1,2,3) are almost zero, i.e. they have no significant autocorrelation. On the other hand, squared series (h_n^2) have emphasized ACFs, which are the evidence of volatility clustering. In addition, the existence of clustering, as a feature of grouping data with low or pronounced volatility, indicates high values of kurtosis, also. This results in the emphasis "tails" of the empirical data distributions (a typical such situation is shown in Figure 3).

Figure 3. Empirical distribution (histogram) of the log-returns in comparison with Gaussian distributions.



Source*:* Authors' computation in statistical programming language "R", 2017.

The following two Tables 2 and 3 show the estimated parameters' values of ARCH (p) model, when p = 1,2,3, as well as GARCH (1,1) model, respectively. In addition, two typical goodness-of-fit statistics: *Residual Standard Errors* (*RSE*) and *Akaike's Information Criterion* (*AIC*) have been estimated. Additionally, in the case ARCH-modelling, the estimated values of the *Fisher's F-statistic* are computed, along with their estimated p-values (shown in brackets).

According to the values shown in Table 2, it can be easily seen that ARCH-models of different order p have similar characteristics. The estimated values of the goodness-of fit statistics are close to each other, whereby the RSE-scores have a relative small and the AIC-scores pronounced negative values. Thus, ARCH-models can be adequate theoretical models for describing the dynamics of the observed agricultural indexes. Finally, it should be noted that F-statistics have relative pronounced values in the case of exchange rate data of the corn and rice time series. This indicates that there is a significant difference between the variances of the squared series (h_n^2), compared to its previous realizations. On the other hand, in the case of wheat and soybeans time series, no significant difference is detected.

Table 2. The estimated values of the ARCH model's parameters and the goodness-of-fit statistics.

Order of models	Estimated values	Products			
		Corn	Rice	Wheat	Soybeans
$p = 1$	α_0	1.820E-4	1.475E-4	2.216E-4	2.369E-4
	α_1	3.935E-3	3.640E-3	2.334E-4	4.834E-4
	RSE	4.411E-4	4.795E-4	1.505E-3	2.327E-3
	AIC	-7262.1	-7166.0	-5848.3	-5346.4
	F-statistic (p-values)	8.311^{**} (4.090E-3)	4.927^{*} (2.683E-2)	3.070E-3 (0.9558)	5.871E-3 (0.9390)
$p = 2$	α_0	1.823E-4	1.468E-4	2.221E-4	2.376E-4
	α_1	3.207E-3	2.961E-3	1.019E-3	2.552E-4
	α_2	2.722E-3	3.157E-3	5.311E-3	1.187E-3
	RSE	4.400E-4	4.784E-4	1.504E-3	2.329E-3
	AIC	-7263.8	-7167.5	-5847.9	-5344.4
	F-statistic (p-values)	4.949^{**} (2.561E-3)	4.249^{**} (1.473E-2)	0.779 (0.4591)	1.994E-2 (0.9803)
$p = 3$	α_0	1.825E-4	1.460E-4	2.227E-4	2.379E-4
	α_1	3.341E-3	3.070 E-3	9.077 E-4	2.278E-4
	α_2	2.060E-3	2.428E-3	2.428E-3	1.073E-3
	α_3	2.344E-3	3.284E-3	4.511E-3	6.172E-3
	RSE	4.394E-4	4.772E-4	5.305E-3	2.331E-3
	AIC	-7264.6	-7169.4	-5847.4	-5342.4
	F-statistic (p-values)	6.030^{**} (2.122E-3)	4.131^{**} (6.509E-3)	1.308 (0.3753)	1.632E-2 (0.9972)

Source: Authors' computation in statistical programming language "R", 2017.

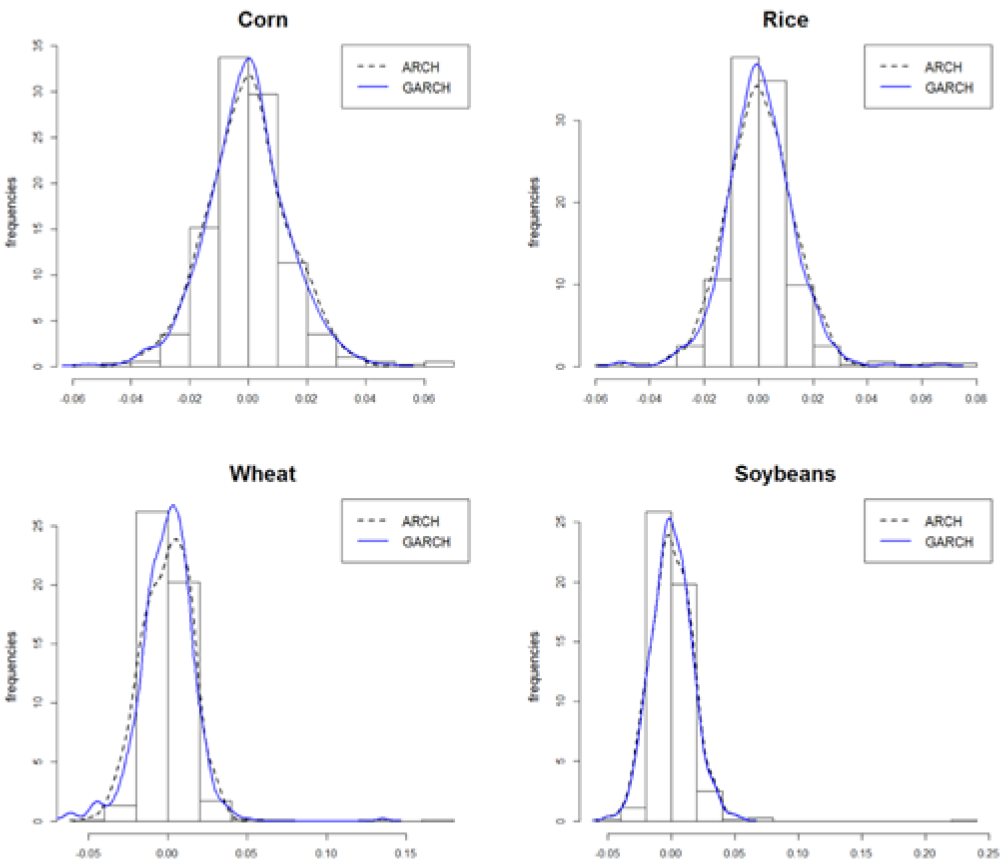
After that, we estimated coefficients of the GARCH (1,1) model. The previous estimated coefficients of ARCH(1) model (wherein β_1=0) were taken as the initial estimates, which were previously determined by the standard QML procedure. The estimated values of GARCH (1.1) model, obtained by using the Newton-Raphson algorithm, for the aforementioned empirical agricultural series of cereals exchange rate indexes, are shown in Table 3. For all of these agricultural empirical data, we have also compared the efficiency of their fitting when the GARCH model was used. Thus, in the same Table 3, the estimated values of *RSE* and *AIC* are also presented. Note that, in comparison to ARCH-modelling, the estimated values of the goodness-of-fit statistics are generally less when the GARCH model has been applied, as an appropriate fitting model. Therefore, the GARCH model can be a more adequate theoretical model for fitting these series. This can also be seen in Fig. 4 where the empirical distributions (histograms) of the all observed data series were compared with the theoretical distributions, obtained by fitting with ARCH, as well as with GARCH models. As it can be easily seen, in all of these cases, GARCH modelling provides somewhat better match to the appropriate empirical distributions.

Table 3. The estimated values of the GARCH(1,1) model's parameters, and the goodness-of-fit statistics.

Estimated values	Products			
	Corn	Rice	Wheat	Soybeans
α_0	4.794E-5	3.137E-5	4.519E-5	4.884E-6
α_1	1.452E-1	1.320E-1	7.098E-1	1.000E-8
β_1	5.884E-1	6.558E-1	4.219 E-1	9.797E-1
RSE	1.677E-4	1.652E-4	6.001E-5	3.979E-6
AIC	-7563.2	-8335.4	-71724.3	-6451.5

Source*:* Authors' computation in statistical programming language "R", 2017.

Figure 4. The empirical distributions of the log-returns of cereals nominal exchange rate in comparison with probability density of the fitted conditional heteroskedastic models.



Source: Authors' computation in statistical programming language "R", 2017.

Conclusion

In this paper, the conditional heteroskedastic processes were used as stochastic models for the description of the dynamics of the agricultural exchange rate of cereals. Using the aforementioned estimation procedures, the appropriate theoretical models were obtained for which it was formally shown that they can qualitatively fit the empirical data, or their distribution. Of course, the above mentioned estimation procedures, as well as the choice of models themselves, should not be understood as universal. In contemporary statistical analysis of the behaviour of financial (or some other) indexes, in addition to different modifications of the (G)ARCH type models, some other related models are used (see, for instance (Durhan, 2007), (Huang, Fok, 2001), (Kapetanios, Tzavalis, 2010), (Pažun et al., 2016). Similarly, various procedures for estimating unknown coefficients of the corresponding theoretical model can be used (Sangjoon et al., 1998), (Singleton, 2001). In this way, one of the future guidelines in further research would be the application of such or similar models in fitting, i.e. precise description of the behaviour of agricultural time series.

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NELINEARNO STOHASTIČKO MODELOVANJE DINAMIKE RAZMENA POLJOPRIVREDNIH PROIZVODA

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Apstrakt

Cilj ovog rada je istraživanje nekih od najvažnijih finansijsko-stohastičkih modela na osnovu kojih se može opisati dinamika razmene poljoprivrednih proizvoda. Ova dinamika, obično, ima svojstva nelinearnosti, zbog čega su takozvani uslovni heteroskedastički modeli korišćeni kao osnovni modeli koji mogu precizno opisati njeno ponašanje. Osnovna stohastička svojstva ovih modela, kao i procedure za ocenu njihovih parametara su ovde takođe istražena. Konačno, uslovni heteroskedastički modeli su primenjeni u fitovanju empirijskih podataka: nominalnih prosečnih indeksa razmene žitarica između SAD i drugih zemalja.

Ključne reči: *vremenske serije, stohastičko modelovanje, razmena poljoprivrednih proizvoda.*

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ECONOMICS OF
AGRICULTURE

CONTENT

1. Drago Cvijanović, Jelena Matijašević – Obradović, Sanja Škorić
THE IMPACT OF AIR QUALITY CONDITIONED BY EMISSION OF POLUTTANTS TO THE DEVELOPMENT OF RURAL TOURISM AND POTENTIALS OF RURAL AREAS . . . 871

2. Dejan Đurić, Jelena Ristić, Dragana Đurić, Ivana Vujanić
EXPORT OF AGRICULTURAL AND FOOD PRODUCTS IN THE FUNCTION OF ECONOMIC GROWTH OF REPUBLIC OF SERBIA 887

3. Tamara Gajić, Aleksandra Vujko, Mirjana Penić, Marko D. Petrović, Milutin Mrkša
SIGNIFICANT INVOLVEMENT OF AGRICULTURAL HOLDINGS IN RURAL TOURISM DEVELOPMENT IN SERBIA 901

4. Muuz Hadush
EXPLORING FARMERS' SEASONAL AND FULL YEAR ADOPTION OF STALL FEEDING OF LIVESTOCK IN TIGRAI REGION, ETHIOPIA 919

5. Mina Kovljenić, Mirko Savić
FACTORS INFLUENCING MEAT AND FISH CONSUMPTION IN SERBIAN HOUSEHOLDS - EVIDENCE FROM SILC DATABASE . 945

6. Bojan Krstić, Jelena Petrović, Tanja Stanišić, Ernad Kahrović
ANALYSIS OF THE ORGANIC AGRICULTURE LEVEL OF DEVELOPMENT IN THE EUROPEAN UNION COUNTRIES 957

7. Mirjana Lukač Bulatović, Veljko Vukoje, Dušan Milić
ECONOMIC INDICATORS OF THE PRODUCTION OF IMPORTANT FRUIT-SPECIFIC SPECIES IN VOJVODINA . . . 973

8. Goran Maksimović, Božidar Milošević, Radomir Jovanović
RESEARCH OF CONSUMERS' ATTITUDES ON THE ORGANIC FOOD CONSUMPTION IN THE SERBIAN ENCLAVES IN KOSOVO 987

9. Ivan Mičić, Zoran Rajić, Jelena Živković, Dragan Orović, Marko Mičić, Ivana Mičić, Marija Mičić
OPTIMAL FLOCK STRUCTURE OF PIG FARM PROVIDING MINIMUM COSTS 1003

10. Miroslav Miškić, Goran Ćorić, Danijela Vukosavljević
BUILDING FINANCIAL AND INSURANCE RESILIENCE IN THE CONTEXT OF CLIMATE CHANGE 1019

11. Vladimir Njegomir, Ljubo Pejanović, Zoran Keković
AGRICULTURAL ENTREPRENEURSHIP, ENVIRONMENTAL PROTECTION AND INSURANCE 1035

12. Nenad Perić, Andrijana Vasić Nikčević, Nenad Vujić
CONSUMERS ATTITUDES ON ORGANIC FOOD IN SERBIA AND CROATIA: A COMPARATIVE ANALYSIS 1049

13. Branko Vučković, Branislav Veselinović, Maja Drobnjaković
FINANCING OF PERMANENT WORKING CAPITAL IN AGRICULTURE 1065

14. Bahrija Kačar, Jasmina Curić, Selma Ikić
ISLAMIC BANKS AND FINANCE AND THE POSSIBILITY OF AGRICULTURAL INVESTMENTS IN THE REPUBLIC OF SERBIA 1081

15. Aleksandar Damnjanović, Neđo Danilović, Erol Mujanović, Zoran Milojević
NONLINEAR STOCHASTIC MODELLING DYNAMIC OF THE AGRICULTURAL PRODUCTS EXCHANGE RATES 1101

16. Filip Đoković, Radovan Pejanović, Miloš Mojsilović, Jelena Đorđević Boljanović, Katarina Plećić
OPPORTUNITIES TO REVITALISE RURAL TOURISM THROUGH THE OPERATION OF AGRARIAN COOPERATIVES 1115

17. Aleksandar Jazić, Miloš Jončić
THE IMPACT OF TRANSITION ON AGRICULTURE AND RURAL AREAS IN HUNGARY 1133

18. Vlado Kovačević, Mirjana Bojčevski, Biljana Chroneos Krasavac
IMPORTANCE OF FEEDBACK INFORMATION FROM FARM ACCOUNTANCY DATA NETWORK OF THE REPUBLIC OF SERBIA 1147

19. Dalibor Krstinić, Nenad Bingulac, Joko Dragojlović
CRIMINAL AND CIVIL LIABILITY FOR ENVIRONMENTAL DAMAGE 1161

20. Boris Kuzman, Nedeljko Prdić, Zoran Dobraš
THE IMPORTANCE OF THE WHOLESALE MARKETS FOR TRADE IN AGRICULTURAL PRODUCTS 1177

21. Nadežda Ljubojev, Marijana Dukić Mijatović, Željko Vojinović
LEGAL PROTECTION OF NEW PLANT VARIETIES IN THE REPUBLIC OF SERBIA 1191

22. Miodrag Mićović
THE LEGAL NATURE AND THE FRAMEWORK FOR COOPERATIVE ACTIVITIES 1205

23. Lana Nastic, Todor Markovic, Sanjin Ivanovic
ECONOMIC EFFICIENCY OF EXTENSIVE LIVESTOCK PRODUCTION IN THE EUROPEAN UNION 1219

24. Goran Paunovic, Dragan Solesa, Marko Ivanis
SITE SELECTION OF THE CONSTRUCTION OF THE SYSTEM FOR THE PRODUCTION OF PASTA IN AP VOJVODINA 1231

25. Milan Počuča, Jelena Matijasevic - Obradovic, Bojana Draskovic
CORRELATION BETWEEN THE AIR QUALITY INDEX SAQI_11 AND SUSTAINABLE RURAL DEVELOPMENT IN THE REPUBLIC OF SERBIA 1249

26. Jovanka Popov-Raljić, Milica Aleksić, Vesna Janković, Ivana Blešić, Milan Ivkov
RISK MANAGEMENT OF ALLERGENIC FOOD INGREDIENTS IN HOSPITALITY 1263

27. Tanja Vujović, Sonja Vujović, Miloš Pavlović
SOCIAL RESPONSIBILITY IN MARKETING OF THE FOOD INDUSTRY AND ITS DISTRIBUTORS 1277