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Price transmission between maize and poultry product markets in the Visegrád Group countries: What is more nonlinear, egg or chicken?

Sergei Kharin[1], Zuzana Kapustova[2], Ivan Lichner[1]*

[1]Institute of Economic Research, Slovak Academy of Sciences, Bratislava, Slovakia
[2]Faculty of Economics and Management, Slovak University of Agriculture in Nitra, Nitra, Slovakia

**Corresponding author: sergei.kharin@savba.sk*

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Abstract: In this article, we present applied research in the field of price transmission modelling with the generalised additive model. In line with recent studies on nonlinear time series models for price transmission, we introduce a non-parametric technique of generalised additive modelling to provide evidence of nonlinear patterns in price linkages and compare the degree of nonlinearity in price transmission between feed maize and poultry product markets in the Visegrád Group countries. The results of our empirical approach contribute to knowledge about market competitiveness in the Visegrád Group countries and provide information to policymakers.

Keywords: generalised additive model; nonlinearity; poultry markets; time series

Recent volatile price developments have added importance to research focused on price transmission in various markets (e.g. Fang et al. 2023; Khedhiri 2023; Xi et al. 2023; Zhang et al. 2023). In this article, we use the generalised additive model (GAM) framework to analyse in detail the degree of nonlinearities between maize and poultry products (i.e. eggs and meat). The results provide evidence of the cross-product price transmission between the feed maize and poultry markets in the Visegrád Group (V4) countries (i.e. Czech Republic, Hungary, Poland and Slovakia).

Poultry is the second most produced and consumed meat in the European Union (EU) after pork. The EU chicken-meat and egg sector shows some diversity within and between European countries in terms of farm and flock size, yield and type of farming, and it is one of the most intensive farming systems in the EU, with some farms including more than 100 000 birds (Augère-Granier 2019). According to Audran (2022), the EU poultry sector has recently experienced significant difficulties owing to the COVID-19 crisis and outbreaks of highly pathogenic avian influenza. Furthermore, the sector has faced rising production costs since 2022 because of the ongoing war in Ukraine that has directly affected global energy, fertiliser and feed commodity prices (Audran 2023). Currently, the

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EU poultry industry has also been experiencing consequences (e.g. effects on the prices of chicken breast fillets in the EU) from a significant rise in poultry meat imports from Ukraine since trade liberalisation (known as the Autonomous Trade Measures from the EU's May 2022 decision) were instituted and renewed for another year.

Cereal grains such as maize, wheat, sorghum and barley are commonly used in poultry diets as major sources of energy, and maize has been recognised worldwide as a major ingredient for energy in poultry diets (Dei 2017; Khalil et al. 2021). Maize is a versatile, multipurpose crop, and it is used as a feed crop with a varied role as an industrial and energy crop in developed countries. With economic development, the consumption of animal sources of food is accelerating and propelling the demand for maize as feed (Erenstein et al. 2022). High-quality feed is critical if poultry production is to remain competitive and continue to grow to meet the demand for animal protein; therefore, feed is the most important input for poultry production (Ravindran 2013). According to Wongnaa et al. (2023), poultry feed alone accounts for approximately 70% of the total cost of production. Hence, the increase in feed price has been a serious problem in the broiler chicken industry, as it may be implied in the increase in total production cost, thus decreasing profit margins (Sugiharto et al. 2019). Summer droughts across Europe in 2022 caused a drop in cereal production and a rise in prices for animal feed, which affected European poultry production (Bukhta 2022). Moreover, growth in farm-gate cereal prices was recorded in almost all EU Member States because the increase in production costs was determined by more costly farm inputs in recent years, especially in 2021 (Popescu 2022). According to Eurostat, there were three broad drivers of higher agricultural prices in all EU countries in 2022. The first driver was the disruption to global agricultural markets caused by the Russia-Ukraine conflict; Russia and Ukraine have been major exporters of grain, wheat, maize, oilseed and fertilisers. The second driver was the widespread drought across the EU, and the third was other inflationary pressures, not least the cost of energy, as actions were taken to phase out the EU's dependency on Russian fossil fuels at the cost of driving up energy prices.

The last few decades have seen a large increase in academic literature concerning price transmission in agrifood markets. Investigators have performed empirical research on price transmission in the poultry sector for markets across the world by using both nonlinear and linear models. For example, nonlinear adjustments of prices were investigated by Shokoohi et al. (2021), who used a smooth transition autoregressive model to investigate the threshold effect of corn prices on the price of chicken meat in Iran. The results showed that the effect of corn price on chicken price was nonlinear and asymmetric. Aghabeygi et al. (2021) used threshold cointegration to investigate the price transmission dynamics between corn and retail egg prices in Iran and found that any price shocks to corn prices were transmitted to egg prices in the long run. Ben-Kaabia et al. (2005) explored nonlinearity in the price transmission mechanism between farm and feed prices in the Spanish poultry marketing chain. Their methodology was based on a threshold autoregressive model, and the results indicated that price transmission was perfect and that any shocks were fully transmitted to all prices in the system in the long run. However, in the short run, price adjustments between the feed and the farmer levels were fairly symmetric, and there was a cost-push transmission mechanism. Pishbahar et al. (2019) used a Markov switching model and concluded that price transmission was asymmetric; rising prices of production inputs were faster in reaching the price of poultry in Iran than were reductions in the prices of production inputs. In contrast, Caldarelli (2013) assumed linear price transmission and evaluated the dynamics of price transmission between corn and poultry markets in Brazil by using a vector error correction model. The results showed that 40% of the variations in corn prices were transmitted to chicken prices, the price transmission between the markets was unidirectional and the corn price seemed to be weakly exogenous. Arikan et al. (2022) analysed the parameters and factors likely to influence the price of broiler chickens in Turkey and concluded that chicken prices were affected by the raw material prices for feed. Xu et al. (2011) examined the vertical price relationship between upstream and downstream products in China's layer industry chain by using cointegration tests, error correction models and finite distributed lag models, and they found that the influence of corn and feed prices on egg prices was still stronger than that of egg-laying chicken prices. Pessoa et al. (2021) analysed the correlation between chicken, soy and corn prices in Brazil by using detrended fluctuation analysis and detrended cross-correlation analysis. Cross-correlations for temporal scales up to 30 days were not confirmed; however, the results indicated that the correlations between chicken and corn prices were stronger than those between chicken and soy prices at larger

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scales. After the 2008 food crisis, the correlations between the daily series of chicken and corn price returns decreased.

Von Cramon-Taubadel and Goodwin (2021) showed that much of the research on price linkages has reflected methodological advances that have led to increasingly nonlinear time series models. Advances in the empirical literature over the last few years have demonstrated that price relationships in the agrifood chain are highly complex. Most research on nonlinear modelling has relied on parametric methods (Xue et al. 2021; Ridha et al. 2022), but interest has been increasing in nonparametric methods (Guney et al. 2019) and machine learning techniques (Kresova and Hess 2022) to estimate price relationships in agrifood markets. Parametric modelling approaches have been criticised for the choice of functional form and the pattern of the transition process between regimes. In contrast, nonparametric methods offer an analysis of price transmission that is more flexible, having first diminished the assumption of linearity. Several nonparametric techniques are documented in the literature on price transmission between agricultural commodity markets, such as copula-based models (Capitanio et al. 2020), local polynomial regressions (Fousekis 2015), penalised smoothing spline regressions within the framework of GAMs (Guney et al. 2019) and semiparametric single index threshold models (Choe and Goodwin 2022).

Price linkage data can be a real mess that is a hybrid of two patterns: linear and nonlinear. Considering this fact, it is reasonable to conclude that a thorough analysis of price relationships requires more flexibility in the models. GAMs allow much greater modelling flexibility, providing a better fit in the presence of more complicated nonlinear price relationships. One can specify the model in terms of parametric, semiparametric or nonparametric smooth functions rather than detailed parametric relationships. Developments in computational technologies may be helpful in the modelling because GAMs use automatic smoothness selection methods to identify the complexity of the nonlinear price relationships.

Although there has been much research on nonlinear time series models of price linkages, only a few researchers have taken GAMs into consideration. To our knowledge, no prior study investigators have examined agrifood price transmission analysis in the V4 countries with a nonparametric approach. Therefore, there is still a lack of robust research on price transmission in EU agrifood markets by means of the GAM approach, which is a gap that we address in our study.

MATERIAL AND METHODS

We performed price transmission analysis by using monthly observations related to average nominal prices for chickens in euros per 100 kg of carcass weight, eggs per 100 kg of shell weight and feed maize per ton at the wholesale stage from May 2004 to June 2023 in the V4 countries. The source of the price data is the European Commission's agricultural and rural development department (Agri-Food Data Portal 2023). To mitigate price series fluctuations, we used the logarithmic transformation of monthly prices measured in euros per unit.

We began our study with preliminary tests for the purpose of identifying time series properties followed by the appropriate model specification. First, we performed unit root tests for each of the time series of logarithmic prices – namely, the sieve bootstrap augmented Dickey-Fuller test (Smeekes 2013). We used the bootUR package in R, written by Smeekes and Wilms (2022). Classical unit root tests, such as the augmented Dickey-Fuller test (Dickey and Fuller 1981), rely on asymptotic inferences and can produce potential size distortions. For this reason, bootstrap unit root tests have become a commonly used alternative to asymptotic inferences (Smeekes and Wilms 2022). The bootstrap approximates the exact distribution of the test statistic by repeatedly drawing new samples from the original sample, thus capturing the features of the price series. The bootstrap unit root tests have accurate size properties under very general conditions.

To select the maximum lag, we used the ad hoc rule suggested by Schwert (1989). The optimal lag order was determined in accordance with the modified version of the Bayesian information criterion (Ng and Perron 2001).

As previously mentioned, a linear pattern may not be appropriate in most cases of price development, even though the assumption of linearity may hold over short periods. Some nonlinear effects can be accommodated in linear models by using polynomials of different orders, dependent variable transformations or regime switching dummies. However, issues persist in specifying the functional form of more complex price relationships and interpreting the results of modelling. GAM has been proposed as an alternative without the necessity of prespecifying the functional form of complex nonlinear relationships. GAM is an extension of the linear model that allows us to maintain interpretability and model nonlinear effects. GAMs are particularly useful for exploratory data analysis

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to allow the data to ‚speak for themselves' (Yee 2015). GAMs have been introduced by Hastie and Tibshirani (1990) and extended further by Reiss and Ogden (2009) and Wood (2004, 2008, 2011, 2013).

GAMs are nonparametric extensions of the generalised linear model (GLM) and can be formally written as follows:

$$g\left[E\left(y_i\right)\right]=\alpha+\sum\nolimits_{i=1}^{k}\left(\beta_i x_i\right)+\sum\nolimits_{j=1}^{m} f_j\left(x_{k+j}\right)+\varepsilon_i \qquad (1)$$

$\varepsilon_i \sim N(0, \sigma^2 I)$

where: $g(\bullet)$ – monotonic function that links the expected value $E(y)$ to the predictors $x_1, x_2 \dots x_{i+j}$ (identical in our study); α – intercept; $f_j(\bullet)$ – smoothing, nonparametric functions of the covariates. The smoothing function f is composed of the sum of base functions b and their corresponding regression coefficients – that is, formally, $f(x)=\sum\nolimits_i b_i\left(x\right)\beta_i$. The model may include smoothing functions alone or jointly with linear terms $\left(\sum\nolimits_i \beta_i x_i\right)$.

The standard coefficients in linear regression are replaced by nonparametric relationships, modelled by smoothing functions in GAM. GAMs are semiparametric because the probability distribution of the dependent variable is specified (e.g. economic variables follow mostly normal distributions), whereas smoothing functions $\sum\nolimits_j f_j\left(x_j\right)$ are nonparametric (e.g. thin plate regression splines). The main advantage of GAMs is that they can deal with highly nonlinear relationships between the dependent variables and the predictors without the necessity of transforming variables or using polynomial terms.

Furthermore, smoothing functions are based on splines, special mathematical functions defined as piecewise low-degree polynomials (called basis functions), joined at points called knots. The smoothing spline is a sum of weighted basis functions evaluated at the values of the data. Splines have variable stiffness. In our study, we used penalised regression splines based on eigenvalues approximation to thin plate splines (TPSs). Unlike other methods, thin plate regression splines do not involve the problem of choosing knot positions or selecting basis functions. Moreover, they can deal with any number of predictors (Wood 2006). To build the model, we used the mgcv package in R, written by Wood (2022).

GAM can be estimated with penalised likelihood maximisation (corresponding to penalised least squares in our study) by minimising the loss function as follows:

$$\sum_{i=1}^{N}\left[y_i-f\left(x_i\right)\right]^2+\lambda J\left(f\right)$$
$$J\left(f\right)=\int_R f''\left(x\right)^2\,dx \qquad (2)$$

where: $\lambda J(f)$ – penalty term, containing penalisation smoothing parameter λ, which is used to regularise the spline smoothness (in a trade-off between the smoothness and distortions of the estimated smoothing function).

The $J(f)$ penalty function equals the integral of the squared second derivative over the interval (a one-dimensional TPS in our study). Accordingly, the more curves there are, the higher the penalty.

As a next step, we chose the optimal smoothing parameter by using the cross-validation technique. Parameter λ is determined by the minimum generalised cross-validation score [Equation (3)].

$$\upsilon_\lambda=\frac{n\sum\nolimits_{i=1}^{n}\left[y_i-\hat{f}\left(x_i\right)\right]^2}{\left[tr\left(I-A\right)\right]^2} \qquad (3)$$

where: $\hat{f}(x)$ – estimate fitted to all the data; tr – trace of the matrix; I – identity matrix; A – projection matrix; that is, the influence matrix $X(X^TX+S)^{-1}X^T$ with a penalty matrix $S=\sum\limits_j \lambda_j S_j$.

As mentioned, the GAM is fitted by penalised least squares or, more precisely, penalised iteratively reweighted least squares (IRLS). In a linear model, we can estimate the regression parameter by using ordinary least squares (OLS) as $\hat{\beta}_{ols}=(X^TX)^{-1}(X^Ty)$. In this case, we have errors with means of zero and constant variance, that is, $\varepsilon \sim N(0, \sigma^2 I)$. However, if the relationship between dependent and independent variables is not linear, OLS errors have an inconstant variance, that is, $\varepsilon \sim N(0, C)$. One solution could be to use weighted least squares; that is, $\hat{\beta}_{wls}=(X^TC^{-1}X)^{-1}(X^TC^{-1}y)$. However, it is not possible to use this solution for the GLM type because of the use of the link function (the y variable of a GLM is different from the predicted variable). To overcome the aforementioned issue, we can use the IRLS algorithm when the parameters are estimated by iterating estimates over specific recursive relationships. Given that GAMs are just semiparametric GLMs, a penalised version of the IRLS method is applicable to them. Therefore, GAM coefficients can be obtained as $\hat{\beta}_{P-IRLS}=(X^TX+S)^{-1}X^Ty$.

The interpretation of GAM results is based mainly on the effective degrees of freedom (*EDF*). To measure GAM flexibility, the EDF are calculated as the

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trace of the projection matrix, that is, $tr(A)$. Unlike the degrees of freedom in a linear regression, the *EDF* of the GAM are estimated and interpreted in a different manner. In standard regression fitted by OLS, the model degrees of freedom equal the number of non-redundant free terms in the model, which is not applicable with GAMs because of the penalised estimation. Because the number of free parameters in GAMs is difficult to define, the *EDF* are instead related to the smoothing parameter λ, such that, from Equation (3), the greater the penalty is, the smaller the *EDF*. Higher values of *EDF* imply more complex, wiggly splines. In other words, a smaller roughness penalty corresponds to a higher *EDF* and a lower smoothing parameter value. *EDF* values close to 1 suggest that the price relationship effect is almost equivalent to that in the linear vector autoregression (VAR) model. Accordingly, a nonlinear effect can be revealed if the values of EDF are greater than 1. In a theoretical sense, *EDF* vary from zero to infinity.

The price development in the V4 countries during the period from 2004 to 2023 is shown in Figure 1, which shows some patterns of cross-commodity price transmission. Moreover, some nonlinear relationship patterns are also visually apparent, and using the GAM approach to capture potential nonlinearities seems to be appropriate. The parametric intercept is worth including in the model.

To describe the basic features of the price series, we summarised descriptive statistics in Table 1. Considering the data in the table, it is reasonable to conclude that egg prices in the V4 countries were almost identically dispersed around the mean value, whereas the coefficient of variation for chicken prices was higher in Poland and lower in Slovakia. Feed maize prices were more dispersed in Hungary and less dispersed in Poland. The distributions had a tail on the right side, and the skewness coefficient values were positive. In addition, the egg price distribution had a sharper peak than did the chicken and maize price distribu-

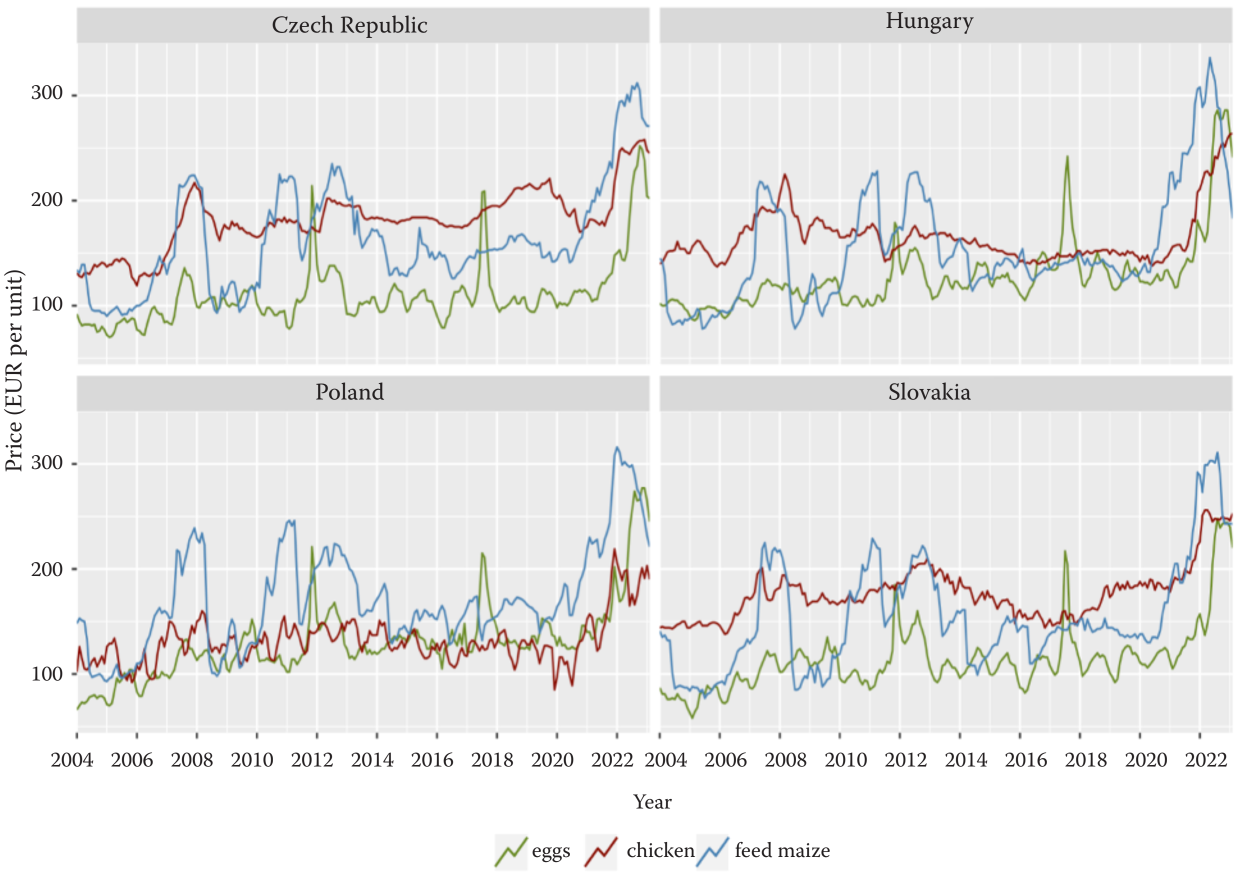

Figure 1. Price development for poultry products and feed maize in Visegrad group countries from May 2004 to June 2023

Source: European Commission's agricultural and rural development department (Agri-Food Data Portal 2023)

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Table 1. Descriptive statistics for the monthly price series over the period of May 2004–June 2023

Country	*N*	Mean	SD	Min	Max	Median	*CV*	*IQR*	Skewness	Kurtosis
Eggs										
CZ	230	110.28	31.32	70	252	104.0	0.28	21.00	2.39	6.67
HU	230	129.17	36.56	86	286	121.5	0.28	28.00	2.59	7.61
PL	230	130.72	37.52	66	277	126.0	0.29	27.00	1.71	4.35
SK	230	114.25	32.93	58	248	109.5	0.29	24.75	2.11	5.73
Chicken										
CZ	230	181.85	28.46	119	258	182.0	0.16	23.75	0.20	0.53
HU	230	164.95	25.14	137	264	157.0	0.15	23.00	1.93	3.91
PL	230	131.60	22.47	85	219	129.0	0.17	20.75	1.23	2.46
SK	230	176.96	25.07	138	256	175.0	0.14	27.75	1.17	1.76
Feed maize										
CZ	230	163.30	50.60	90	312	153.0	0.31	60.00	0.90	0.53
HU	230	154.95	54.23	78	336	141.0	0.35	64.75	1.07	0.91
PL	230	171.08	48.75	93	316	160.0	0.28	57.75	0.75	0.37
SK	230	153.63	51.41	77	311	142.5	0.33	66.50	0.95	0.65

CV – coefficient of variation; *SD* – standard deviation; *IQR* – interquartile range
Source: European Commission's agricultural and rural development department (Agri-Food Data Portal 2023)

tions because the lower the kurtosis coefficient is, the flatter the peak of the data.

After assessing the time series properties of the price data, we fitted GAM in VAR representation with lagged values of logarithmic prices as thin plate regression splines. The specification of the model relates to the egg-feed maize and chicken-feed maize price series of each V4 market.

RESULTS AND DISCUSSION

Taking the methodology we have described into account, we started our analysis by checking the log transformed price series for stationarity. Figure 1 shows that the time series had a changing mean; therefore, the intercept was worth incorporating in the regressions for unit root tests. Furthermore, visual examination of the price series suggests that the model for the unit root test should contain a time trend. Our findings are shown in Table 2.

Given the results, we can reject the null hypothesis of nonstationarity for the egg price variables. Testing based on time series in levels had results that showed significance at 5% for Czech Republic, Slovakia and Hungary and 10% for Poland. Similarly, Hungarian chicken and maize price series in levels were stationary as indicated by a 5% level of significance and Polish maize prices in levels as indicated

Table 2. Results of the bootstrap Dickey-Fuller (DF) unit root test

Price series*	Largest root**	Test statistic	*P*-value***
Eggs			
CZ	0.8846	–3.303	0.049
HU	0.8740	–4.989	0.001
PL	0.9143	–3.216	0.075
SK	0.8848	–3.649	0.029
Chicken			
CZ	0.9601	–2.769	0.212
HU	0.9566	–3.342	0.042
PL	0.8968	–2.586	0.443
SK	0.9565	–2.547	0.292
Feed maize			
CZ	0.9626	–2.145	0.515
HU	0.9496	–3.257	0.043
PL	0.9460	–2.997	0.096
SK	0.9606	–2.137	0.522

*logarithmic prices in levels; **the largest root of the autoregressive lag polynomial, corresponding to the coefficient of the lagged series in the DF regression; ***calculations are made using 1 000 bootstrap replications of size $n = 1.75T^{1/3}$; the deterministic specification contains an intercept and trend, and lag length selection is done with the modified version of the Bayesian Information Criterion (*mBIC*).
Source: Authors' own calculations

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by a 10% level of statistical significance. However, the bootstrap unit root test results showed that the remaining log transformed price variables in levels were not stationary.

Given the different orders of integration of price series and our goal to compare the degree of nonlinearity in price transmission between countries, we fitted models with the GAM approach in VAR representations to capture potential nonlinearities in price relationships. In the empirical literature, there is an issue of whether the variables in a VAR need to be stationary. Investigators in some studies have argued that nonstationary variables can be directly involved in the VAR model without prior transformation into stationary variables (Kilian and Lütkepohl 2017; Guney et al. 2019). In other words, we can estimate the VAR model with raw data. Sims et al. (1990) recommended nonstationary variables against differencing even if ones

Table 3. Penalized GAM model estimates in VAR representation: Czech Republic (CZ)

GAM component	*EDF*	Smoothing parameter λ	*F*-value
Feed maize / eggs: Model 1			
Equation (1) (eggs ~ maize)			
Intercept	1.000	4.67[a]	1 072.000[b]***
$s(E_{t-1})$	7.093	0.0089590	68.270***
$s(E_{t-2})$	4.009	0.0986682	16.990***
$s(M_{t-1})$	3.152	0.5126727	0.715
$s(M_{t-1})$	1.000	35 617 340	1.116
Total *EDF*[c] = 17.254; LR-test of linear VAR *vs*. GAM, test statistic = 2.7629***			
Equation (2) (maize ~ eggs)			
Intercept	1.000	5.05[a]	1 196.000[b]***
$s(M_{t-1})$	1.000	55 125 660	340.400***
$s(M_{t-1})$	1.000	456 093 500	14.360***
$s(E_{t-1})$	1.000	35 874 100	0.669
$s(E_{t-2})$	2.382	1.479	0.497
Total *EDF*[c] = 7.382; LR-test of linear VAR *vs*. GAM, test statistic = 1.2847			
Feed maize / chicken: Model 2			
Equation (1) (chicken ~ maize)			
Intercept	1.000	5.19[a]	3 863.000[b]***
$s(C_{t-1})$	8.392	0.0015132	62.000***
$s(C_{t-2})$	1.000	1 906 041	18.560***
$s(M_{t-1})$	8.372	0.0021545	3.116***
$s(M_{t-1})$	2.590	0.2937383	2.351*
Total *EDF*[c] = 22.354; LR-test of linear VAR *vs*. GAM, test statistic = 4.1035***			
Equation (2) (maize ~ chicken)			
Intercept	1.000	5.05[a]	1 246.000[b]***
$s(M_{t-1})$	1.000	78 969 000	256.530***
$s(M_{t-1})$	1.476	8.800506	4.035**
$s(C_{t-1})$	5.221	0.0503848	1.805*
$s(C_{t-2})$	1.421	1.554928	0.085
Total *EDF*[c] = 11.118;LR-test of linear VAR *vs*. GAM, test statistic = 2.1061**			

[a]estimate for a constant by penalized MLE in place of the smoothing parameter (λ); [b]*t*-value instead of *F*-value; [c]taking the parametric dispersion term into account; *, **, *** $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively; GAM – Generalized Additive model; VAR – Vector Autoregression; *EDF* – effective degrees of freedom; *s* – thin plate splines; *E* – price variable for eggs ; *M* – price variable for feed maize; *C* – price variable for chicken; *t* – time lag; LR – likelihood ratio

Source: Authors' own calculations

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contain a unit root. They argued that the goal of a VAR analysis is to determine the interrelationships among the variables, not to calculate the parameter estimates. The goal in our study was to estimate the degrees of nonlinearity for price relationships in a nonparametric manner compared with OLS estimates of regression coefficients. The main argument against differencing is that it 'throws away' information about the comovements in the data (Enders 2014).

We defined a lag length in accordance with the Schwarz-Bayesian information criteria. We allowed all lagged price variables to have nonlinear effects in price transmission representation. In addition, we incorporated the parametric intercept in the model. We built GAMs with identical link functions. We estimated the GAM models in the VAR model representation with the penalised OLS algorithm described earlier. We fitted the GAMs as the sum of smooth functions

Table 4. Penalized GAM model estimates in a VAR representation: Hungary (HU)

GAM component	*EDF*	Smoothing parameter λ	*F*-value
Feed maize / eggs: Model 1			
Equation (1) (eggs ~ maize)			
Intercept	1.000	4.83[a]	1 438.000[b]***
$s(E_{t-1})$	5.193	0.052013	94.430***
$s(E_{t-2})$	1.000	5 726 361	67.480***
$s(M_{t-1})$	1.000	12 645 590	0.004
$s(M_{t-1})$	1.170	27.15328	0.045
Total *EDF*[c] = 10.363; LR-test of linear VAR *vs*. GAM, test statistic = 1.8673*			
Equation (2) (maize ~ eggs)			
Intercept	1.000	4.99[a]	1 223[b]***
$s(M_{t-1})$	2.531	0.372709	170.800***
$s(M_{t-1})$	3.655	0.149452	15.000***
$s(E_{t-1})$	2.244	0.821625	1.005
$s(E_{t-2})$	2.432	0.755912	0.777
Total *EDF*[c] = 12.862; LR-test of linear VAR *vs*. GAM, test statistic = 2.122**			
Feed maize / chicken: Model 2			
Equation (1) (chicken ~ maize)			
Intercept	1.000	5.09[a]	3 041[b]***
$s(C_{t-1})$	1.000	3 205 013	277.110***
$s(C_{t-2})$	1.000	3 021 120	4.010**
$s(M_{t-1})$	1.105	7.85859	1.714
$s(M_{t-1})$	7.184	0.00854	1.629
Total *EDF*[c] = 12.289; LR-test of linear VAR *vs*. GAM, test statistic = 1.6203			
Equation (2) (maize ~ chicken)			
Intercept	1.000	4.99[a]	1 232.000[b]***
$s(M_{t-1})$	2.488	0.345787	156.290***
$s(M_{t-1})$	4.638	0.065342	9.351***
$s(C_{t-1})$	1.856	2.546939	4.130**
$s(C_{t-2})$	1.000	136 007 200	4.576**
Total *EDF*[c] = 11.982; LR-test of linear VAR *vs*. GAM, test statistic = 1.9016**			

[a]estimate for a constant by penalized MLE in place of the smoothing parameter (λ); [b]*t*-value instead of *F*-value; [c]taking the parametric dispersion term into account; *, **, *** $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively; GAM – Generalized Additive model; VAR – Vector Autoregression; *EDF* – effective degrees of freedom; *s* – thin plate splines; *E* – price variable for eggs ; *M* – price variable for feed maize; *C* – price variable for chicken; *t* – time lag; LR – likelihood ratio

Source: Authors' own calculations

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of the inputs. Unlike with other nonparametric approaches, the significant advantage of GAMs is that they are relatively interpretable, and we were able to estimate the degree of nonlinearity in price relationships. The results are summarised in Tables 3–6.

Tables 3–6 show the GAM estimated parameters for each country—namely, modelling transmissions between feed maize and egg prices as well as feed maize and chicken prices. The *EDF* represent the measure of nonlinearity implied by the responses. They can be interpreted as the intensity of smoothing of a given price variable; consequently, a higher *EDF* value implies more complex splines and more nonlinear price transmission between agrifood market pairs in the V4 countries.

According to Hunsicker et al. (2016), an *EDF* equal to 1 is equivalent to a linear relationship, an *EDF* value range of 1 to 2 can be considered a weakly nonlinear relationship and an *EDF* value exceeding 2 represents

Table 5. Penalized GAM model estimates in a VAR representation: Poland (PL)

GAM component	*EDF*	Smoothing parameter λ	*F*-value
Feed maize / eggs: Model 1			
Equation (1) (eggs ~ maize)			
Intercept	1.000	4.83[a]	1 438.000[b]***
$s(E_{t-1})$	8.135	0.00183486	42.880***
$s(E_{t-2})$	6.087	0.01140409	5.740***
$s(M_{t-1})$	1.000	166 731 500	0.906
$s(M_{t-1})$	1.000	490 071 300	1.753
Total *EDF*[c] = 18.222; LR-test of linear VAR vs. GAM, test statistic = 4.0189***			
Equation (2) (maize ~ eggs)			
Intercept	1.000	5.10[a]	1 239.000[b]***
$s(M_{t-1})$	2.976	0.313448	161.800***
$s(M_{t-1})$	3.191	0.263205	20.770***
$s(E_{t-1})$	1.000	107 561 100	0.032
$s(E_{t-2})$	1.000	57 314 630	0.710
Total *EDF*[c] = 10.167; LR-test of linear VAR vs. GAM, test statistic = 2.0538*			
Feed maize / chicken: Model 2			
Equation (1) (chicken ~ maize)			
Intercept	1.000	4.86[a]	1 120.000[b]***
$s(C_{t-1})$	7.180	0.013849	25.200***
$s(C_{t-2})$	1.000	288 864 500	11.690***
$s(M_{t-1})$	2.843	0.576789	3.890***
$s(M_{t-1})$	1.000	13 602 040	6.530**
Total *EDF*[c] = 14.023; LR-test of linear VAR vs. GAM, test statistic = 3.5024***			
Equation (2) (maize ~ chicken)			
Intercept	1.000	5.10[a]	1 240.000[b]***
$s(M_{t-1})$	3.233	0.236373	128.240***
$s(M_{t-1})$	2.976	0.287582	17.910***
$s(C_{t-1})$	1.000	73 791 560	0.556
$s(C_{t-2})$	5.893	0.038767	1.167
Total *EDF*[c] = 15.102; LR-test of linear VAR vs. GAM, test statistic = 1.9437**			

[a]estimate for a constant by penalized MLE in place of the smoothing parameter (λ); [b]*t*-value instead of *F*-value; [c]taking the parametric dispersion term into account; *, **, *** $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively; GAM – Generalized Additive model; VAR – Vector Autoregression; *EDF* – effective degrees of freedom; *s* – thin plate splines; *E* – price variable for eggs ; *M* – price variable for feed maize; *C* – price variable for chicken; *t* – time lag; LR – likelihood ratio

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a highly nonlinear price relationship. Moreover, the upper values of *EDF* correspond to the smaller smoothing parameters. In our analysis, the largest EDF value of 8.392 for the smoothed individual covariate occurred in the GAM model of price transmission between chicken and maize in the Czech Republic. Above all, most of the nonlinear effects were highly statistically significant, as shown by the *F* statistics in Table 3, so we can conclude that the markets were well integrated.

Analysing the price transmission within the V4 countries, we found that chicken-maize price relationships in the Czech Republic are more nonlinear than are egg-maize price transmission (the sum of total values of *EDF* for Model 1 is 24.363 and for Model 2 is 33.472), whereas the state of play is the opposite in Slovakia (Table 6). By way of contrast to Slovakia, in Poland and Hungary the degree of nonlinearity in the chicken-maize price transmissions was slightly larger than were

Table 6. Penalized GAM model estimates in a VAR representation: Slovakia (SK)

GAM component	*EDF*	Smoothing parameter λ	*F*-value
Feed maize / eggs: Model 1			
Equation (1) (eggs ~ maize)			
Intercept	1.000	4.70[a]	1 169.000[b]***
$s(E_{t-1})$	7.859	0.002925	61.310***
$s(E_{t-2})$	6.458	0.010915	11.700***
$s(M_{t-1})$	1.922	2.589915	0.926
$s(M_{t-1})$	1.000	6 317 920	0.181
Total *EDF*[c] = 19.239; LR-test of linear VAR vs. GAM, test statistic = 4.8508***			
Equation (2) (maize ~ eggs)			
Intercept	1.000	4.98[a]	1 019.000[b]***
$s(M_{t-1})$	1.000	391 180 596	384.730***
$s(M_{t-1})$	1.000	2 511 426 361	23.400***
$s(E_{t-1})$	1.000	131 744 988	0.015
$s(E_{t-2})$	1.000	174 182 310	0.500
Total *EDF*[c] = 6.000; LR-test of linear VAR vs. GAM, test statistic = 0.6066			
Feed maize / chicken: Model 2			
Equation (1) (chicken ~ maize)			
Intercept	1.000	5.16[a]	2 674.000[b]***
$s(C_{t-1})$	4.357	0.053652	37.410***
$s(C_{t-2})$	1.000	3 446 101	0.232
$s(M_{t-1})$	1.000	227 466 400	6.390**
$s(M_{t-1})$	1.000	167 366 100	5.820**
Total *EDF*[c] = 9.357; LR-test of linear VAR vs. GAM, test statistic = 1.7279			
Equation (2) (maize ~ eggs)			
Intercept	1.000	4.98[a]	1 232.000[b]***
$s(M_{t-1})$	1.000	1 230 286 319	367.190***
$s(M_{t-1})$	1.000	1 128 752 669	25.370***
$s(C_{t-1})$	1.000	366 591 273	0.061
$s(C_{t-2})$	1.000	388 568 638	0.580
Total *EDF*[c] = 6.000; LR-test of linear VAR vs. GAM, test statistic = 0.4546			

[a]estimate for a constant by penalized MLE in place of the smoothing parameter (λ); [b]*t*-value instead of *F*-value; [c]taking the parametric dispersion term into account; *, **, *** $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively; GAM – Generalized Additive model; VAR – Vector Autoregression; *EDF* – effective degrees of freedom; *s* – thin plate splines; *E* – price variable for eggs ; *M* – price variable for feed maize; *C* – price variable for chicken; *t* – time lag; LR – likelihood ratio

Source: Authors' own calculations

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the egg-maize chains (*EDF* = 29.125 / 28.389 in Poland, *EDF* = 24.271 / 23.225 in Hungary).

In a cross-country comparison of price transmission, we found that the degree of nonlinearity of the transmission between chicken and maize prices was highest in Czech Republic and lowest in Slovakia. Conversely, in the case of the egg and feed maize markets, the price relationships were most nonlinear in Poland, whereas the remaining countries had almost the same degree of nonlinearity (*EDF* values of the equation systems are 23.2–25.2 in Model 1). In most cases, we showed that the semiparametric GAM representation of price transmission is better than the typical linear VAR model, as evidenced by likelihood ratio test results showing that the test statistics were highly significant in some cases. However, as Table 6 shows, the chicken-maize price transmission on the Slovak market was better described with classic linear regressions than with the nonparametric GAMs.

CONCLUSION

In this study, we used nonparametric generalised additive models to provide evidence of the nonlinear nature of price relationships in the V4 markets, which is consistent with findings from recent studies on nonlinear time series models in agrifood price transmission. The benefit of the GAM approach is that a penalised TPS base is used, which better adapts to price data rather than imposing a concrete functional form. Indeed, concrete functions can be significantly inflexible for complex nonlinear interactions.

The nonlinear GAMs provide a better description of price transmission in the agrifood markets of the V4 countries than does the classic VAR approach. However, the analysis results showed that in the case of Slovakia, typical linear regression was better for modelling price relationships between chicken and feed maize. On the basis of nonparametric modelling, our study fills the gap in the empirical literature on price transmission in EU agrifood markets.

We estimated and compared the degree of nonlinearities in price relationships between and within V4 markets. The price transmission dynamism was contrasted between countries. The most wiggly nonlinear pattern occurred in the Czech maize-chicken and Polish maize-egg price transmissions. Our findings suggest that it is essential to identify market instability and provide farmers and processors with accurate information about the market situation to implement measures to increase market competition and improve price transmission efficiency. Ignoring nonlinearities in the price transmission may result in inaccurate assessment of the effects of policy changes affecting agrifood supply chains. We recommend policymakers from the V4 countries to take into account the magnitude of nonlinearities in the price transmission on the poultry markets while forecasting prices.

Supporting better value chain cooperation could also help to stabilise markets. The other main strategy to stabilise egg-chicken prices is to control feed maize prices. Furthermore, as mentioned earlier, the Russia-Ukraine conflict has recently been the main contributor to higher energy prices; thus, high production costs have become the largest challenge facing the poultry industry in the V4 countries. Therefore, governments should cap energy prices and provide appropriate and effective measures for farmers. In addition, access to adequate compensation should be provided for losses that farmers incur because of a significant increase in imports of poultry from Ukraine while trade liberalisation is in place. However, it is also important that the bureaucracy associated with applications for subsidies be easy to handle. In addition, governments should accept responsibility for regulating the market in case of sudden shocks to demand, such as during the COVID-19 pandemic, when consumption decreased because of quarantine and confinement policies keeping citizens at home and limiting the consumption of poultry meat in schools and other public catering facilities.

Our study provides valuable insights concerning the application of GAM representation of price transmission, but further future research directions could be considered to investigate the studied relationships further. This study can be extended with other spline alternatives and factors to build more flexible GAM models. Among the factors that stand out are market structure, industry characteristics, significance of cross-border trade and policies in the area of the poultry production. Findings of more detailed research could provide important information for decision-making in areas related to market regulations and efficiency.

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