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FOREWORD

Agriculture has always been the backbone of human civilization, providing sustenance, livelihood, and the basis for economic growth. In today's rapidly evolving world, where technology, climate change and changing demographics have a significant impact on agricultural practices, the need for a skilled, informed, and adaptable human capital has never been more urgent. Human capital is, therefore, crucial for finding ways to deal with all the challenges effectively and fulfil the mission of agriculture, both in terms of production and non-production functions.

It is already a tradition that the conference Agrarian Perspectives, reflecting topical issues and trends, takes place every year in September at the Czech University of Life Sciences in Prague. This year's 32nd "Agrarian Perspectives" conference, held on the 6th and 7th of September 2023, is focused on the topic of Human Capital and Education in Agriculture. It aims to point out the importance of human capital for the further sustainable development of agriculture and emphasize the role of education in this process.

The conference intends to contribute to the discussion of what is essential for forming agricultural experts and how scientific disciplines from the fields of economics, management, social and natural sciences can contribute to a better understanding and solving problems that face current agriculture. This traditional event serves as a forum for researchers, educators, practitioners, and policy makers to come together and discuss from different perspectives the significant and sometimes somewhat omitted relationship between human capital and agriculture.

We strongly believe that the conference will create an inspiring environment for all participants and will contribute not only to the scientific knowledge in this area, but also to the deepening of personal contacts and cooperation.

doc. Ing. Karel Tomšík, Ph.D.

Vice-Dean FEM CZU Prague

HOW WIGGLY IS THE PRICE TRANSMISSION BETWEEN PIG MEAT MARKETS IN VISEGRAD COUNTRIES?

Sergei Kharin[1] and Ivan Lichner[2]

[1, 2] Institute of Economic Research, Slovak Academy of Sciences (IER SAS), Slovakia

[1]sergei.kharin@savba.sk, [2]ivan.lichner@savba.sk

Annotation: In the twenty first century horizontal price transmission has become the topic of a great interest in applied microeconomics research in terms of the perspective of understanding on how geographically separated markets function. The paper provides detailed review of applied research in the field of the spatial price transmission modelling. Most popular econometric models are discussed in the light of the main advantages and disadvantages with a special focus on nonlinear techniques. Being in line with the last studies on non-linear time series models of spatial agri-food price transmission and market integration, we introduce non-parametric technique of generalized additive modelling in order to provide evidence of agri-food market integration efficiency and non-linear patterns in price linkages. The results of our empirical approach contribute to the knowledge about market efficiency and competitiveness as well as provide information to policymakers.

Key words: Horizontal price transmission, market integration, nonlinear time series, generalized additive model

JEL classification: Q110, C510

1. Introduction

The spatial separation has led to vast increase in number of studies that are evaluating the price linkages between goods at the same stage of the supply chain with different origin in terms of changes in speed, magnitude and nature. Spatial price transmission and market integration has become the topic of a great interest in applied microeconomics research from the perspective of understanding on how geographically separated markets interact.

The applied analysis of market integration has mostly used models of horizontal price linkages in selected agro-commodities markets. In recent research a wide variety of empirical techniques are used to study spatial price transmission. From conceptual point of view, the literature on the spatial price transmission and market integration in agri-food markets has been categorized into three empirical approaches, namely ”pre-co-integration”, ”co-integration” and ”other” (”post co-integration”) (von Cramon-Taubadel, 2017; von Cramon-Taubadel and Goodwin, 2021).

The first strand of studies characterize the use of spatial correlation coefficients and simple linear regression models for estimating the relationships between agri-food prices in various regions (Ravallion, 1986; Stigler and Sherwin, 1985). However, the correlation analysis does not illustrate the extent to which markets are integrated. Criticism of correlation technique resulted in introduction of linear regression-based approaches.

Second stream of literature on spatial price transmission relies on co-integration technique and error correction modeling. This strand of research is based on assumption that price series tend to move identically over time and have common stochastic trend, i.e. series are co-integrated. In such case, one can obtain super-consistent ordinary least squares estimates for the model parameters. Granger (1981) pointed out, that a vector of non-stationary time series could have linear combinations which are stationary in levels. The co-integration approach introduced by Nobel laureates Engle and Granger in 1987 after British economists Granger and Newbold (1974) published the spurious regression concept. However, there exist some limitations of the Engle-Granger framework which have been addressed in co-integration tests by Johansen (1988), Phillips and Ouliaris (1990), Gregory and Hansen (1996) and Maki (2012). Many latest studies use linear vector error correction model (VECM) of spatial price transmission between agri-food markets in Europe (Penone et al., 2022; Svanidze et al., 2022), in the Asian region (Dong et al., 2018; Thong et al., 2020), in the Southern and Northern American continent (Villanueva, 2022) and in Africa (Martey et al., 2020; Nzuma and Kirui, 2021). Several researchers have previously explored agri-food market integration among Visegrad Group (also known as ”V4”) countries by using VECM approach. For instance, Vargova and Rajcaniova (2018) examined the linkages among the prices of raw cow milk in V4 countries. They found some patterns in price transmission, namely the fastest adjustment speed in Hungarian market as a response to the price shocks of the other countries, Slovak market fast reaction to the price shocks from Poland, the most sensitive reaction in Slovak and Czech markets to the price shocks from Hungary. In like manner, Roman and Kroupová (2022) evaluated spatial processes between Polish and Czech markets based on trade flows and prices for raw milk, butter, skimmed milk powder and Edam cheese. Researchers concluded that the Czech Republic and Poland characterize a long range of linkages that are strong indication of the market integration for the all analyzed products. Apart from VECMs, these authors and other researchers (e.g. Gao et al., 2022) built vector autoregressive models (VAR). In fact, VECM is a restricted VAR model designed to be used with nonstationary price series that are known to be co-integrated. If co-integration exists, then VECM, which combines price variables in levels and differences, should be estimated instead of a VAR in levels. By way of contrast, in academic literature there is an issue of whether the variables in a VAR need to be stationary. Indeed, some studies argued that non-stationary variables can be directly involved in VAR model without prior transformation into stationary ones (Kilian and Lütkepohl, 2017). Given the limitation of VAR-VECMs in the aspect of linearity, further development in spatial agri-food price transmission analysis has been carried out within the framework of regime-dependent models.

Trade arbitrage requires that the prices of related goods move together, but the presence of transaction costs can produce a band-threshold effect, where only deviations above a threshold will have an effect on price movements (Hansen, 2011). A threshold brings nonlinearities into the functional relationships between prices (Tong, 1990). In order to incorporate transaction costs effect, threshold autoregressive (TAR) models in different modifications became widely used, where transaction costs from one agri-food market to another one could be estimated by a threshold parameter (Durborow et al., 2020; Yovo and Adabe, 2022). These models relate to piecewise linear regressions. Closely related to the TAR models are the smooth transition autoregressive (STAR) models, where the patterns of price adjustment are smooth rather than discrete and allow for a continuous transition between regimes (Goodwin et al., 2011).

Balke and Fomby (1997) introduced the threshold co-integration approach, more precisely, a combination of Tong’s TAR model and Engle-Granger’s VECM. Extensions to a threshold VECM have been made by several researchers (e.g. Enders and Siklos, 2001; Hansen and Seo, 2002). The threshold vector error correction model (TVECM) has been substantially influential in agricultural economics research, specifically, spatial price transmission studies

(Kharin, 2019). In the context of modelling regime-dependent price volatility transmissions between agri-food markets, it is worth mentioning about a large number of empirical studies related to asymmetric price transmission that are highly heterogeneous in the sense of type of asymmetries and applied approaches. Analysis of asymmetry in price linkages is important because it provides valuable information on market structure and performance.

Surveys of Frey and Manera (2007) and von Cramon-Taubadel and Goodwin (2021) present a review of the empirical techniques on asymmetric price transmission in agri-food markets. Asymmetric error correction models (AECM) has been reliable enough to be widely used as a tool to estimate spatial price asymmetries and adequately represents price series behavior in the presence of non-stationary and co-integration. In those models the correction of deviations from the long-run equilibrium relationship between price variables switches between regimes depending on whether the deviation from equilibrium is positive or negative.

Indeed, recent literature has progressed to display threshold-type nonlinearity in the error correction of the prices (Alam et al., 2022) instead of linear relationships (Wiranthi, 2021). On the other hand, the AECM hypothesizes that the long-run price relationship is characterized by a symmetric linear combination of nonstationary price variables. According to research from Rezitis (2019), the assumption of a linear long-run equilibrium price relationship may lead to misleading empirical findings in cases where transaction costs (or policy interventions) are significant factors. To identify both long- and short-run asymmetric price transmission between prices, the nonlinear autoregressive distributed lag (NARDL) model introduced by Shin et al. (2014) is widely used. The NARDL model has several advantages over the aforementioned empirical techniques. First, the model is estimable by ordinary least squares and reliable long-run inference can be achieved by bounds-testing, regardless of the integration orders of the variables. In contrast to ECMs, which impose the assumption that all regressors should be integrated of the same order. Second, it allows the joint modeling of asymmetries and co-integration dynamics. Currently, there are a few studies on spatial (Kamaruddin et al., 2021) and vertical (Rezitis, 2019) price transmission by means of NARDL modeling in the agri-food markets.

The third strand of literature on agri-food market integration relies on non-parametric approaches as well as parity bounds models (PBM). The PBM describes spatial price equilibrium in switching regime framework, first introduced by Spiller and Wood (1988), and extended further by Baulch (1997), Barrett and Li (2002). Trade costs are included directly in the PBM unlike VECM-based approach, which only uses data on prices. However, despite the advantages, the PBM has been criticized for some reasons (von Cramon-Taubadel, 2017). In recent years, PBM analysis has received far less attention in the literature unlike co-integration methods, nonetheless there are studies of agri-food market integration based on PBM technique (e.g. Durborow et al., 2020).

In fact, aforementioned parametric modelling approaches have been criticized for the choice of functional form and pattern of the transition process between regimes. In contrast, non-parametric methods offer to analyze price transmission in a more flexible way, having diminished, first of all, the assumption of linearity. Several non-parametric techniques are documented in the literature on spatial price transmission between agro-commodities markets. Only a few works in literature on agri-food market integration demonstrate such methods as copula-based models (Capitanio et al., 2020), local polynomial regressions (Fousekis, 2015), penalized smoothing spline regressions within the framework of generalized additive models (GAM) (Guney et al., 2019) and semi-parametric single index threshold models (Choe and Goodwin, 2022). To our best knowledge, no prior studies have examined spatial agri-food price transmission analysis in Visegrad group countries within non-parametric approach.

2. Data and Methods

Spatial price transmission analysis in this paper is based on weekly observations related to average nominal prices for pigmeat in slaughter weight of the class E at the wholesale stage from May 2004 to February 2023 in the Visegrad group countries. The number of observations equals to 981 that is sufficient and desirable sample to obtain robust results. The source of the price data is the European Commission's agricultural and rural development department.

We begin our study with the preliminary tests for the purpose of identifying time series properties followed by the appropriate model specification. Firstly, we perform unit root tests for each of the time series of logarithmic prices, namely the sieve bootstrap ADF test1 (Smeekes, 2013). Classical unit root tests, such as ADF test (Dickey and Fuller, 1981), rely on asymptotic inference and suffer from potentially size distortions. For this reason, bootstrap unit root tests have become a commonly used alternative to asymptotic inference (Smeekes and Wilms, 2020). The bootstrap approximates the exact distribution of the test statistic by repeatedly drawing new samples from the original sample, thus capturing the features of price series. The bootstrap unit root tests have accurate size properties under very general conditions.

In order to select maximum lag, we apply ad-hoc rule, suggested by Schwert (1989). The optimal lag order is determined in accordance with the modified version of Bayesian Information Criterion (mBIC) (Ng and Perron, 2001).

As a next step, to check the price series and determine the co-integrating rank we use the Johansen procedure (Johansen, 1988) based on maximum likelihood estimation.

As previously mentioned in the section 1, a linear pattern may not be appropriate in most cases of price development, whereas the assumption of linearity may hold only over short periods. Some non-linear effects can be accommodated in linear models by using polynomials of different order, dependent variable transformation or regime-switching dummies. However, there exist some issues related to specifying functional form of more complex price relationships and interpreting the results of modelling. Generalized Additive Model (GAM) has been proposed as an alternative without necessity to pre-specify the functional form of complex non-linear relationships. The GAM is an extension of the linear model in such a way that allows to maintain the interpretability and to model the non-linear effects. The GAMs are particularly useful for exploratory data analysis to allow the data to "speak for themselves" (Yee, 2015). GAMs have resulted from additive models and have been introduced by Hastie and Tibshirani (1990) and was extended further by Reiss and Todd Ogden (2009), and Wood (2004, 2008, 2011, 2013).

GAMs are non-parametric extensions of the generalized linear model (GLM) and can be formally written as:

$$g\big(\mathrm{E}(y_i)\big) = \alpha + \sum_{i=1}^{k}(\beta_i x_i) + \sum_{j=1}^{m} f_j\big(x_{k+j}\big) + \varepsilon_i \qquad \mathbf{(1)}$$

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

where $g(.)$ is a monotonic function that links the expected value E(y) to the predictors x_1, $x_2 \ldots x_{i+j}$ (identical in our study), α is an intercept, the terms $f_j(.)$ denote smoothing, non-parametric functions of the covariates. Smoothing function f is composed by sum of base functions b and their corresponding regression coefficients, i.e. formally $f(x) = \sum_i b_i(x)\beta_i$. The model may include smoothing functions alone or jointly with linear terms ($\sum_i \beta_i x_i$).

The standard coefficients in linear regression are replaced by non-parametric relationships, modelled by smoothing functions in GAM. GAMs are semi-parametric because the probability distribution of the dependent variable is specified (e.g. economic variables follow mostly normal distribution), whereas smoothing functions $\sum_j f_j(x_j)$ are non-parametric (e.g. thin plate regression splines). The main advantage of GAMs is that they can deal with highly non-linear relationships between the dependent variables and the predictors without the necessity to transform variables or use polynomial terms.

In fact, the smoothing functions are based on *splines*, special mathematical functions defined piecewise low-degree polynomials (called basis functions), joined at points called knots. Smoothing spline is a sum of weighted basis functions, evaluated at the values of the data. Splines have variable stiffness. In our study, we use penalized regression splines based on eigen approximation to a thin plate splines (TPS). Unlike others, thin plate regression splines do not suffer from the problem of choosing knot positions or selecting basis functions. Moreover, they can deal with any number of predictors (Wood, 2006).

The GAM can be estimated with penalized likelihood maximization (corresponds to penalized least squares in our study) by minimizing loss function as follows:

$$\sum_{i=1}^{N}(y_i - f(x_i))^2 + \lambda J(f)$$

$$J(f) = \int_{\mathbb{R}} f''(x)^2 dx \qquad (2)$$

where $\lambda J(f)$ is the penalty term, containing λ - penalization smoothing parameter is used to regularize the spline smoothness (trade-off between the smoothness and wiggliness of the estimated smoothing function) and $J(f)$ - penalty function equals to the integral of the squared second derivative over the interval (one-dimensional thin plate spline in our study). Accordingly, the more curves the higher the penalty.

As a next step, we choose optimal smoothing parameter by using cross validation technique. Parameter λ is determined based on the minimum generalized cross-validation score (see *Eq.3*).

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

where $\hat{f}(x)$ is the estimate from fitting to all the data, tr is the trace of matrix, $\boldsymbol{I}$ is the identity matrix and $\boldsymbol{A}$ is the projection matrix, i.e. influence matrix $X(X^T X + S)^{-1} X^T$ with penalty matrix $S = \sum_j \lambda_j S_j$ (Wood, 2004).

As mentioned above, the GAM is fitted by penalized least squares, more precisely penalized iteratively re-weighted least squares (P-IRLS). In a linear model, we can estimate the regression parameter using ordinary least squares (OLS) as $\hat{\beta}_{ols} = (X^T X)^{-1}(X^T y)$. In this case, we have errors with means of zero and constant variance, i.e. $\epsilon \sim \mathcal{N}(0, \sigma^2 I)$. However, if the relationship between dependent and independent variables is not linear, OLS errors have an unconstant variance, i.e. $\epsilon \sim \mathcal{N}(0, C)$. The solution could be using weighted least squares (WLS), i.e. $\hat{\beta}_{wls} = (X^T C^{-1} X)^{-1}(X^T C^{-1} y)$. In fact, it is not possible to apply that for GLM type due to using link function (y-variable of a GLM is different from the predicted variable). In order to overcome the aforementioned issue, we can use the IRLS algorithm, when the parameters are estimated by iterating over specific recursive relationships. Given the fact, that GAMs are just semi-parametric GLMs, penalized version of the IRLS method is applicable to them. Therefore, GAM-coefficients can be obtained as $\hat{\beta}_{P-IRLS} = (X^T X + S)^{-1} X^T y$.

The interpretation of GAM results is mainly based on the effective degrees of freedom (EDF). To measure the GAMs flexibility, the effective degrees of freedom are calculated as the trace of the projection matrix, i.e. $tr(\mathbf{A})$. Unlike the degrees of freedom in a linear regression, the EDF of the GAM are estimated and interpreted in different manner. In standard regression fitted by OLS, the model degrees of freedom equal to the number of non-redundant free terms in model. This is not applicable with GAMs due to the penalized estimation. Since the number of free parameters in GAMs is difficult to define, the EDF are instead related to the smoothing parameter λ, such that from *Eq.3* the greater the penalty, 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 value of smoothing parameter. The EDF with values close to one suggest that price relationships effect is almost equivalent to the one in linear VAR model. Accordingly, a non-linear effect can be revealed if the values of EDF are greater than one. In a theoretical sense, the EDF vary from zero to infinity. After assessing the time series properties of the price data, we fit the GAM in Vector Autoregression (or Vector Error Correction model) representation with lagged values of logarithmic prices as the thin plate regression splines. The specification of the model relates to pair-wise price series of each agri-food market.

3. Results and Discussion

In Figure 1 the price development in Visegrad countries over the period of 2004-2023 is depicted. The observations relate to the weekly prices of pigmeat carcasses at the wholesale stage in Euro per unit. Original prices appear to move synchronously with the common upward trend since the end of 2021. Hence, some pattern of spatial price transmission with potential long-run linkages might be present. Furthermore, some non-linear relationships pattern is also visually apparent.

In order to describe the basic features of the price series, we summarized descriptive statistics in Table 1. Considering the results, it is reasonable to conclude that prices in Czech Republic are less dispersed around the mean value. Compared to other price series, the coefficient of variation is higher for prices in Poland. The standard deviation is rather low, so prices are close to the mean of our samples. The distributions have a right skew and skewness coefficient value is close to zero (as in normal distribution). Additionally, kurtosis is also close to zero (Fisher's definition) but with negative values meaning the flatter peaks and lighter tails than the normal distribution.

Table 1. Descriptive statistics for the weekly price series over the period of May 2004-February 2023

Country	N	Mean	Std.Dev	Min	Max	Median	CV	IQR	Skewness	Kurtosis
CZ	981	154.42	19.24	119.91	216.88	151.43	0.12	27.10	0.62	-0.22
HU	981	156.42	20.34	118.71	225.34	151.96	0.13	26.78	0.72	-0.05
PL	981	150.48	22.64	111.53	227.41	146.81	0.15	34.04	0.58	-0.20
SK	981	158.17	20.42	112.21	218.10	153.39	0.13	28.31	0.63	-0.17

Source: European Commission's agricultural and rural development department

Taking the algorithm described above into account, we start our analysis with checking the log-transformed price series for stationarity. From the Figure 1 time series have a changing mean, therefore intercept worth being incorporated in the regressions for unit root tests. Moreover, visual examination of the price series suggests that the model for unit root test should contain a time trend. (Non)stationarity is detected with the bootstrap version of Dickey-Fuller test. Results are shown in the Table 2. According to the test, the null hypothesis of non-stationarity can be rejected for the price variables. Testing based on time series in levels has revealed significant test statistics at 1 % for Czechia and Poland, 5 % for Hungary, 10 % for Slovakia. Hence, the bootstrap unit root tests show, that log-transformed price variables are stationary in levels, i.e. I(0).

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

Price series*	Largest root**	Test statistic	p-value***
CZ	0.9889	-3.375	0.009
HU	0.9864	-3.249	0.014
PL	0.9859	-3.363	0.007
SK	0.9904	-2.505	0.089

Source: Own calculations

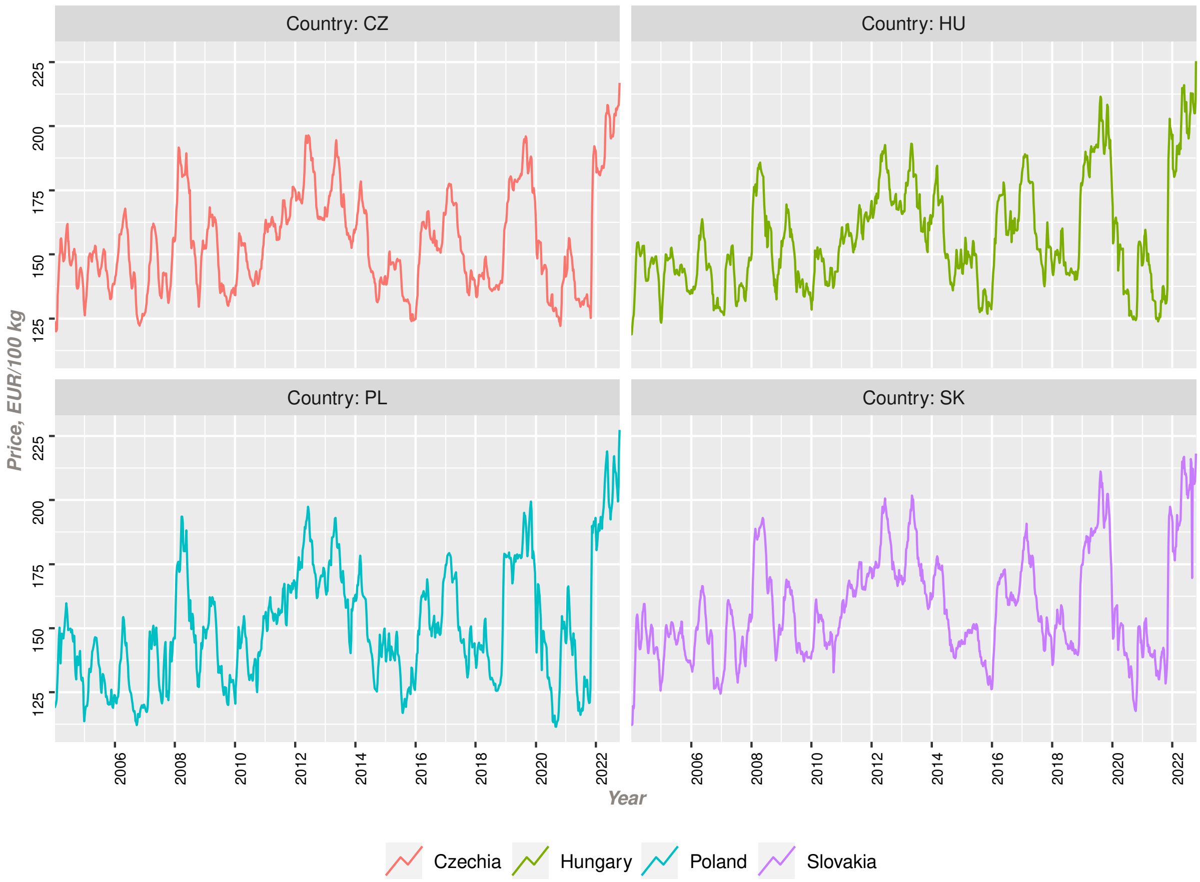
*Note: * - Logarithmic prices in levels; ** - The largest root of the autoregressive lag polynomial, corresponding to the coefficient of the lagged series in the DF regression; *** - Calculations are made using 1000 bootstrap replications of size* $n = 1.75T^{1/3}$*, the deterministic specification contains intercept and trend, lag length selection is done with mBIC. Instead of standard augmented DF test, we use DF-GLS test.*

In our study we fit time series with GAM approach in VAR representation to capture potential non-linearities in price relationships. Our GAMs in VAR model representation of pairwise price linkages have been estimated with the penalized maximum likelihood algorithm described above. We built the GAMs as the sum of smooth functions s of the input. The idea is that each predictor makes a separate contribution to the response, and these just add up, but these contributions are not strictly proportional to the inputs.

All lagged price variables are allowed to have non-linear effects in price transmission represenatation. Additionally, parametric intercept is also incorporated in the model. We assumed that the residuals of the GAMs are normally distributed. Lag lengths of 2-3 have been defined in accordance with Schwartz-Bayesian information criteria (BIC). The model diagnostics given the indication that the model assumptions are not violated.

Tables 3 - 6 show the GAM estimated parameters for each price pairs, namely price series for pigmeat markets in Czechia, Slovakia, Hungary and Poland. The effective degrees of freedom (EDF) represent the measure of non-linearity implied by the responses. They can be interpreted as intensity of smoothing of given price variable, consequently higher EDF value implies more complex splines and more "wiggly" price transmission between agri-food markets pair in V4 countries. According to Hunsicker et al. (2016) the EDF equal to 1 is equivalent to a linear relationship, the EDF value range of 1-2 can be considered a weakly non-linear relationship, and EDF value exceeding 2 represents a highly non-linear price relationships. Moreover, the upper values of EDF correspond to the smaller smoothing parameters. In our analysis, the largest EDF value of 9 for the smoothed individual covariate can be seen in the GAM model of spatial price transmission between Slovak and Polish markets (see Table 4).

Figure 1. Pigmeat price development in Visegrad group countries for the period of May 2004 to February 2023



Source: European Commission's agricultural and rural development department

Above all, most of the nonlinear effects are highly statistically significant as shown with the F-statistics in the tables. Given that fact, we can conclude that pigmeat markets in V4 countries are well integrated. Weak non-linearity can be observed when pigmeat prices "transmit" from Hungarian market to Czech, Czech one to Polish, Slovak market to Hungarian and from Hungarian to Polish. We have revealed the most "wiggly" non-linear pattern in spatial price transmission between Slovak and other V4 countries markets, especially in the pairs between Slovakia-Czechia with total EDF equals to 27.886 as well as Slovakia-Poland, where total EDF is 41.605 and all the splines are significant at the 1 % level of significance (see Table 4).

Table 3. Bivariate penalized GAM model estimates: Czechia (CZ_t)

GAM component	EDF	Smoothing parameter, λ	F-value
Model I (CZ ~HU, 2 lags)			
Intercept	1.000	5.033[a]	10740[b]***
s(CZ_{t-1})	1.000	1799501	1230.57***
s(CZ_{t-2})	3.068	2.68388	30.07***
s(HU_{t-1})	1.000	2798774	46.75***
s(HU_{t-2})	1.000	3655286	32.80***
Total EDF[c] = 8.068; adj.R^2 = 0.985; GCV score: GAM=0.000217, VAR=0.000218; AIC (GAM) = -5480.41, AIC(VAR)=-5471.65; LR-test of linear VAR vs. GAM, test statistic=4.5028***			
Model II (CZ ~SK, 2 lags)			
Intercept	1.000	5.033[a]	10874[b]***
s(CZ_{t-1})	1.000	123322	1591.43***
s(CZ_{t-2})	5.416	0.159217	23.20***
s(SK_{t-1})	5.414	0.098419	10.10***
s(SK_{t-2})	4.171	0.181794	10.08***
Total EDF[c] = 18.001; adj.R^2 = 0.986; GCV score: GAM=0.000213, VAR=0.000219; AIC (GAM) = -5494.82, AIC(VAR)=-4893.35; LR-test of linear VAR vs. GAM, test statistic=3.3548***			
Model III (CZ ~PL, 3 lags)			
Intercept	1.000	5.033[a]	11477[b]***
s(CZ_{t-1})	1.000	2215946	1158.62***
s(CZ_{t-2})	1.000	841692	20.04***
s(CZ_{t-3})	1.000	1353147	4.73**
s(PL_{t-1})	4.593	0.162814	20.92***
s(PL_{t-2})	6.212	0.039258	5.76***
s(PL_{t-3})	6.730	0.039226	2.90***
Total EDF[c] = 22.535; adj.R^2 = 0.987; GCV score: GAM=0.000192, VAR=0.000196; AIC (GAM) = -5591.19, AIC(VAR)=-5571.57; LR-test of linear VAR vs. GAM, test statistic=2.7178***			

Source: Own calculations

*Note: [a] estimate for constant by penalized MLE in place of the smoothing parameter (λ); [b] t-value instead of F-value; [c] – taking parametric dispersion term into account; ***p<0.01, **p<0.05, *p<0.1.*

Table 4. Bivariate penalized GAM model estimates: Slovakia (SK_t)

GAM component	EDF	Smoothing parameter, λ	F-value
Model I (SK ~HU, 2 lags)			
Intercept	1.000	5.056[a]	8645[b]***
s(SK_{t-1})	8.965	0.000283	90.54***
s(SK_{t-2})	3.837	0.160175	15.39***
s(HU_{t-1})	7.215	0.020438	19.17***
s(HU_{t-2})	1.717	1.527770	27.93***
Total EDF[c] = 23.734; adj.R^2 = 0.979; GCV score: GAM=0.000343, VAR=0.000383; AIC (GAM) = -5030.84, AIC(VAR)= -4922.11; LR-test of linear VAR vs. GAM, test statistic=7.3839***			
Model II (SK ~CZ, 2 lags)			
Intercept	1.000	5.056[a]	8598[b]***
s(CZ_{t-1})	6.404	0.033608	18.86***
s(CZ_{t-2})	6.697	0.031371	11.06***
s(SK_{t-1})	8.540	0.003934	97.66***
s(SK_{t-2})	4.245	0.105740	15.37***

Total EDF[c] = 27.886; adj.R^2 = 0.978; GCV score: GAM=0.000348, VAR=0.000394; AIC (GAM) = -5016.25, AIC(VAR)=-4893.35; LR-test of linear VAR vs. GAM, test statistic=6.8538***			
Model III (SK ~PL, 3 lags)			
Intercept	1.000	5.056[a]	9591[b]***
s(SK_{t-1})	6.592	0.021549	101.55***
s(SK_{t-2})	8.161	0.003024	7.14***
s(SK_{t-3})	9.000	0.00000002	10.51**
s(PL_{t-1})	3.955	0.237344	39.43***
s(PL_{t-2})	6.135	0.043090	7.77***
s(PL_{t-3})	5.762	0.063100	2.54**
Total EDF[c] = 41.605; adj.R^2 = 0.987; GCV score: GAM=0.000284, VAR=0.000342; AIC (GAM) = -5212.54, AIC(VAR)= -5029.15; LR-test of linear VAR vs. GAM, test statistic=7.0103***			

Source: Own calculations

*Note: [a] estimate for constant by penalized MLE in place of the smoothing parameter (λ); [b] t-value instead of F-value; [c] – taking parametric dispersion term into account; ***p<0.01, **p<0.05, *p<0.1.*

Table 5. Bivariate penalized GAM model estimates: Hungary (HU_t)

GAM component	EDF	Smoothing parameter, λ	F-value
Model I (HU ~SK, 2 lags)			
Intercept	1.000	5.045[a]	8237[b]***
s(SK_{t-1})	4.441	0.245521	9.61***
s(SK_{t-2})	3.933	0.322377	11.02***
s(HU_{t-1})	1.000	4464692	1107***
s(HU_{t-2})	1.000	1812938	50.72***
Total EDF[c] = 12.374; adj.R^2 = 0.977; GCV score: GAM=0.000372, VAR=0.000381; AIC (GAM) = -4951.76, AIC(VAR)= -4926.45; LR-test of linear VAR vs. GAM, test statistic=4.5567***			
Model II (HU ~CZ, 2 lags)			
Intercept	1.000	5.045[a]	8047[b]***
s(CZ_{t-1})	1.000	1686169	5.01**
s(CZ_{t-2})	4.196	0.568944	1.92*
s(HU_{t-1})	4.871	0.195969	161.03***
s(HU_{t-2})	1.991	1.588069	27.68***
Total EDF[c] = 14.058; adj.R^2 = 0.976; GCV score: GAM=0.000348, VAR=0.000394; AIC (GAM) = -4904.52, AIC(VAR)= -4895.77; LR-test of linear VAR vs. GAM, test statistic=2.2892***			
Model III (HU ~PL, 3 lags)			
Intercept	1.000	5.045[a]	8850[b]***
s(HU_{t-1})	6.092	0.050456	80.13***
s(HU_{t-2})	3.582	0.153899	0.72
s(HU_{t-3})	4.611	0.138168	1.23
s(PL_{t-1})	4.850	0.158263	25.35***
s(PL_{t-2})	3.472	0.213861	9.80***
s(PL_{t-3})	5.833	0.082775	1.44
Total EDF[c] = 30.377; adj.R^2 = 0.980; GCV score: GAM=0.000328, VAR=0.000334; AIC (GAM) = -5070.36, AIC(VAR)= -5050.31; LR-test of linear VAR vs. GAM, test statistic=2.2238***			

Source: Own calculations

*Note: [a] estimate for constant by penalized MLE in place of the smoothing parameter (λ); [b] t-value instead of F-value; [c] – taking parametric dispersion term into account; ***p<0.01, **p<0.05, *p<0.1.*

Indeed, we have showed that semi-parametric GAM representation of price transmission has improvements over typical linear VAR model. The first evidence of that can be found with a comparison of the Akaike information criterias (AIC) and generalized cross validation (GCV) scores. In order to define the better model, we orient on the lowest AIC and GCV values. The second one is that the likelihood ratio tests are used. They have shown that test statistics are highly significant in every case (see Tables 3 - 6).

Table 6. Bivariate penalized GAM model estimates: Poland (PL_t)

GAM component	EDF	Smoothing parameter, λ	F-value
Model I (PL ~SK, 3 lags)			
Intercept	1.000	5.004[a]	7877[b]***
s(SK_{t-1})	1.000	5353725	4.55**
s(SK_{t-2})	3.160	2.044594	2.25*
s(SK_{t-3})	1.000	161046	0.088
s(PL_{t-1})	1.000	4075391	2550.9***
s(PL_{t-2})	6.496	0.047295	40.49***
s(PL_{t-3})	6.547	0.046662	11.98***
Total EDF[c] = 21.203; adj.R^2 = 0.982; GCV score: GAM=0.000403, VAR=0.000416; AIC (GAM) = -4868.49, AIC(VAR)= -4835.90; LR-test of linear VAR vs. GAM, test statistic=3.7464***			
Model II (PL ~CZ, 3 lags)			
Intercept	1.000	5.004[a]	7866[b]***
s(CZ_{t-1})	1.000	1644205	4.53**
s(CZ_{t-2})	2.836	1.620458	2.96**
s(CZ_{t-3})	1.000	2531997	4.41**

Table 6 (**continued**)

s(PL_{t-1})	1.000	33811870	2317.42***
s(PL_{t-2})	6.987	0.033371	37.38***
s(PL_{t-3})	6.268	0.053058	10.13***
Total EDF[c] = 21.091; adj.R^2 = 0.982; GCV score: GAM=0.000404, VAR=0.000416; AIC (GAM) = -4865.16, AIC(VAR)= -4836.77; LR-test of linear VAR vs. GAM, test statistic=3.3936***			
Model III (PL ~HU, 3 lags)			
Intercept	1.000	5.004[a]	7870[b]***
s(HU_{t-1})	1.000	10762970	7.33***
s(HU_{t-2})	1.000	14249270	7.99***
s(HU_{t-3})	1.817	4.380433	2.54*
s(PL_{t-1})	1.000	5368609	1961.52***
s(PL_{t-2})	6.736	0.039270	34.86***
s(PL_{t-3})	6.589	0.043820	9.92***
Total EDF[c] = 20.142; adj.R^2 = 0.982; GCV score: GAM=0.000403, VAR=0.000415; AIC (GAM) = -4867.02, AIC(VAR)= -4838.31; LR-test of linear VAR vs. GAM, test statistic=3.5802***			

Source: Own calculations

*Note: [a] estimate for constant by penalized MLE in place of the smoothing parameter (λ); [b] t-value instead of F-value; [c] – taking parametric dispersion term into account; ***p<0.01, **p<0.05, *p<0.1.*

Unlike other non-parametric approaches, the significant advantage of GAMs is that they are relatively interpretable. Typical approach for GAMs is plotting the partial effects and inspect the relationships between response price variables (in our case CZ_t, SK_t, Hu_t and PL_t) and predictors visually. Visual GAM model output in the aspect of partial effects shows the impact of selected lagged price variable on the response, assuming that the rest of model predictors equals to their mean values[3]. The findings imply that asymmetry exists in terms of the disproportionate response to the appropriate predictor increase. We can observe non-linear asymmetry in price transmission between Polish market and others. In other words, response price variable reacts differently to the changes of the same lagged variables.

4. Conclusion

Being in line with the last studies on non-linear time series models of spatial agri-food price transmission and market integration, we use non-parametric generalized additive model to give evidence of non-linear nature in price relationships. The advantage of the GAM approach is that researcher is not limited to global basis expansions of model covariates. Instead a wide range of penalized spline bases is used which may better adapt to the price data rather than imposing a concrete functional form (for instance, polynomial regressions). Indeed, the polynomial can be significantly inflexible for complex nonlinear interactions. The non-parametric GAMs reveal better description for spatial price transmission in pig-meat markets of V4 countries in comparison with linear VAR modelling, that is in line with the findings of Guney et al. (2019) and B. Goodwin et al. (2021) for USA food markets. Our study fills the gap in the empirical literature on horizontal price transmission in EU agri-food markets based on GAM modeling.

A consideration of horizontal price transmission by means of the advanced econometric techniques is used to address a variety of economic issues. We have detected the assumption about well integrated pig-meat V4 markets in terms of non-linear price relationships. The price transmission ”wiggliness” has been estimated and the most ”wiggly” non-linear pattern has been revealed between Slovak-Polish and Slovak-Czech pig-meat markets. Asymmetries also exist in the non-linear relationships between V4 markets in terms of the disproportionate response to the appropriate price predictor increase. The findings of our research will provide important information for the decision-making field. Understanding the nature of spatial price transmission can have considerable welfare and policy implications. We suggest the following measures in order to stabilize Slovak pig-meat market and mitigate the price asymmetry. Firstly, it is important to balance the regulatory environment and avoid cutting off state support: the support system for the pig-meat producers must be effective and sustainable. Secondly, there is also scope for improving the transparency in price formation along the supply chain.

This study can be extended with considering multivariate GAM in VAR representation. In order to build more flexible GAM models, another spline alternatives could be used with incorporating interactions between lagged price variables, generalized impulse response function analysis might also be of interest.

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[3] Plots of GAM partial effects of one particular predictor on response are not presented, but available from the authors upon request.

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D2 Production and Organizations
D3 Distribution
D4 Market Structure, Pricing, and Design†
D5 General Equilibrium and Disequilibrium
D6 Welfare Economics
D7 Analysis of Collective Decision-Making
D8 Information, Knowledge, and Uncertainty
D9 Intertemporal Choice

E. Macroeconomics and Monetary Economics
E1 General Aggregative Models
E2 Consumption, Saving, Production, Investment, Labor Markets, and Informal Economy
E3 Prices, Business Fluctuations, and Cycles
E4 Money and Interest Rates
E5 Monetary Policy, Central Banking, and the Supply of Money and Credit
E6 Macroeconomic Policy, Macroeconomic Aspects of Public Finance, and General Outlook

F. International Economics
F1 Trade
F2 International Factor Movements and International Business
F3 International Finance
F4 Macroeconomic Aspects of International Trade and Finance
F5 International Relations, National Security, and International Political Economy
F6 Economic Impacts of Globalization

G. Financial Economics
G1 General Financial Markets
G2 Financial Institutions and Services
G3 Corporate Finance and Governance

H. Public Economics
H1 Structure and Scope of Government
H2 Taxation, Subsidies, and Revenue
H3 Fiscal Policies and Behavior of Economic Agents
H4 Publicly Provided Goods
H5 National Government Expenditures and Related Policies
H6 National Budget, Deficit, and Debt
H7 State and Local Government • Intergovernmental Relations
H8 Miscellaneous Issues

I. Health, Education, and Welfare
I1 Health
I2 Education and Research Institutions
I3 Welfare, Well-Being, and Poverty

J. Labor and Demographic Economics
J1 Demographic Economics
J2 Demand and Supply of Labor
J3 Wages, Compensation, and Labor Costs
J4 Particular Labor Markets
J5 Labor–Management Relations, Trade Unions, and Collective Bargaining
J6 Mobility, Unemployment, Vacancies, and Immigrant Workers
J7 Labor Discrimination
J8 Labor Standards: National and International

K. Law and Economics
K1 Basic Areas of Law
K2 Regulation and Business Law
K3 Other Substantive Areas of Law
K4 Legal Procedure, the Legal System, and Illegal Behavior

L. Industrial Organization
L1 Market Structure, Firm Strategy, and Market Performance
L2 Firm Objectives, Organization, and Behavior
L3 Nonprofit Organizations and Public Enterprise
L4 Antitrust Issues and Policies
L5 Regulation and Industrial Policy
L6 Industry Studies: Manufacturing
L7 Industry Studies: Primary Products and Construction
L8 Industry Studies: Services
L9 Industry Studies: Transportation and Utilities

M. Business Administration and Business Economics • Marketing • Accounting • Personnel Economics†
M1 Business Administration
M2 Business Economics
M3 Marketing and Advertising
M4 Accounting and Auditing
M5 Personnel Economics

N. Economic History
N1 Macroeconomics and Monetary Economics • Industrial Structure • Growth • Fluctuations
N2 Financial Markets and Institutions
N3 Labor and Consumers, Demography, Education, Health, Welfare, Income, Wealth, Religion, and Philanthropy
N4 Government, War, Law, International Relations, and Regulation
N5 Agriculture, Natural Resources, Environment, and Extractive Industries
N6 Manufacturing and Construction
N7 Transport, Trade, Energy, Technology, and Other Services
N8 Micro-Business History

N9 Regional and Urban History

O. Economic Development, Innovation, Technological Change, and Growth†

O1 Economic Development
O2 Development Planning and Policy
O3 Innovation • Research and Development • Technological Change • Intellectual Property Rights†
O4 Economic Growth and Aggregate Productivity
O5 Economywide Country Studies

P. Economic Systems

P1 Capitalist Systems
P2 Socialist Systems and Transitional Economies
P3 Socialist Institutions and Their Transitions
P4 Other Economic Systems
P5 Comparative Economic Systems

Q. Agricultural and Natural Resource Economics • Environmental and Ecological Economics

Q1 Agriculture
Q2 Renewable Resources and Conservation
Q3 Nonrenewable Resources and Conservation
Q4 Energy
Q5 Environmental Economics

R. Urban, Rural, Regional, Real Estate, and Transportation Economics

R1 General Regional Economics
R2 Household Analysis
R3 Real Estate Markets, Spatial Production Analysis, and Firm Location
R4 Transportation Economics
R5 Regional Government Analysis

Y. Miscellaneous Categories

Y1 Data: Tables and Charts
Y2 Introductory Material
Y3 Book Reviews (unclassified)
Y4 Dissertations (unclassified)
Y5 Further Reading (unclassified)
Y6 Excerpts
Y7 No Author General Discussions
Y8 Related Disciplines
Y9 Other

Z. Other Special Topics

Z1 Cultural Economics • Economic Sociology • Economic Anthropology
Z2 Sports Economics
Z3 Tourism Economics