https://doi.org/10.17221/376/2016-AGRICECON

Nonlinear Granger causality between grains and livestock

Piotr FISZEDER[1]*, Witold ORZESZKO[2]

[1]*Department of Econometrics and Statistics, Faculty of Economic Sciences and Management, Nicolaus Copernicus University in Torun, Torun, Poland*

[2]*Department of Applied Informatics and Mathematics in Economics, Faculty of Economic Sciences and Management, Nicolaus Copernicus University in Torun, Torun, Poland*

*Corresponding author: piotr.fiszeder@umk.pl

Fiszeder P., Orzeszko W. (2018): **Nonlinear Granger causality between grains and livestock**. Agric. Econ. – Czech, 64: 328–336.

Abstract: Linear and nonlinear Granger causality between three grains: corn, soybean, wheat and two livestock commodities: live cattle and lean hogs, was verified. Weak evidence of linear causal relationships was found, supporting the results published in other studies. However, strong nonlinear causal relationships between grain and livestock returns were found, which had not yet been documented in the literature on this subject. The revealed relationships have different patterns and features, and in some cases, they arise from second moment dependencies, but nonlinearities of a different type were also found. Most of the discovered nonlinear relationships are bidirectional.

Keywords: agricultural futures contracts, grain and livestock prices, multivariate GARCH model, nonlinear causality tests

The relation between input and output products has always been of interest in agricultural production and the relationship between grain and livestock is no different. Many studies have explored the relationships between grain and livestock prices. In the initial studies of this subject spurious relations were frequently identified due to the inadequate development of statistical methods. Many later studies have shown the lack of dependencies however, a few significant relationships have been detected (Tejeda and Goodwin 2011; Pozo and Schroeder 2012; Xu et al. 2012). The following properties of the meat industry have been identified as possible reasons for the lack of strong evidence of dependence between grain and livestock prices, among others: increase in productivity, inflexibility, greater specialisation, use of production contracts and other factors outside the meat industry (such as, for instance, the use of corn for ethanol production) and the financial crisis.

The concept of Granger causality has been analysed in a vast body of econometric literature since the 70s of the twentieth century. It is usually considered in the context of linear economic relationships, represented by a vector autoregression model (VAR). However, in contemporary econometrics we can observe a strong tendency to describe mechanisms and relationships using methods of nonlinear time series analysis. It should also be noted that the idea of Granger causality is not restricted to the linear framework. The general definition of Granger causality is formulated in terms of conditional probability density, which makes it applicable to any functional form of the relationship. In the econometric literature, the test introduced by Baek and Brock (1992), and later developed by Hiemstra and Jones (1994), is the most popular method of testing for nonlinear Granger causality. However, Diks and Panchenko (2006) pointed out that the Hiemstra and Jones test is not generally compatible with the definition of Granger causality; therefore, it may overreject the null hypothesis of non-causality. Diks and Panchenko (2006) introduced a new and alternative test statistic which overcomes these shortcomings.

The empirical literature which employs methods of nonlinear analysis to study causal relations of agricultural commodity prices has become more abundant.

Supported by the National Science Centre under Grant 2013/11/B/HS4/00578 titled "Nonparametric identification and forecasting of nonlinear financial time series".

https://doi.org/10.17221/376/2016-AGRICECON

Such research for grains and meat has been performed by Nazlioglu (2011), Rosa and Vasciaveo (2012), Al-Ayoubi et al. (2014) and Diks and Wolski (2016), but according to our knowledge, none of the previous studies in the literature have analysed nonlinear causality between grains and livestock. Obviously, detecting causal relationships between these commodities provides a strong insight into the mechanism of price formation. However, from a practical point of view, the most important consequence of the presence of causal relationships is the ability to predict a time series. This issue stems directly from the definition of Granger causality, which implies that if Y is a cause of X, then the lagged values of Y may help to predict X. Despite some reservations, among which the most important is the lack of relevance to the structural causality, the concept of Granger causality still remains one of the most widely used methods for the identification of causal relationships. Moreover, it has been widely noted in the literature that a linear approach to causality testing can have low power in the case of nonlinear relationships (Baek and Brock 1992; Hiemstra and Jones 1994; Bekiros and Diks 2008). The fact that many financial and economic time series exhibit significant nonlinear features strongly implies that nonlinear causality tests should be included in the analysis. Otherwise, important characteristics of the investigated relationships which potentially could be exploited to build an effective predictor might be omitted. For this reason, the results of this study might be interesting not only for scientists but also for producers, consumers, governments as well as for speculators.

In this research, we analyse three selected grains: corn, soybean and wheat as well as two selected livestock commodities: live cattle and lean hogs. The criteria for the selection of grains included not only their close relationship to the livestock market, but also their large production volumes. The above-mentioned livestock commodities were selected due to their leading position in the livestock market, and due to the fact that they are listed on the futures market. Futures contracts from the CME Group (Chicago Mercantile Exchange & Chicago Board of Trade) were investigated (there is no futures contract for broilers on this exchange).

We applied two nonlinear causality tests, namely the Hiemstra and Jones test and the Diks and Panchenko test. Despite the shortcomings of the Hiemstra and Jones test which were mentioned above, both tests were applied to check the robustness of the obtained results. Firstly, we tested for Granger causality in the daily log returns of the investigated series. Next, in order to determine the nature of the detected relationships, the log returns filtered with the use of VAR and BEKK models were analysed, too. By removing linear dependencies with a VAR model, one can verify whether the detected relationships are nonlinear. Also, the application of a BEKK model allows investigation of whether they arise from second moment dependencies.

The article draws two major conclusions. Firstly, strong nonlinear causal relationships between grain and livestock returns were found, which had not yet been documented in the literature on the subject. Secondly, different patterns and features of relationships were identified. In some cases, they arise from the second moment dependencies but nonlinearities of a different type were also found. Strong nonlinear relationships exist between livestock returns and both corn and wheat returns. On the other hand, the results indicate the lack of causality between soybean and livestock. Most discovered nonlinear relationships are bidirectional.

LITERATURE REVIEW

Information on factors affecting market conditions and prices for grains and livestock commodities has become more important as farming has become more market-oriented under agricultural policy changes during the last 20 years. A connection between grain and livestock prices is expected, especially nowadays when an increased level of integration can be observed in agriculture. Corn, wheat and soybean are crucial elements of relationships between various crops and between crops and livestock within the agricultural sector. Each competes with other crops for land in farmers' production decisions, e.g., corn with soybean in the Corn Belt and wheat with barley in the Northern Plains. Moreover, corn is a major component of livestock feed. Obviously, its use as feed is closely related to the number of animals (especially cattle, hogs and poultry) that are fed corn. However, the amount of corn used for feed also depends on this crop's supply and price, the amount of supplemental ingredients used in feed rations and the supplies and prices of competing ingredients. Cattle are not huge consumers of soybean but hogs are one of the biggest soybean-meal consumers (the second after broilers). Some wheat is also used for

https://doi.org/10.17221/376/2016-AGRICECON

feed, particularly in the summer, when wheat prices are seasonally low following the wheat harvest but before new crops of corn and sorghum are harvested (Westcott and Hoffman 1999).

We can anticipate that, when grain prices are increasing, livestock prices will follow, sooner or later. How long this takes depends on the lifespan of animals, but more important is perhaps the flexibility of the industry and its ability to respond to increases in feed costs. When producers face higher grain prices, they might not make adjustments to production. They are required by contracts to deliver livestock continuously and livestock prices might not be strongly linked to grain prices, but to other price arrangements made with the packer (Tegle 2013). The influence of feed prices on livestock prices should also depend on the share of feed costs in the total expenses of the farm. This ratio is more than two times higher for hog farms (44%) than for cattle farms (21%) (Census of Agriculture 2007). The larger the share of feed cost in total expenses, the more responsive livestock prices should be to changes in grain prices. The opposite relationship, i.e., an influence of livestock prices on grain prices also makes economic sense. An increase in the demand for meat can cause the rise of its prices. It can induce an increase in meat supply and consequently a rise in the demand for grain feed and, as a result, a rise in grain prices.

Dynamic regression models like the vector autoregression (VAR) and vector error correction (VEC) models have become dominant in empirical studies on agricultural price transmission. In particular, VAR models provide the basis for Granger causality tests between stationary processes. If the investigated processes are cointegrated, causality testing should not be based on VAR models but rather on VEC models. Otherwise, the outcomes may be significantly skewed towards the detection of causality (Bekiros and Diks 2008). In the case of grain and meat prices such tests have been conducted within numerous studies (Tejeda and Goodwin 2011; Pozo and Schroeder 2012; Xu et al. 2012). In general, the obtained results can be regarded as ambiguous. They depend not only on the processes being studied but also on the period of time for which the analysis is conducted.

It should be emphasised, however, that testing for Granger causality based on VAR or VEC models is aimed at detecting only linear relations. Concentrating solely on linear dependencies may lead to the exclusion of important properties of investigated dependencies which potentially could be effectively used in modelling and forecasting. Therefore, in modern econometrics, interest in the analysis of nonlinear time series is growing. The results of empirical studies confirm that many financial and economic time series are nonlinear. These nonlinearities arise in both the dynamics of the individual series and the relations between two or more times series. Nonlinear analysis seems to be a promising field also in the context of agricultural commodity prices. The application of nonlinear analysis can be justified by the fact that agricultural data often have features typical for nonlinear time series, such as the non-normality of distributions, non-stationarity, long term dependence and non-periodical cycles (Kovács et al. 2013). There are some sources of potential nonlinearity in such data. The first is the time-varying volatility, which is often related with volatility spillovers. The time-varying volatility is revealed by the fact that large fluctuations of agricultural prices tend to be followed by other large changes and small price changes tend to be followed by other small fluctuations. Secondly, it is reported that natural animal population dynamics are capable of giving rise to complex (i.e., nonlinear) behaviour in livestock markets (Holt and Craig 2006). Thirdly, nonlinearity may be induced by considerable technological innovations in agricultural production. Moreover, the inability of competitive speculators to hold negative inventories which causes the asymmetry in storage behaviour should also be noted. In turn, this asymmetry results in the nonlinear dynamics of price processes. The next source of asymmetry in the behaviour of market participants is the inherent biological nature of livestock production – it is far easier to sell breeding stock when expected profits are low than it is to rebuild breeding herds when expected profits are large (Holt and Craig 2006). Furthermore, the asymmetric response of one price to another implies nonlinearity of price transmission. One can mention also other sources of this asymmetry, such as policy changes in commodity markets, inventory holding behaviours of farmers and governments and different reactions to changes in input costs (Nazlioglu 2011). There exists now a large body of empirical literature wherein methods of nonlinear analysis are applied to agricultural commodity prices. The conducted studies often confirm the nonlinear character of such series. In particular, the nonlinear dynamics of individual series were detected in the case of grain or meat data (Kohzadi and Boyd 1995; Chatrath et al. 2002). Nonlinear Granger causality has been also investigated among these series in the

https://doi.org/10.17221/376/2016-AGRICECON

literature. Nazlioglu (2011) tested nonlinear causality between oil and three agricultural commodities – corn, soybean and wheat. He found that there are nonlinear feedbacks between oil and agricultural prices. Rosa and Vasciaveo (2012) studied relationships between series of wheat, corn, soybean and crude oil. Their findings provide evidence of strong nonlinear relationships among some of the investigated commodities. Nonlinear relationships between crude oil and wheat were also analysed by Al-Ayoubi et al. (2014). They confirmed the existence of nonlinear feedbacks between both commodities. Diks and Wolski (2016) proposed a new test to detect nonlinear causality in multidimensional data and implemented it to investigate the causal relationships between corn, beans and wheat, conditioning on the weather forecasts. Their results indicate that the grain market exhibits nonlinear relationships.

TESTS FOR NONLINEAR GRANGER CAUSALITY

In the nonlinear framework the most general definition of Granger causality should be addressed (Granger 1980). It is expressed in terms of conditional probability distributions. For a strictly stationary bivariate stochastic process $\{(X_t, Y_t)\}$, it is said that X_t does not Granger-cause Y_t if

$$F(Y_t|(X_{t-1}, X_{t-2}, \ldots; Y_{t-1}, Y_{t-2}, \ldots)) = F(Y_t|(Y_{t-1}, Y_{t-2}, \ldots)) \quad (1)$$

where F denotes the conditional cumulative distribution function. When condition (1) is not satisfied it is said that X_t is a Granger cause of Y_t (denote: $X \rightarrow Y$).

In practice, conditioning on the infinite past is impossible. Therefore, in causality testing, one assumes that the order of the process is finite so the null hypothesis of noncausality takes the following form:

$$F(Y_t|(X_{t-1}, \ldots, X_{t-lx}; Y_{t-1}, \ldots, Y_{t-ly})) = F(Y_t|(Y_{t-1}, \ldots, Y_{t-ly})) \quad (2)$$

for the given lags $lx \geq 1$, $ly \geq 1$.

Baek and Brock (1992) proposed a statistical method for detecting nonlinear Granger causality based on the concept of the correlation integral, which is a measure of the local spatial correlation of a time series. Hiemstra and Jones (1994) modified this method by relaxing assumptions of independent and identically distributed series and mutual independence. Diks and Panchenko (2006) pointed out that the Hiemstra and Jones test (H-J test) is not generally compatible with the definition of Granger causality; therefore, it may overreject the null hypothesis of non-causality. They introduced a new and alternative test statistic (D-P test) which overcomes these shortcomings (Diks and Panchenko 2006).

The H-J and D-P tests are the most popular methods for detecting nonlinear causal relationships and are still frequently used today (Alzahrani et al. 2014; Bekiros 2014; Bampinas and Panagiotidis 2015). It should be emphasised that both tests are nonparametric, which means that the null hypothesis of noncausality is tested against an unspecified alternative. This has important advantages: it eliminates possible problems resulting from model misspecification and allows detection of causal relationships of a different kind – linear and nonlinear ones. On the other hand, a disadvantage of such an approach is that after the rejection of the null hypothesis there is no information on the functional form of the detected relationship. However, this shortcoming may be overcome by applying the test not only to the raw data but also to data filtered using the models of specific types. If the null hypothesis of noncausality is not rejected for the residuals from the specific model, it means that this model can be used to describe the analysed dependencies. Such a procedure can determine not only whether causal relationships exist but can also show how to model them. For example, in order to determine if the existed dependencies are truly nonlinear, the H-J and D-P tests should be applied to data filtered using a linear model, e.g., the vector autoregressive (VAR) model or in the case of cointegrated series – the vector error correction (VEC) model (Bekiros and Diks 2008). Moreover, a multivariate GARCH model like the BEKK (p, q) model can be applied in order to analyse whether the causal relationships between investigated processes arise from second moment dependencies.

DATA AND PRELIMINARY RESULTS

The investigated data concerned three selected grains: corn, soybean, wheat as well as two selected livestock commodities: live cattle and lean hogs. Futures contracts from the CME Group were investigated. In each case the nearby contract was considered, as it was rolled over as soon as the current contract expired. The period after the US financial crisis, i.e., from January 4, 2010 to February 6, 2015 was analysed

https://doi.org/10.17221/376/2016-AGRICECON

Table 1. Contemporaneous correlation coefficients for returns

Commodity	Corn	Soybean	Wheat	Cattle	Hogs
Corn	1.000	0.562*	0.676*	0.125*	0.052
Soybean		1.000	0.473*	0.075*	0.037
Wheat			1.000	0.113*	0.045
Cattle				1.000	0.284*
Hogs					1.000

*indicates that the null of zero correlation is rejected at the 0.05 level

(we wanted to avoid turbulent periods of financial crisis and the 2007–08 world food price crisis). The sample consisted of 1285 daily closing prices.

At the beginning, for all price series the Ng-Perron unit root test and the KPSS stationarity test were conducted. The results indicate that processes of all the commodities are integrated of order one. The Engle-Granger and Johansen cointegration tests were applied to test for common stochastic trends. According to the results, there is no long-term relationship between grain and livestock prices both for all the pairs and also for five commodities together (the outcomes of unit root, stationarity and cointegration tests are not presented to save space, but they are available from the authors upon request).

In view of the obtained results, daily log returns were calculated. Table 1 reports the contemporaneous correlation matrix for the investigated commodities. Since Granger causality refers to lagged relations (Equation 1), such correlation does not say anything about causal relations. As was expected, strong correlations were detected between all the grain returns. Moreover, we can observe a lower but also highly significant correlation between cattle and hog returns. The correlations between grain and livestock commodities are substantially lower and significant at the 0.05 level only for cattle.

Table 2. Results of the test of linear Granger causality

Bivariate VAR models				Lags of VAR
Corn→cattle	**0.030**	Cattle→corn	**0.015**	4
Soybean→cattle	0.158	Cattle→soybean	0.132	4
Wheat→cattle	**0.010**	Cattle→wheat	**0.041**	3
Corn→hogs	0.779	Hogs→corn	0.175	4
Soybean→hogs	0.818	Hogs→soybean	0.771	1
Wheat→hogs	0.305	Hogs→wheat	0.225	1
Five-variate VAR model				
Corn→cattle	0.568	Cattle→corn	**0.049**	5
Soybean→cattle	0.572	Cattle→soybean	0.345	
Wheat→cattle	0.305	Cattle→wheat	0.093	
Corn→hogs	0.323	Hogs→corn	0.527	
Soybean→hogs	0.851	Hogs→soybean	0.904	
Wheat→hogs	0.483	Hogs→wheat	0.646	

P-values are reported, the values not greater than 0.05 are bolded; VAR – vector autoregression

Next, seasonality was removed from the mean and variance of the data using the procedure outlined in Gallant et al. (1992). In this way, month-of-the-year effect is removed from the data. In the analysis performed in the next section the seasonally adjusted log returns were used.

RESULTS OF THE GRANGER CAUSALITY TESTS

We considered two approaches. The first one concerns the examination of the relationships for each pair of commodities, i.e., one grain and one meat. In the second one, all five commodities were analysed together. It can be assumed that the latter approach may be preferable since it accounts for the possible effect of the other variables.

At the beginning, linear Granger causality (the Wald variant) was tested separately in the bivariate and five-variate VAR models. The numbers of lags were determined using the Schwarz information criterion, additionally taking into account that the residuals of the selected VAR model should not have any significant cross-correlations. The results are given in Table 2. As can be seen, we either detected a lack of linear causality relationships or the existence of only weak ones between grain and livestock returns.

Nonlinear Granger causality between the commodities was verified using the H-J and D-P tests (both tests were applied to gain more reliable and definitive results) in three steps. In the first step, the tests were applied to the raw data, i.e., seasonally adjusted log returns. These results indicate whether causal relationships exist, but do not elucidate the nature of these relations. For this reason, two other steps were considered in the research. In the second step, the tests were applied for the residuals from the VAR models. Since the rejection of the null hypothesis for such residuals means that the detected causality is nonlinear, this filtering enables control of the linear interdependencies among the commodities. In the third step we further filtered the residuals from the VAR models using the BEKK (1,1) models and used the H-J and D-P tests for the standardised residuals

https://doi.org/10.17221/376/2016-AGRICECON

Table 3. Results of the test of nonlinear Granger causality for corn↔cattle and corn↔hogs

Relation	*Corn→cattle*				*Cattle→corn*				*Corn→hogs*				*Hogs→corn*			
Lags $lx = ly$	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Seasonally adjusted log returns																
H-J test	0.306	0.290	0.058	**0.017**	0.221	**0.028**	**0.034**	0.071	**0.007**	**0.013**	**0.031**	**0.013**	0.692	0.125	**0.045**	0.065
D-P test	0.279	0.294	0.060	**0.025**	0.202	**0.026**	**0.033**	0.100	**0.008**	**0.014**	**0.043**	**0.022**	0.680	0.167	0.060	0.103
Residuals from the bivariate VAR model																
H-J test	0.154	0.329	**0.027**	**0.017**	0.164	**0.020**	**0.028**	**0.050**	**0.005**	**0.007**	**0.021**	**0.027**	0.710	0.148	0.079	0.135
D-P test	0.155	0.361	**0.035**	**0.025**	0.178	**0.022**	**0.029**	0.068	**0.006**	**0.008**	**0.030**	**0.038**	0.721	0.214	0.118	0.206
Residuals from the bivariate BEKK model																
H-J test	0.592	0.847	0.426	0.400	0.307	0.186	0.414	0.609	**0.015**	**0.025**	0.082	0.162	0.858	0.378	0.316	0.388
D-P test	0.605	0.852	0.524	0.528	0.310	0.186	0.359	0.595	**0.018**	**0.028**	0.099	0.147	0.869	0.416	0.378	0.470
Residuals from the five-variate VAR model																
H-J test	0.159	0.401	**0.029**	**0.033**	**0.222**	**0.022**	0.061	0.094	**0.031**	**0.038**	0.150	0.174	0.855	0.227	0.141	0.234
D-P test	0.149	0.438	**0.039**	0.059	0.218	**0.024**	0.071	0.119	**0.037**	**0.040**	0.175	0.171	0.910	0.311	0.184	0.303
Residuals from the five-variate BEKK model																
H-J test	0.179	0.163	0.496	0.417	0.443	0.294	0.447	0.833	0.251	0.271	0.092	0.142	0.996	0.577	0.373	0.583
D-P test	0.181	0.169	0.571	0.515	0.482	0.314	0.432	0.842	0.275	0.291	0.077	0.192	0.997	0.637	0.386	0.555

P-values are reported, the values not greater than 0.05 are bolded; D-P test – Diks and Panchenko test; H-J test – Hiemstra and Jones test; VAR – vector autoregression;

from BEKK models. In this way, we can examine if the detected nonlinear causality arises from second moment dependencies.

In all the cases, the H-J and D-P tests were applied to standardised data. Four values of lags, $lx = ly = 1, 2, 3, 4$ and a distance measure equal to 1.5 were considered in the analysis (Baek and Brock 1992; Hiemstra and Jones 1994; Diks and Panchenko 2006). Following the advice of others, we implemented a right-tailed version of both tests (Hiemstra and Jones 1994; Diks and Panchenko 2006). The obtained results are presented in Tables 3–5. Each cell in the tables contains

Table 4. Results of the test of nonlinear Granger causality for soybean↔cattle and soybean↔hogs

Relation	*Soybean→cattle*				*Cattle→soybean*				*Soybean→hogs*				*Hogs→soybean*			
Lags $lx = ly$	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Seasonally adjusted log returns																
H-J test	0.575	0.767	0.682	0.208	0.112	0.064	0.388	0.236	0.283	0.465	0.692	0.805	0.772	0.262	0.577	0.631
D-P test	0.611	0.727	0.633	0.233	0.131	0.070	0.436	0.287	0.253	0.450	0.687	0.742	0.788	0.272	0.651	0.657
Residuals from the bivariate VAR model																
H-J test	0.574	0.829	0.601	0.119	0.067	0.051	0.473	0.168	0.276	0.455	0.654	0.814	0.749	0.275	0.605	0.623
D-P test	0.613	0.839	0.612	0.133	0.076	0.054	0.555	0.181	0.247	0.435	0.648	0.778	0.761	0.289	0.681	0.668
Residuals from the bivariate BEKK model																
H-J test	0.641	0.911	0.800	0.459	0.122	0.075	0.476	0.296	0.414	0.681	0.836	0.938	0.949	0.547	0.816	0.879
D-P test	0.688	0.909	0.831	0.530	0.129	0.083	0.471	0.270	0.393	0.643	0.827	0.915	0.946	0.519	0.839	0.898
Residuals from the five-variate VAR model																
H-J test	0.520	0.663	0.354	0.057	0.078	0.072	0.426	0.126	0.250	0.423	0.758	0.938	0.712	0.408	0.719	0.740
D-P test	0.568	0.688	0.374	0.074	0.089	0.085	0.530	0.174	0.235	0.375	0.768	0.931	0.702	0.404	0.739	0.744
Residuals from the five-variate BEKK model																
H-J test	0.523	0.806	0.833	0.425	0.102	0.177	0.613	0.677	0.489	0.818	0.954	0.963	0.860	0.613	0.838	0.672
D-P test	0.517	0.800	0.840	0.458	0.130	0.187	0.643	0.719	0.470	0.809	0.956	0.944	0.856	0.582	0.801	0.596

P-values are reported, the values not greater than 0.05 are bolded; D-P test – Diks and Panchenko test; H-J test – Hiemstra and Jones test; VAR – vector autoregression;

https://doi.org/10.17221/376/2016-AGRICECON

Table 5. Results of the test of nonlinear Granger causality for wheat↔cattle and wheat↔hogs

Relation	***Wheat→cattle***				***Cattle→wheat***				***Wheat→hogs***				***Hogs→wheat***			
Lags *lx = ly*	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
	Seasonally adjusted log returns															
H-J test	0.114	**0.009**	**0.000**	**0.000**	**0.006**	**0.000**	**0.000**	**0.000**	**0.035**	**0.014**	**0.004**	**0.016**	**0.002**	**0.001**	**0.002**	**0.007**
D-P test	0.141	**0.014**	**0.001**	**0.000**	**0.006**	**0.000**	**0.000**	**0.002**	**0.038**	**0.017**	**0.005**	**0.028**	**0.001**	**0.001**	**0.003**	**0.013**
	Residuals from the bivariate VAR model															
H-J test	0.124	**0.008**	**0.000**	**0.000**	**0.003**	**0.000**	**0.000**	**0.000**	**0.036**	**0.010**	**0.003**	**0.013**	**0.004**	**0.003**	**0.003**	**0.006**
D-P test	0.150	**0.013**	**0.001**	**0.000**	**0.004**	**0.000**	**0.000**	**0.001**	**0.037**	**0.012**	**0.004**	**0.025**	**0.004**	**0.003**	**0.004**	**0.010**
	Residuals from the bivariate BEKK model															
H-J test	0.412	0.323	0.130	0.110	**0.012**	**0.003**	**0.008**	0.054	0.097	0.291	0.158	0.465	**0.049**	0.134	0.164	0.235
D-P test	0.422	0.355	0.175	0.138	**0.012**	**0.003**	**0.005**	**0.047**	0.111	0.322	0.163	0.512	0.054	0.152	0.162	0.211
	Residuals from the five-variate VAR model															
H-J test	0.091	**0.008**	**0.000**	**0.000**	**0.005**	**0.000**	**0.000**	**0.000**	**0.033**	**0.011**	**0.005**	**0.019**	**0.005**	**0.003**	**0.003**	**0.011**
D-P test	0.094	**0.014**	**0.001**	**0.000**	**0.006**	**0.000**	**0.000**	**0.001**	**0.031**	**0.011**	**0.006**	**0.028**	**0.004**	**0.003**	**0.004**	**0.018**
	Residuals from the five-variate BEKK model															
H-J test	0.742	0.373	0.108	0.067	**0.028**	**0.017**	**0.036**	0.261	0.084	**0.039**	**0.023**	0.144	**0.044**	0.076	0.077	0.256
D-P test	0.747	0.424	0.182	0.108	**0.030**	**0.016**	**0.042**	0.398	0.090	**0.037**	**0.031**	0.172	**0.046**	0.085	0.090	0.281

P-values are reported, the values not greater than 0.05 are bolded; VAR – vector autoregression; H-J test – Hiemstra and Jones test; D-P test – Diks and Panchenko test

p-values; values not greater than 0.05 mean that the null hypothesis of noncausality is rejected at the 0.05 significance level.

The null hypothesis of noncausality was rejected for most of the seasonally adjusted log returns, except for the following relationships: soybean→cattle, cattle→soybean, soybean→hogs and hogs→soybean. In order to decide whether discovered relationships are truly nonlinear, the results of the tests for the data filtered using linear models should be analysed. The obtained results for the residuals from the bivariate VAR models confirm the nonlinear character of the following relationships: corn→cattle, cattle→corn, wheat→cattle, cattle→wheat, corn→hogs, wheat →hogs and hogs→wheat. It can be noted that most of the discovered nonlinear relationships are bidirectional, i.e., if a certain grain return was the Granger-cause of a livestock return, then at the same time the livestock was the Granger-cause of the grain (such bidirectional relationships make economic sense, as was mentioned in Literature review). This result is interesting since expectations formulated in the literature mainly refer to the influence of grain on livestock. Moreover, it is worth adding that regardless of whether the bivariate or five-variate VAR models were applied in the filtering process, the conclusions about causality are similar.

The results for the standardised residuals from the BEKK models imply that not all of the discovered nonlinearities arise from second moment dependencies. The application of the bivariate BEKK models made it possible to find the nonlinear causality of another type in the relations: cattle→wheat, corn →hogs, hogs→wheat. It should be noted that the usage of the five-variate BEKK model revealed the additional causal relationship of wheat→hogs, but at the same time the relationship corn→hogs was not detected. Therefore, unlike in the case of the VAR models, the usage of the five-variate BEKK model led to some differences in the inference about causality.

The results indicate a lack of causality between soybean and livestock returns. Cattle are not huge consumers of soybean; therefore, such a result was expected in this case. However, for hogs, the results are quite surprising, since hogs are one of the biggest soybean-meal consumers. On the other hand, strong nonlinear relationships exist between livestock returns and both corn and wheat returns. In contrast to wheat, this result is not unanticipated for corn as it is the most important feed input. Although wheat and corn are not direct competitors in the production decisions of farmers, it has been reported that their prices may significantly influence each other (Westcott and Hoffman 1999; Malcolm et al. 2009). As can be seen in Table 1, high contemporaneous correlation (the strongest of all the analysed commodities) exists between the returns of these grains. This statistical relationship probably caused indirect connections

https://doi.org/10.17221/376/2016-AGRICECON

between wheat and livestock returns similar to those between corn and livestock returns, despite the fact that wheat is a small part of the diet of cattle and hogs.

As can be seen, the *p*-values obtained in the H-J test are usually smaller than those from the D-P test. In consequence, in some cases the H-J test rejected the hypothesis of noncausality, while the D-P test failed to do so. This situation may be because the H-J test tends to lead to spurious rejections of the null hypothesis, which has been reported in the literature (Diks and Panchenko 2006).

Moreover, it is worth mentioning that not all of the detected relationships were indicated for the lags $lx = ly = 1$. The exceptions are corn→cattle, cattle→corn, wheat→cattle and hogs→corn. This may suggest that the time lag between the cause and its effect is longer than one day in the case of these four relationships.

CONCLUSION

In this article, nonlinear Granger causality between grain and livestock returns was tested. The relationship between input and output products has always been of interest in agricultural production. However, according to our knowledge, no previous studies have analysed nonlinear Granger causality between grain and livestock returns. It has been widely noted in the literature that a linear approach to causality testing can have low power in the case of nonlinear relationships. Since many financial and economic time series exhibit significant nonlinear features, nonlinear causality tests should be included in the analysis. Otherwise, some important characteristics of the investigated relationships, which potentially could be exploited to build an effective predictor, might be overlooked.

The research futures contracts from the CME Group were analysed for three grains: corn, soybean and wheat and two livestock commodities: live cattle and lean hogs. Two approaches were taken into consideration. The first one concerned the examination of the relationships for each pair of the commodities, i.e., one grain and one meat. In the second one, all the five commodities were analysed together.

The linear Granger causality test was applied and weak evidence of linear causal relationships was found. Therefore, the outcomes of this study have confirmed the results published in other studies. Furthermore, two nonlinear causality tests – the Hiemstra and Jones test and the Diks and Panchenko test – were applied. They were used not only on the raw data but also on data filtered with the use of VAR and BEKK models in order to determine the nature of these relationships. Strong nonlinear causal relationships between grain and meat returns were discovered. These have not yet been documented in the literature. It should be noted that the described relationships exhibit differing patterns and features. In particular, in some cases the detected nonlinearities arise from second moment dependencies. Yet, nonlinearities of a different type were also found. Some pairs of commodities seem to be linked more closely than others. Strong nonlinear relationships exist between livestock returns and both corn and wheat returns. On the other hand, the results indicate a lack of causality between soybean and livestock. Most of the discovered nonlinear relations are bidirectional, i.e., if a certain grain is the Granger-cause of a livestock, then this livestock is the Granger-cause of the grain at the same time.

The dependencies between different classes of commodities are important from the point of view of hedgers, investors and policy makers since knowledge of the directionality of relationships may help them to take effective decisions from the price signals received from these commodities. Our findings provide a much better understanding of the dynamic relationships between grain and livestock returns; therefore, they may be effectively used in the modelling of agricultural markets. Moreover, they may have important implications for market efficiency and predictability. Since the consequence of causal relationships is the ability to predict time series, the presented results show that it is possible to predict livestock returns based on grain returns, and vice versa. This subject can be further examined in future studies on the accuracy of forecasts based on different parametric and nonparametric methods.

REFERENCES

Al-Ayoubi M., Chikhi M., Terraza M. (2014): The dynamic relationship between oil and wheat markets. Applied Economics and Finance, 1: 116–126.

Alzahrani M., Mansur M., Al-Titi O. (2014): Linear and non-linear Granger causality between oil spot and futures prices: A wavelet based test. Journal of International Money and Finance, 48: 175–201.

Baek E.G., Brock W.A. (1992): A General Test for Nonlinear Granger Causality: Bivariate Model. Technical report, Iowa State University and University of Wisconsin.

https://doi.org/10.17221/376/2016-AGRICECON

Bampinas G., Panagiotidis T. (2015): On the relationship between oil and gold before and after financial crisis: linear, nonlinear and time-varying causality testing. Studies in Nonlinear Dynamics & Econometrics, 19: 657–668.

Bekiros S.D. (2014): Exchange rates and fundamentals: co-movement, long-run relationships and short-run dynamics. Journal of Banking & Finance, 39: 117–134.

Bekiros S.D., Diks C. (2008): The relationship between crude oil spot and futures prices: Cointegration, linear and nonlinear causality. Energy Economics, 30: 2673–2685.

Census of Agriculture 2007 (2009): USDA, Summary and State Data, Volume 1, Geographic Area Series, Part 51.

Chatrath A., Adrangi B., Dhanda K.K. (2002): Are commodity prices chaotic? Agricultural Economics, 27: 123–137.

Diks C., Panchenko V. (2006): A new statistic and practical guidelines for nonparametric Granger causality testing. Journal of Economic Dynamics and Control, 30: 1647–1669.

Diks C., Wolski M. (2016): Nonlinear Granger causality: guidelines for multivariate analysis. Journal of Applied Econometrics, 31: 1333–1351.

Gallant R., Rossi P., Tauchen G. (1992): Stock prices and volume. Review of Financial Studies, 5: 199–242.

Granger C.W.J. (1980): Testing for causality: A personal viewpoint. Journal of Economic Dynamic and Control, 2: 329–352.

Hiemstra C., Jones J.D. (1994): Testing for linear and nonlinear Granger causality in the stock price volume relation. Journal of Finance, 49: 1639–1664.

Holt M.T., Craig L.A. (2006): Nonlinear dynamics and structural change in the U.S. hog-corn cycle: A time-varying STAR approach. American Journal of Agricultural Economics, 88: 215–233.

Kohzadi N., Boyd M.S. (1995): Testing for chaos and nonlinear dynamics in cattle prices. Canadian Journal of Agricultural Economics, 43: 475–484.

Kovács S., Huzsvai L., Balogh P. (2013): Investigating the long memory property of the Hungarian market pig prices by using detrended fluctuation analysis. Journal of Agricultural Informatics, 4: 1–9.

Malcolm S., Aillery M., Weinberg M. (2009): Ethanol and a changing agricultural landscape. Economic Research Report No. 86, Economic Research Service, USDA.

Nazlioglu S. (2011): World oil and agricultural commodity prices: Evidence from nonlinear causality. Energy Policy, 39: 2935–2943.

Pozo V.F., Schroeder T.C. (2012): Price and volatility spillover between livestock and related commodity markets. In: Proceedings of Agricultural & Applied Economics Association's Annual Meeting, Seattle, Washington, Aug 12–14, 2012.

Rosa F., Vasciaveo M. (2012): Agri-commodity price dynamics: the relationship between oil and agricultural market. In: Proceedings of International Association of Agricultural Economists Triennial Conference, Foz do Iguaçu, Brazil, Aug 18–24, 2012.

Tegle A. (2013): An explorative study of grain and meat price relationships. [Master thesis.] Norwegian University of Life Sciences, UMB School of Economics and Business, Ås.

Tejeda H.A., Goodwin B.K. (2011): Dynamic price relationships in the grain and cattle markets, pre and post-ethanol mandate. In: Proceedings of Agricultural & Applied Economics Association AAEA & NAREA Joint Annual Meeting, Pittsburgh, Pennsylvania, July 24–26, 2011.

Westcott P.C., Hoffman L.A. (1999): Price Determination for Corn and Wheat: The Role of Market Factors and Government Programs. Technical Bulletin No. 1878, Market and Trade Economics Division, Economic Research Service, USDA.

Xu S., Li Z., Cui L., Dong X., Kong F., Li G. (2012): Price transmission in China's swine industry with an application of MCM. Journal of Integrative Agriculture, 11: 2097–2106.

Received November 14, 2016
Accepted December 19, 2016
Published online April 9, 2018