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WORKING PAPERS

113

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SPATIAL PRICE TRANSMISSION BETWEEN PIGMEAT MARKETS IN VISEGRAD COUNTRIES: A GENERALIZED ADDITIVE MODELLING APPROACH

ISSN 1337-5598 (electronic version)

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This study is funded by the EU "Next Generation EU through the Recovery and Resilience Plan for Slovakia" under the project No. 09I03-03-V01-00054.

Financované EÚ "Next Generation EU prostredníctvom Plánu obnovy a odolnosti SR" v rámci projektu č. 09I03-03-V01-00054.

ABSTRACT

Spatial Price Transmission Between Pigmeat Markets in Visegrad Countries: A Generalized Additive Modelling Approach

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, also the most popular econometric models have been 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 give evidence of agri-food market integration efficiency and non-linear patterns in price linkages. The results of our empirical approach may contribute to the knowledge about market efficiency and competitiveness as well as provide information to policymakers.

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

ABSTRAKT

Téma horizontálnej cenovej transmisie sa z hľadiska pochopenia fungovania geograficky oddelených trhov stala v oblasti aplikovaného mikroekonomického výskumu významnou najmä v dvadsiatom prvom storočí. Tento príspevok poskytuje detailný prehľad aplikovaného výskumu v oblasti modelovania priestorového prenosu cien, diskutuje aplikované ekonometrické modely s prezentáciou ich hlavných výhod a nevýhod s osobitným zameraním na nelineárne modelovacie techniky. V súlade s poslednými štúdiami o nelineárnych modeloch časových radov priestorového prenosu agropotravinárskych cien a trhovej integrácie je predstavená neparametrická metóda zovšeobecneného aditívneho modelovania (GAM, z angl. generalized additive modelling). Táto metóda umožňuje overenie efektívnosti integrácie agropotravinárskych trhov a odhalenie nelinearít v cenových prepojeniach. Výsledky nášho empirického prístupu môžu prispieť k poznaniu efektívnosti trhov a konkurencieschopnosti, ako aj poskytnúť informácie tvorcom politík.

Kľúčové slová: Horizontálny prenos cien, trhová integrácia, nelineárne časové rady, zovšeobecnený aditívny model

JEL CLASSIFICATION: Q110, C510

The view expressed in the WP and language revision is those of the author.

Layout by: Sergei Kharin, Cand. Sc.

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Contents

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 function.

A consideration of horizontal price relationships has been used to address a variety of economic issues. Horizontal (spatial) price transmission analysis contributes to the knowledge about market efficiency, provides information to policymakers (Braha et al., 2019; Dong et al., 2018; Olipra, 2020; Ozturk, 2020; Roman & Kroupová, 2022) and insights into the infrastructure efficiency of markets (Kharin, 2019; Salazar, 2018) as well as gives specific evidence concerning the markets competitiveness and arbitrage effectiveness (Bakucs et al., 2015; Goodwin et al., 2021; Goodwin & Piggott, 2001; Serra et al., 2006). In research from Shen et al. (2022), analyzing price forming mechanism is a critical means to guide farmers' behaviors, regulate their economic activities and price transmission is one important reason to affect marketing prices. Additionally, comprehension of the spatial price transmission mechanism could shed light on trade strategy adjustment to boost some industries (Alam et al., 2022).

The *Law of one price* and spatial arbitrage theory is the base of the analysis of spatial market integration and market efficiency. Muwanga and Snyder (1999) argued that adherence to the law of one price is a sufficient condition for spatial price efficiency, implying perfect market integration, and completely excluding long-run arbitrage opportunities. In literature the terms *"market integration"* and *"market efficiency"* are closely related and often used interchangeably. Horizontal price transmission reflects the degree of market integration and efficiency. Vargova and Rajcaniova (2018) came to a similar conclusion, that integrated markets are considered to be efficient markets and market efficiency estimation is carried out through the examination of spatial market integration. According to the research from Sexton et al. in 1991, geographic markets are especially relevant to agri-food sector because agricultural products are mostly bulky and perishable, as well as areas of production and consumption are separated, hence transportation is expensive. To return to our main argument, it is clear that the horizontal price transmission has a significant microeconomics impact and, according to the research from von Cramon-Taubadel (2017), offers a lot of fascinating opportunities for work by applied researchers who are concerned with the functioning and outcomes of agricultural markets.

An extensive empirical literature considering spatial price transmission on agri-food markets has been accumulated over the last few decades. Study from von Cramon-Taubadel and Goodwin (2021) has shown that much of the research on spatial market linkages has reflected methodological advances that have led to increasingly nonlinear time-series models. Indeed, most research on nonlinear modelling has relied on parametric methods (Ridha et al., 2022; Xue et al., 2021), whereas there has been an increasing interest in the non-parametric (Guney et al., 2019) and machine learning (Kresova & Hess, 2022) techniques to estimate spatial price relationships on agri-food markets. According to the new research (von Cramon-Taubadel & Goodwin, 2021), advances in the empirical literature over the last few years have demonstrated that price relationships in the agri-food chain are highly specific and complex. Indeed, price linkages data can be a real "mess" that is hybrid of two patterns: linear and nonlinear. Considering this fact, it is reasonable to conclude that thorough analysis of spatial price relationships needs a more flexibility in the models. Generalized additive models (GAM) allow much greater modeling flexibility, providing a better fit in the presence of more complicated nonlinear price relationships. One can specify the model in terms of parametric, semi-parametric or non-parametric smooth functions rather than detailed parametric relationships. Developments in computational technologies may be helpful in the modelling since GAMs use automatic smoothness selection methods to identify the complexity of the nonlinear price relationships.

While there has been much research on nonlinear time-series models of horizontal agri-food price linkages, just few researchers have taken GAMs into consideration. Therefore, there is still a lack of robust research on spatial price transmission in EU agri-food markets based on GAM approach - this is a gap that we could address in our study.

The reminder of the paper is organised as follows. Section 2 reviews the relevant literature on spatial price transmission in agri-food markets, section 3 describes the empirical methodology, the findings are discussed in section 4 and the final section concludes the paper.

2 Literature Review

The applied analysis of market integration has mostly used models that are the mathematical representation of horizontal price linkages in selected agro-commodities markets. A wide variety of empirical techniques are used in the literature 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 categorised into three empirical approaches, namely "pre-co-integration", "co-integration" and "other" ("post-co-integration") (von Cramon-Taubadel, 2017; von Cramon-Taubadel & Goodwin, 2021).

The first strand of studies can be characterized by using spatial correlation coefficients and simple linear regression models for estimating the relationships between agri-food prices in various regions (Ravallion, 1986; Richardson, 1978; Stigler & Sherwin, 1985; Timmer, 1974). However, the correlation analysis did not illustrate the extent to which markets are integrated. As a result of the criticism in correlation technique, linear regression-based approaches have been introduced. Mundlak and Larson (1992) built static regression models of linkages between domestic and world prices of agricultural commodities for 58 countries of the United Nations and for the countries of the European Community. Indeed, there is the effect time lag when price in one location changes. These dynamic effects have been captured by adding lagged prices as a right-hand-side variables in the regression equation (Ravallion, 1986; Timmer, 1987). Although this was rationale, ignoring the non-stationary and nonlinear nature of price data was leading to the model misspecification.

Second stream of literature on spatial price transmission relies on co-integration technique and error correction modeling. Price series tend to move identically over time and have common stochastic trend, i.e. series are co-integtated. 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 a linear combinations which are stationary in levels. The co-integration approach was first 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 cointegration tests by Johansen(1988, 1991, 1995), Phillips and Ouliaris (1990), Gregory and Hansen (1996), Hatemi-J (2009) and Maki (2012).

Many latest studies use linear vector error correction model (VECM) representation of spatial price transmission between agri-food markets in Europe (Esposti & Listorti, 2018; Fernández-Polanco & Llorente, 2019; Hillen & von Cramon-Taubadel, 2019; Ozturk, 2020; Penone et al., 2022; Svanidze & Ðurić, 2021; Svanidze et al., 2022), in the Asian region (Dong et al., 2018; Thong et al., 2020), in the Southern and Northern American continent (Gálvez-Soriano & Cortés, 2021; Martignone et al., 2022; Villanueva, 2022) and in Africa (Martey et al., 2020; Nzuma & 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 responce to the price shocks of the other countries, Slovak market faster 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 are characterized by a long range of linkages, which is a strong indication of the market integration for the all analyzed products. Apart from VECMs, these authors and other reserchers (Brown et al., 2021; Gao et al., 2022; Shen 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 cointegration exists, then VECM, which combines price variables in levels and differences, can 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 (Fanchon & Wendel, 1992; Kilian & Lütkepohl, 2017; Stock et al., 1990).

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; Goodwin & Piggott, 2001; Hamulczuk et al., 2019; Yovo & 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 (Enders & Siklos, 2001; Hansen & Seo, 2002; Seo, 2006). The threshold vector error correction model (TVECM) has been substantially influential in agricultural economics research, specifically, spatial price transmission studies (Ahoba & Gaspart, 2019; Kharin, 2019; Lence et al., 2018; Lizama-Fuentes et al., 2018).

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 sence 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. There exist surveys that have presented a review of the empirical techniques on asymmetric price transmission in agri-food markets (Frey & Manera, 2007; Meyer & von Cramon-Taubadel, 2004; von Cramon-Taubadel & Goodwin, 2021).

Assymetric error correction model (AECM) has been reliable enough to be widely used as a tool to estimate spatial price assymetries and adequately represents price series behavior in the presence of non-stationary and cointegration. In the model 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. Indeeed, recent literature has progressed to display threshold-type nonlinearity in the error correction of the prices (Alam et al., 2022; Braha et al., 2019; Gizaw et al., 2021; Xue et al., 2021) instead of linear relationships (Jaramillo-Villanueva & Palacios-Orozco, 2019; Purwasih et al., 2020; Schulte & Musshoff, 2018; Wiranthi, 2021).

On the other hand, the AECM hypothesises 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 cointegration dynamics. Currently, there are a few studies on spatial (Kamaruddin et al., 2021; Ridha et al., 2022) and vertical (Fousekis et al., 2016; Liu et al., 2022; 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 a a switching regime framework, first introduced by Spiller and Huang (1986), Spiller and Wood (1988), and extended further by Sexton et al. (1991), 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 criticised for some reasons (Negassa & Myers, 2007; von Cramon-Taubadel, 2017). In recent years, PBM analysis has received far less attention in the literature unlike co-integartion methods, nonetheless there are studies of agri-food market integration based on PBM technique (Durborow et al., 2020; Hu & Brorsen, 2017).

In fact, aforementioned parametric modelling approaches have been criticised for the choice of functional form and pattern of the transition process between regimes. In contrast, non-parametric methods offer to analyse price transmission in a more flexible way, having diminished, first of all, the assumption of linearity. Several non-parametric techniques have been 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; Serra et al., 2006), penalized smoothing spline regressions within the framework of generalized additive models (GAM) (Guney et al., 2019; Rosales & von Cramon-Taubadel, 2015) and semi-parametric single index threshold models (Choe & 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.

Finally, agricultural economists have traditionally been more interested in the transmission of prices in levels than in the transmission of price volatilities. However, it is worth mentioning that lately, an increasing number of studies employ dynamic conditional volatility methods, namely univariate and multivariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models with several specifications (dynamic or constant conditional correlation), to examine spatial *price-volatility* transmission in agri-food markets. (Assefa et al., 2015; Guo & Tanaka, 2020; Tanaka & Guo, 2020; Zheng & Pan, 2022).

3 Methodology

We will carry out spatial price transmission analysis using 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 since the larger sample, the more robust our results are. The source of the price data is the European Commission's agricultural and rural development department. In order to calculate price elasticities and mitigate price series fluctuations, we use the logarithmic transformation of weekly prices measured in Euro per unit that allows the results to be interpreted in percentage change terms.

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 test[1] (Palm et al., 2008; Smeekes, 2013).

[1] We use the *bootUR* package in R, written by Smeekes and Wilms (2022).

Classical unit root tests, such as ADF test (Dickey & 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 & 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) as follows:

$$p_{max} = \left[12 \cdot \left(\frac{T}{100} \right)^{1/4} \right] \tag{1}$$

where T is the sample size, $\left[\cdot \right]$ denotes the integer part.

The optimal lag order is determined in accordance with the modified version of Bayesian Information Criterion (mBIC) (Ng & Perron, 2001) as follows:

$$p_{opt} = \arg \min_{p \leqslant p_{max}} mBIC(p) \tag{2}$$

where $mBIC(p)$ is computed as follows:

$$\begin{aligned} mBIC(p) &= \ln\left(\hat{\sigma_p}^2\right) + \frac{\Big(\ln\left(T - p_{max}\right)\Big)\Big(\tau_T(p) + p\Big)}{T - p_{max}}, \\ \hat{\sigma_p}^2 &= \left(\frac{1}{T - p_{max}}\right) \sum_{p_{max}+1}^{T} \hat{\epsilon_t}^2 \\ \tau_T(p) &= \left(\frac{\hat{\pi}^2}{\hat{\sigma_p}^2}\right) \sum_{p_{max}+1}^{T} y_{t-1}^d \end{aligned} \tag{3}$$

where $\hat{\epsilon_t}$ are obtained from ADF test regression $\Delta y_t^d = \pi y_{t-1}^d + \sum_{j=1}^{p} \psi_j \Delta y_{t-j}^d + \epsilon_t$, based on the generalized least squares (GLS) detrended data.

Ng and Perron have showed that that mBIC has improvements over the traditional BIC (Schwarz, 1978), while testing the time series stationarity.

As a next step, to check the price series and determine the cointegrating rank we use the Johansen procedure (Johansen, 1988; Johansen, 1991) based on maximum likelihood estimation. Unlike Engle-Granger (Engle & Granger, 1987) technique, it avoids the issue of choosing a dependent variable and deals with multivariate system of price variales. In order to identify the number of cointegrating vectors, there have been proposed two different likelihood ratio tests, namely the trace and the maximum eigenvalue ones as follows:

$$LR_{(r,n)} = -T \sum_{i=r+1}^{n} \ln(1-\widetilde{\lambda}_i),$$
$$LR_{(r,r+1)} = -T \ln(1-\widetilde{\lambda}_{r+1}) \tag{4}$$

where $LR_{(r,n)}$ is the likelihood ratio statistic for testing whether rank $(\prod) = r$ versus the alternative hypothesis rank $(\prod) \leqslant n$; $LR_{(r,r+1)}$ is the likelihood ratio test statistic for testing whether rank $(\prod) = r$ versus the alternative hypothesis that rank $(\prod) = r+1$; n is the number of variables; r is the number of cointegrating relationships; T is the sample size; $\widetilde{\lambda}_i$ is the i-th largest canonical correlation; $\prod$ is the coefficient matrix obtained from the VAR model, where $\prod = \alpha\beta'$, α are known as the error correction terms and each column of β is a cointegrating vector in the long run.

If two tests provide contradictory results, we are going to rely on trace statistic since it tends to have superior power in empirical studies (Lütkepohl et al., 2001).

As previously mentioned, 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 prespecify 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 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 (Friedman & Stuetzle, 1981) and have been introduced by Hastie and Tibshirani (1990). GAM framework was extended further by Wahba (1990), Eilers and Marx (1996), Ruppert et al. (2003), Reiss and Ogden (2009), Wood (2000, 2003, 2004, 2008, 2011, 2013).

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

$$g(E(y_i)) = \alpha + \sum_{i=1}^{k} \beta_i x_i + \sum_{j=1}^{m} f_j(x_{k+j}) + \epsilon_i,$$
$$\epsilon_i \sim \mathcal{N}(0, \sigma^2 I) \tag{5}$$

where $g(\cdot)$ is a monotonic function that links the expected value $E(y)$ to the predictors $x_1, x_2....x_{i+j}$ (identical in our study), α is an intercept, the terms $f_j(\cdot)$ denote smoothing, non-parametric functions of the covariates. Smoothing function f is composed by sum of basis 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 $(\sum_i \beta_i x_i)$.

Indeed, 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)[2]. 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:

$$\begin{aligned} &\sum_{i=1}^{N}(y_i - f(x_i))^2 + \lambda J(f) \\ &J(f) = \int_{\mathbb{R}} f''(x)^2 dx \end{aligned} \tag{6}$$

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 $J(f)$[3] - 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. 7)*.

[2]To build the model, *mgcv* package in R, written by Wood (2022), is used.

[3]TPS may incorporate more than one covariate. In the case of interactions between model predictors, we can design two, three or multidimensional TPS. For instance, two-dimentional TPS can be written as $J_2(f) = \int_{\mathbb{R}}\int_{\mathbb{R}}\left[\left(\frac{\partial^2 f(\mathbf{x})}{\partial x_1^2}\right)^2 + 2\left(\frac{\partial^2 f(\mathbf{x})}{\partial x_1 \partial x_2}\right)^2 + \left(\frac{\partial^2 f(\mathbf{x})}{\partial x_2^2}\right)^2\right] dx_1 dx_2$, where (x_1, x_2) are the two coordinates of the vector $\mathbf{x}$. The formula of multidimensional TPS can be found in the book by Wood (2006).

$$\nu_\lambda = \frac{n\sum_{i=1}^{n}(y_i - \hat{f}(x_i))^2}{\Big[tr(\mathbf{I}-\mathbf{A})\Big]^2} \tag{7}$$

where $\hat{f}(x)$ is the estimate from fitting to all the data, tr is the trace of matrix, $\mathbf{I}$ is the identity matrix and $\mathbf{A}$ is the projection matrix, i.e. influence matrix $X(X^TX+S)^{-1}X^T$ with penalty matrix $S=\sum_j \lambda_j S_j$.[4]

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 $\hat{\beta}_{ols} = (X^TX)^{-1}(X^Ty)$. 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. $\hat{\beta}_{wls} = (X^TC^{-1}X)^{-1}(X^TC^{-1}y)$. In fact, we can not 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 $\hat{\beta}_{P-IRLS} = (X^TX+S)^{-1}X^Ty$.

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. $tr(\mathbf{A})$. Indeed, 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.7 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 equivalent to 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 sence, the EDF vary from zero to infinity.

After assessing the time series properties of the price data, we fit the GAM in VAR (or VECM) 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

[4] See Wood (2004, 2006) for additional details and discussion of generalized cross-validation score calculation.

market.

4 Results and Discussion

The price development in Visegrad countries over the period of 2004-2023 can be observed in Figure 1. The observations relate to the weekly prices of pigmeat carcasses at the wholesale stage in Euro per unit. As seen from the Figure 1, 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 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. Unlike 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.

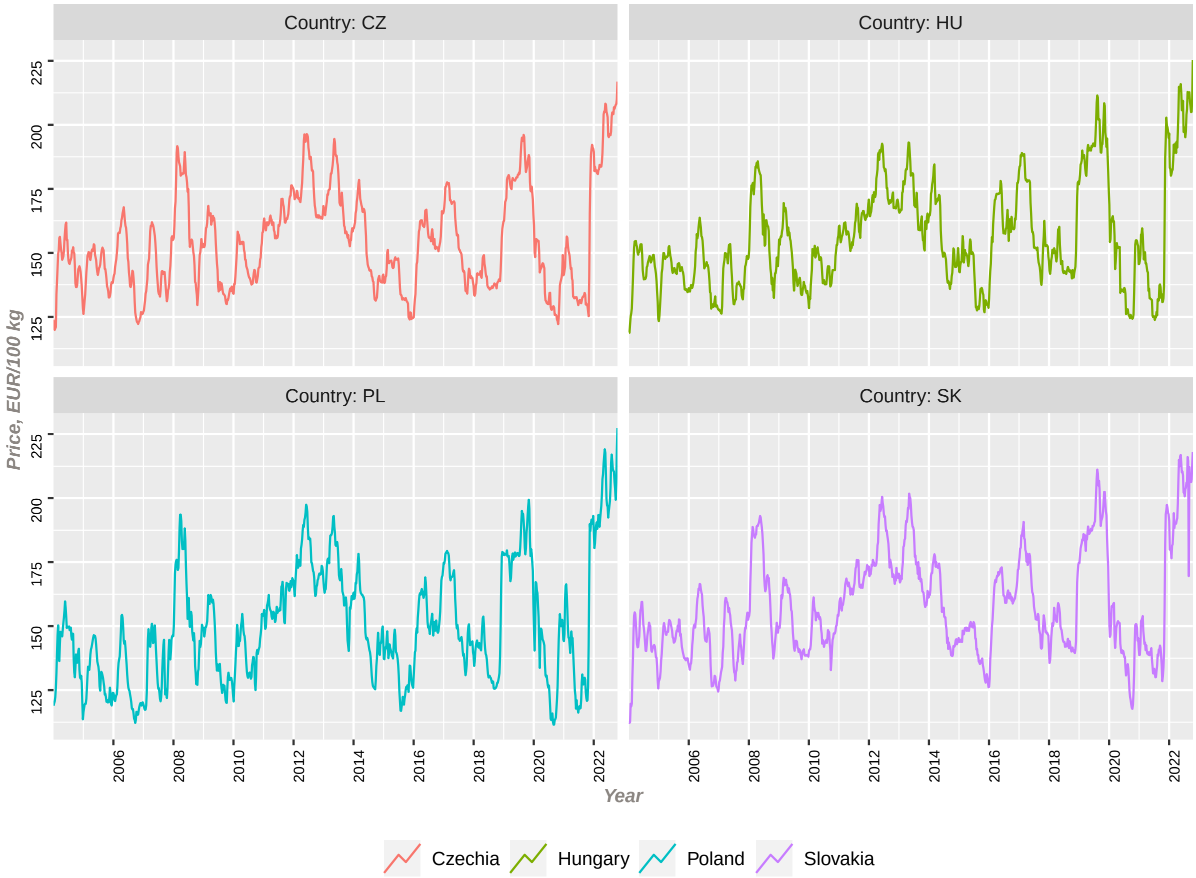
Table 1: Descriptive statistics for the weekly price series over the period of May 2004-February 2023

	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 bootsrap 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[5]. Hence, the bootstrap unit root tests show,

[5]Bootstrap augmented Dickey-Fuller test with OLS estimation (DF-OLS) has detected stationarity for Slovak price series at 1 % of significance.



Source: European Commission's agricultural and rural development department

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

that log-transformed price variables are stationary in levels, i.e. $I(0)$.

But for detecting stationarity in the price series we would test our time series for cointegration and deal with them within vector error correction modeling. Otherwise, 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 algotithm described above. We built the GAMs as the sum of smooth functions $s(\cdot)$ of the input. The idea is that each predictor makes a separate contribution to the response, and these just add up, but these contributions don't have to be strictly proportional to the inputs. In the same way as parameter β represents in linear regression, the partial response function $f(\cdot)$ still captures the change of the response variable to the change of the inputs (see A).

All lagged price variables are allowed to have non-linear effects in representing price transmission. 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

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

Price series[a]	Largest root[b]	Test statistic	p-value[c]
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

[a] Logarithmic prices in levels
[b] The largest root of the autoregressive lag polynomial, corresponding to the coefficient of the lagged series in the DF regression
[c] 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, minimum lag length in the regressions equals to zero. Instead of standard augmented DF test, we use DF-GLS test.

Source: Own calculations

have been defined in accordance with Schwartz-Bayesian information criteria (BIC). The model diagnostics seem to give the indication that the model assumptions are not violated (see B).

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 like how much given price variable is smoothed, consequently higher EDF value implies more complex splines and more "wiggly" price transmission between agri-food markets in V4 countries. 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 (Hunsicker et al., 2016). 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).

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).

Indeed, we have showed that semi-parametric GAM representation of price transmis-

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

GAM component	EDF	Smoothing parameter, λ	F value
Model I (CZ∼HU, 2 lags)			
Parametric components			
Intercept, β_0	1.000	5.033 [a]	10740[b]***
Non-parametric components			
$s(CZ_{t-1})$	1.000	1799501	1230.57***
$s(CZ_{t-2})$	3.068	2.683882	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: 0.00021652, VAR:0.00021846			
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)			
Parametric components			
Intercept, β_0	1.000	5.033 [a]	10874[b]***
Non-parametric components			
$s(CZ_{t-1})$	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: 0.00021341, VAR:0.000219456			
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)			
Parametric components			
Intercept, β_0	1.000	5.033 [a]	11477[b]***
Non-parametric components			
$s(CZ_{t-1})$	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	0.0392578	5.76***
$s(PL_{t-3})$	6.730	0.0392260	2.90***
Total EDF[c]	22.535		
adj.R^2 =0.987			
GCV score, GAM: 0.00019231, VAR:0.000196122			
AIC(GAM)=-5591,19;AIC(VAR)=-5571.57			
*LR-test of linear VAR vs.GAM, Test statistic=2.7178****			

[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
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Source: Own calculations

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

GAM component	EDF	Smoothing parameter, λ	F value
Model I (SK∼HU, 2 lags)			
Parametric components			
Intercept, β_0	1.000	5.056 [a]	8645[b]***
Non-parametric components			
$s(SK_{t-1})$	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: 0.00034288, VAR:0.00038296			
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)			
Parametric components			
Intercept, β_0	1.000	5.056 [a]	8598[b]***
Non-parametric components			
$s(CZ_{t-1})$	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: 0.00034811, VAR:0.00039437			
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)			
Parametric components			
Intercept, β_0	1.000	5.056 [a]	9591[b]***
Non-parametric components			
$s(SK_{t-1})$	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: 0.0002836, VAR:0.0003415			
AIC(GAM)=-5212,54;AIC(VAR)=-5029.15			
*LR-test of linear VAR vs.GAM, Test statistic=7.0103****			

[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
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Source: Own calculations

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

GAM component	EDF	Smoothing parameter, λ	F value
Model I (HU~SK, 2 lags)			
Parametric components			
Intercept, β_0	1.000	5.045 [a]	8237[b]***
Non-parametric components			
$s(SK_{t-1})$	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: 0.00037157, VAR:0.00038126			
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)			
Parametric components			
Intercept, β_0	1.000	5.045 [a]	8047[b]***
Non-parametric components			
$s(CZ_{t-1})$	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: 0.00034811, VAR:0.00039437			
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)			
Parametric components			
Intercept, β_0	1.000	5.045 [a]	8850[b]***
Non-parametric components			
$s(HU_{t-1})$	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: 0.0003277, VAR:0.0003342			
AIC(GAM)=-5070.36;AIC(VAR)=-5050.31			
*LR-test of linear VAR vs.GAM, Test statistic=2.2238****			

[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
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Source: Own calculations

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

GAM component	EDF	Smoothing parameter, λ	F value
Model I (PL∼SK, 3 lags)			
Parametric components			
Intercept, β_0	1.000	5.004 [a]	7877[b]***
Non-parametric components			
$s(SK_{t-1})$	1.000	5353725	4.55**
$s(SK_{t-2})$	3.16	2.044594	2.25*
$s(SK_{t-3})$	1.000	161046	0.088
$s(PL_{t-1})$	1.000	4075391	2550.90***
$s(PL_{t-2})$	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: 0.0004026,VAR:0.0004161			
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)			
Parametric components			
Intercept, β_0	1.000	5.004 [a]	7866[b]***
Non-parametric components			
$s(CZ_{t-1})$	1.000	1644205	4.53**
$s(CZ_{t-2})$	2.836	1.620458	2.96**
$s(CZ_{t-3})$	1.000	2531997	4.41**
$s(PL_{t-1})$	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:0.000415745			
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)			
Parametric components			
Intercept, β_0	1.000	5.004 [a]	7870[b]***
Non-parametric components			
$s(HU_{t-1})$	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: 0.0004032,VAR:0.0004151			
AIC(GAM)=-4867.02;AIC(VAR)=-4838.31			
*LR-test of linear VAR vs.GAM, Test statistic=3.5802****			

[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
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Source: Own calculations

sion 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).

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 it's mean value (see A). The findings from plots in appendix A imply that asymmetry exists in terms of the disproportionate response to the appropriate predictor increase. We can observe 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. More precisely, price SK_t responds to the changes of lagged price variable SK_{t-1} with non-linear increasing, to the lagged price variable SK_{t-2} with "wiggly" decreasing and increasing, to the lagged variable PL_{t-3} with non-linear increasing and then decreasing. At the same time, price PL_t reacts to the changes of the lagged price variables (SK_{t-1}, SK_{t-2}, PL_{t-3}) in a different way, namely to the lagged price SK_{t-1} with linear increasing, to the lagged price SK_{t-2} with slight non-linear decreasing, to the lagged price PL_{t-3} with non-linear increasing. Similarly, we can find asymmetries in other price pairs with Polish market (see appendix A.6).

5 Conclusions

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 pigmeat markets of V4 countries in comparison with linear VAR modelling, that is in line with the findings of Guney et al. (2019) and 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 modelling.

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 stabilise 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.

In the aspect of food security, it is necessary to prevent the import of food products to Slovakia at dumping prices, as well as margin distribution and the misuse of the dominant market position of retailers should be solved at the national and EU levels.

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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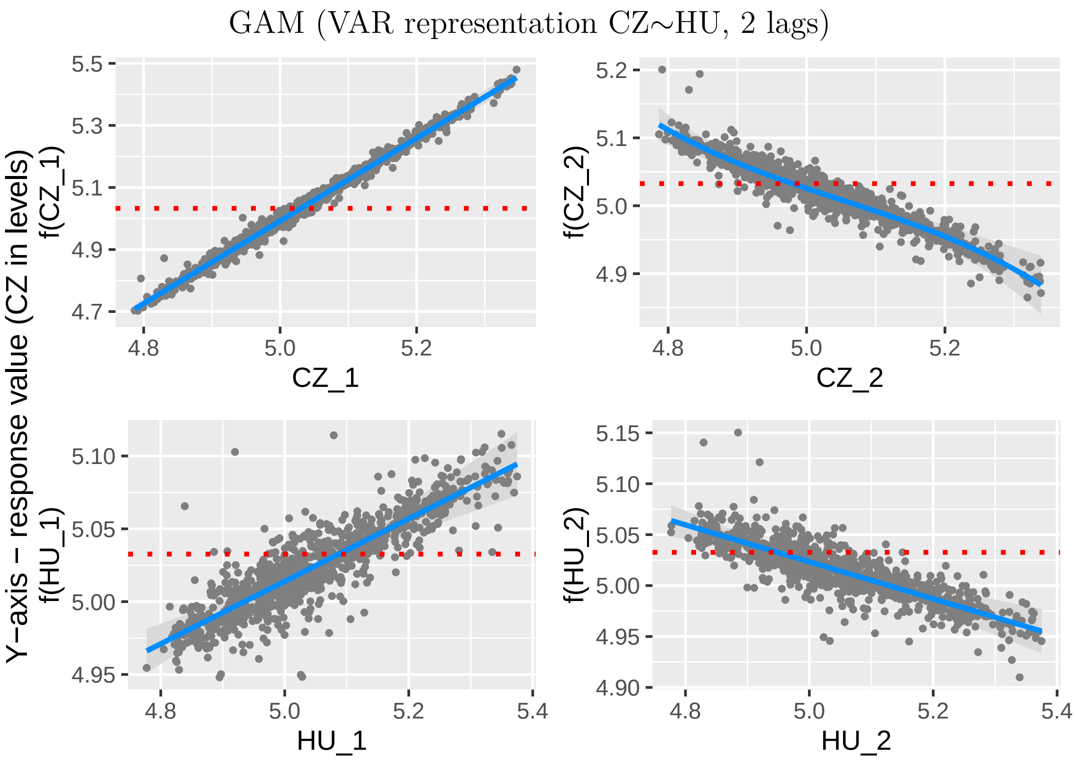
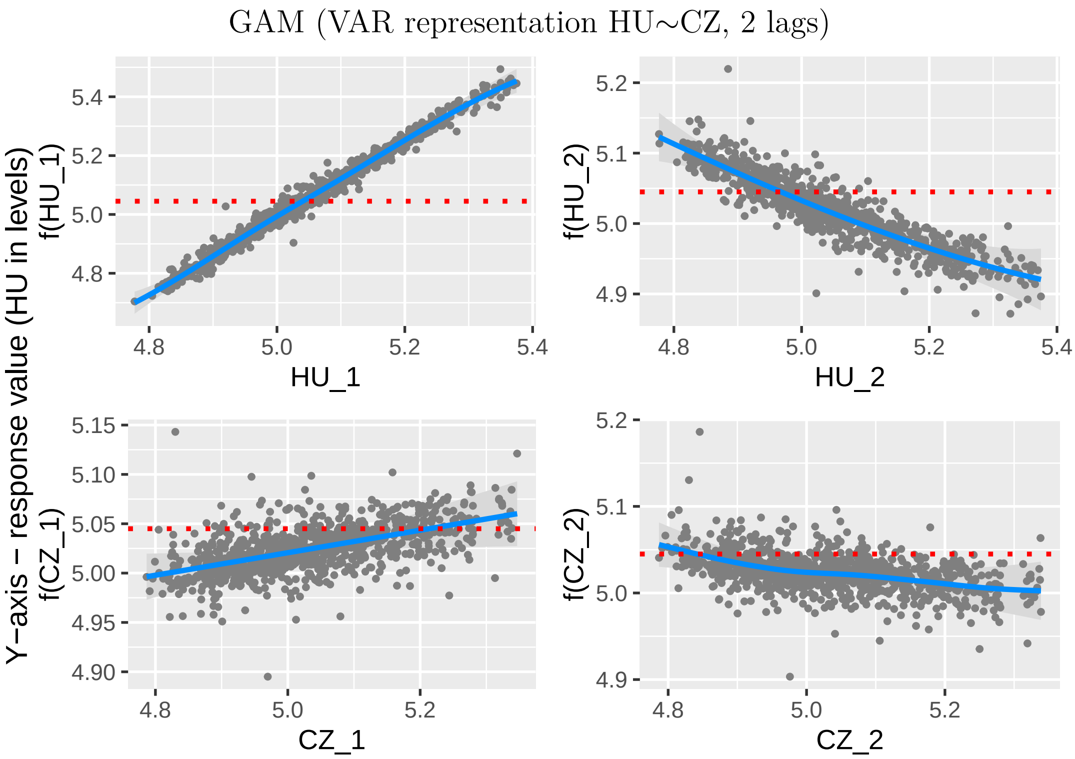
A GAM partial effects of one particular predictor on response

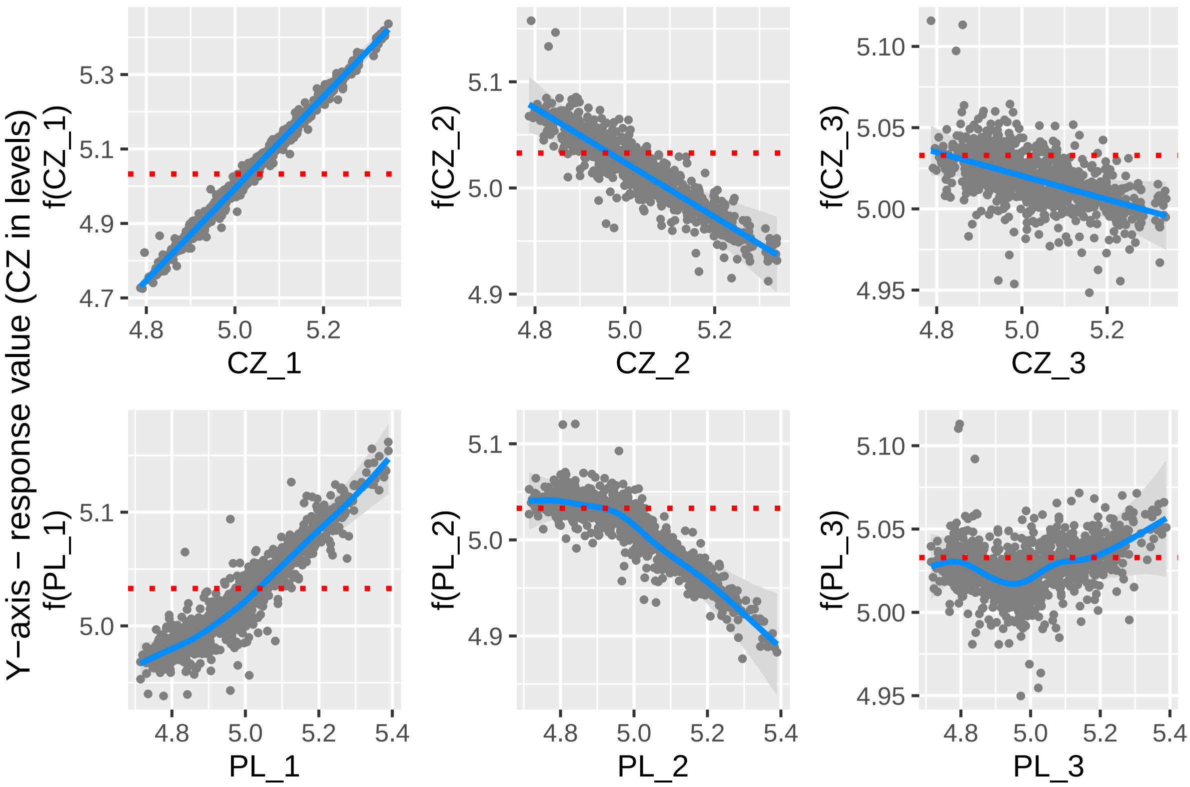
A.1 Czechia & Hungary



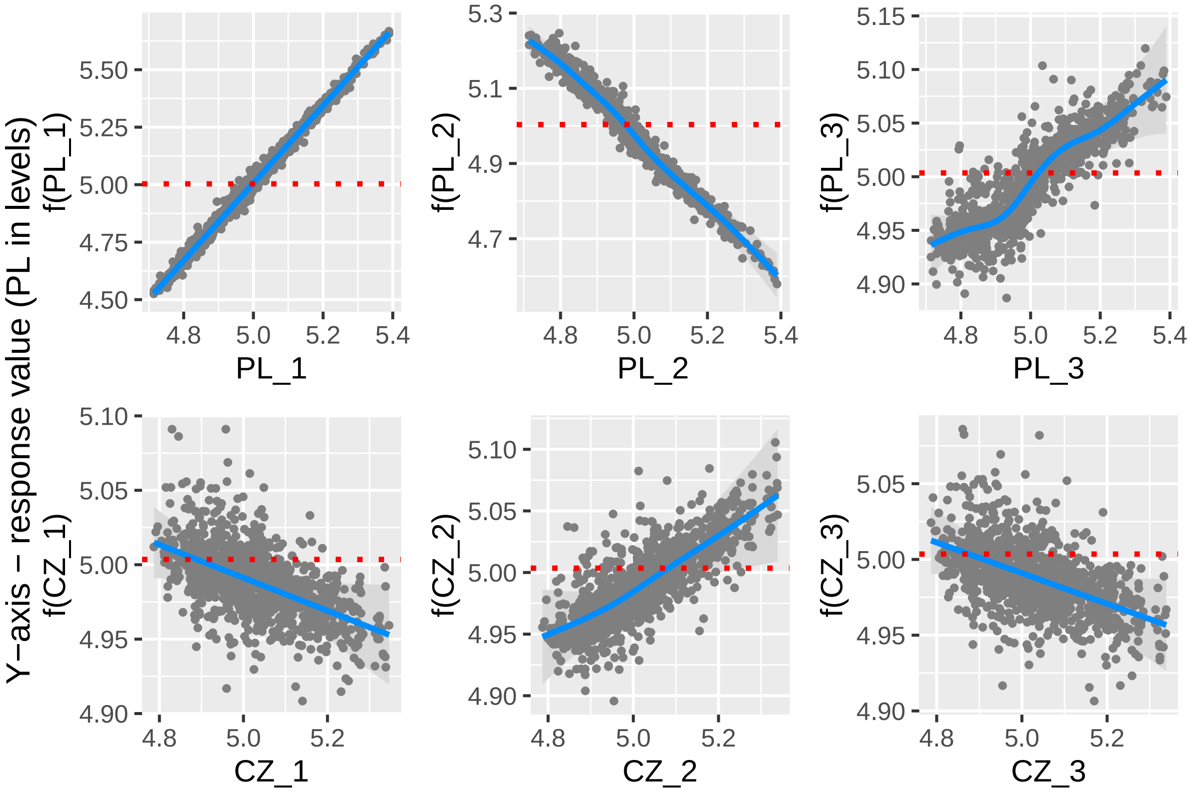


A.2 Czechia & Poland

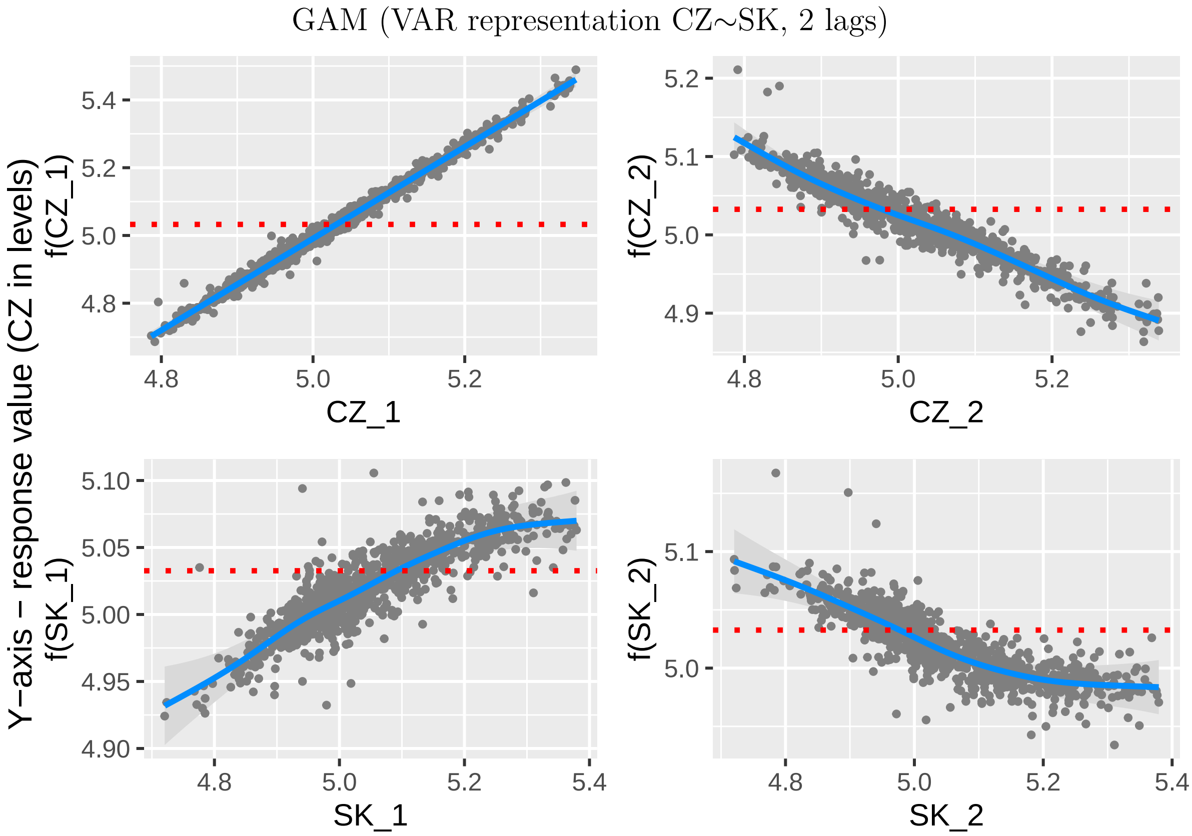
GAM (VAR representation CZ∼PL, 3 lags)

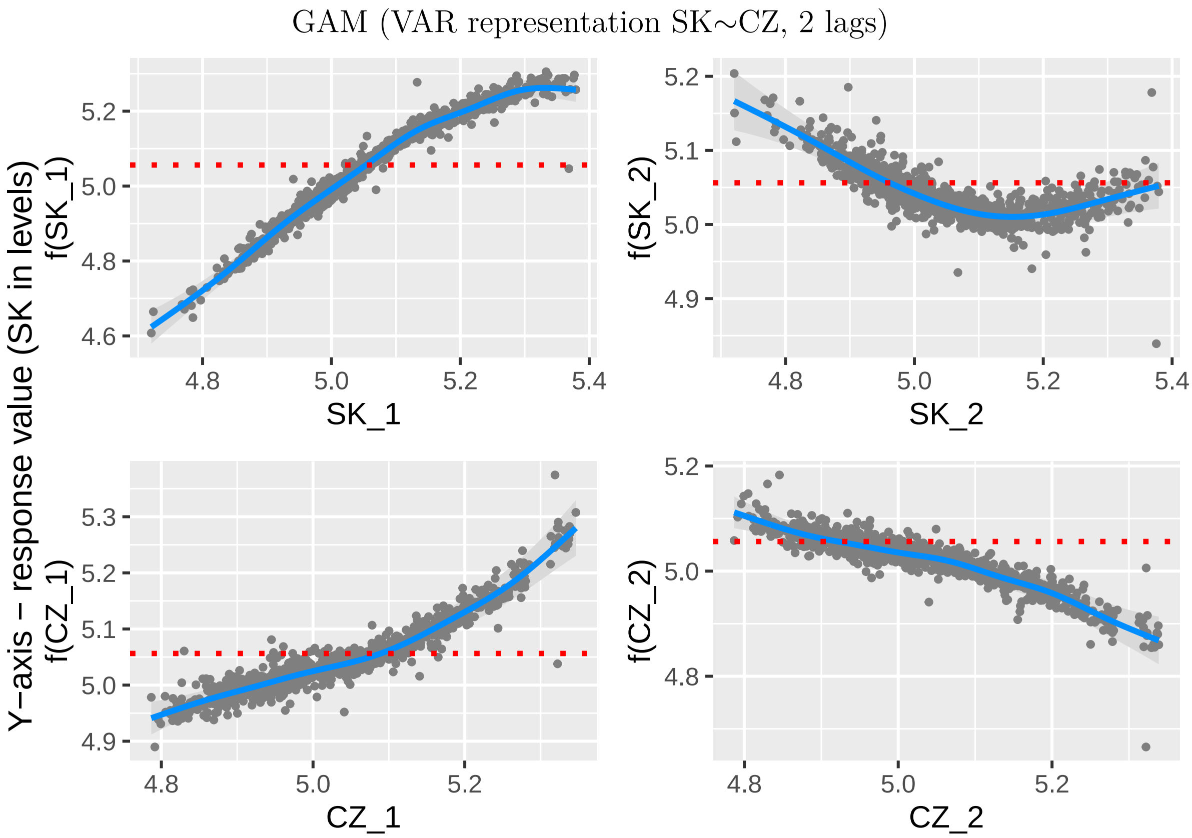


GAM (VAR representation PL∼CZ, 3 lags)



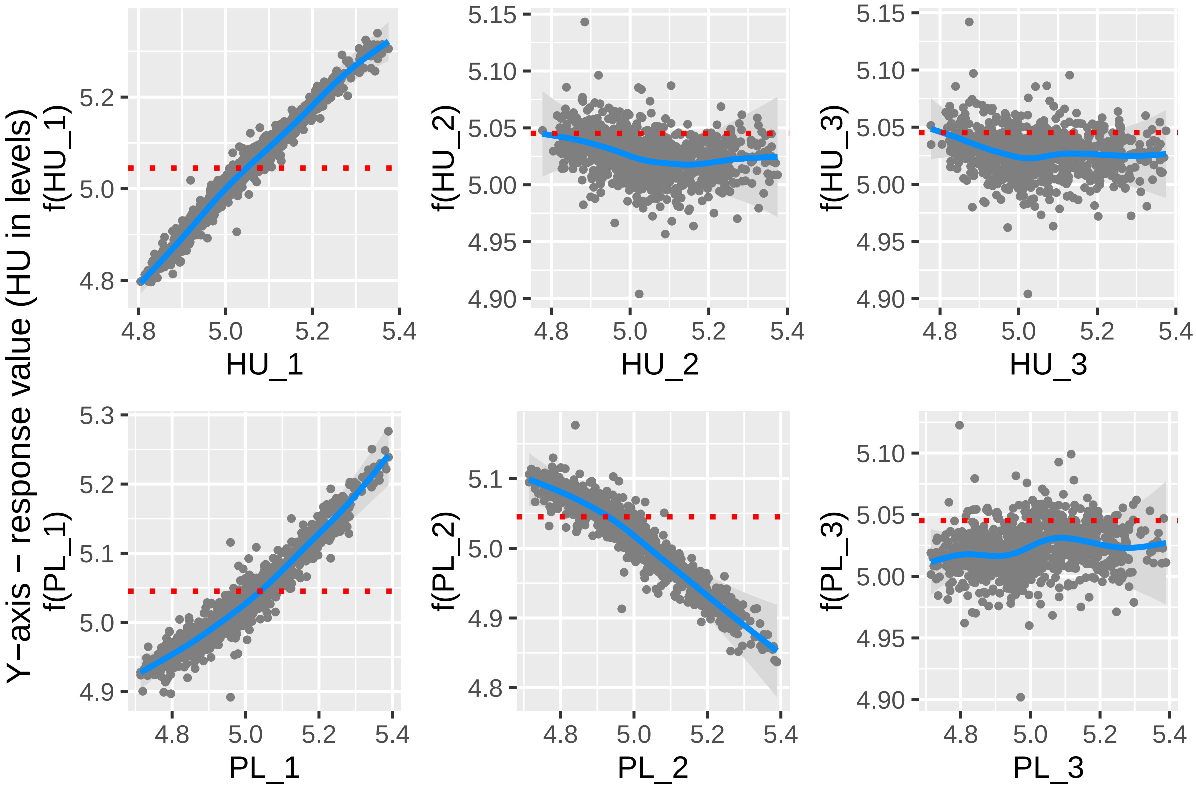
A.3 Czechia & Slovakia



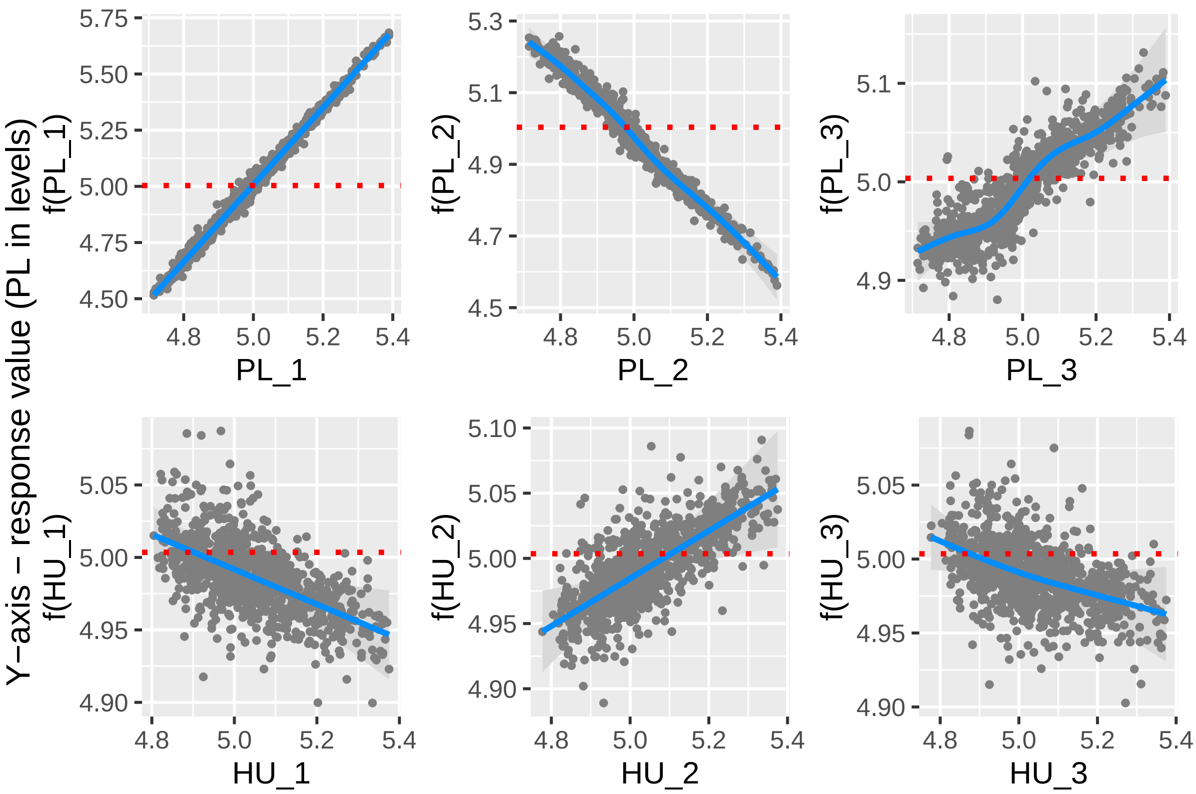


A.4 Hungary & Poland

GAM (VAR representation HU∼PL, 3 lags)

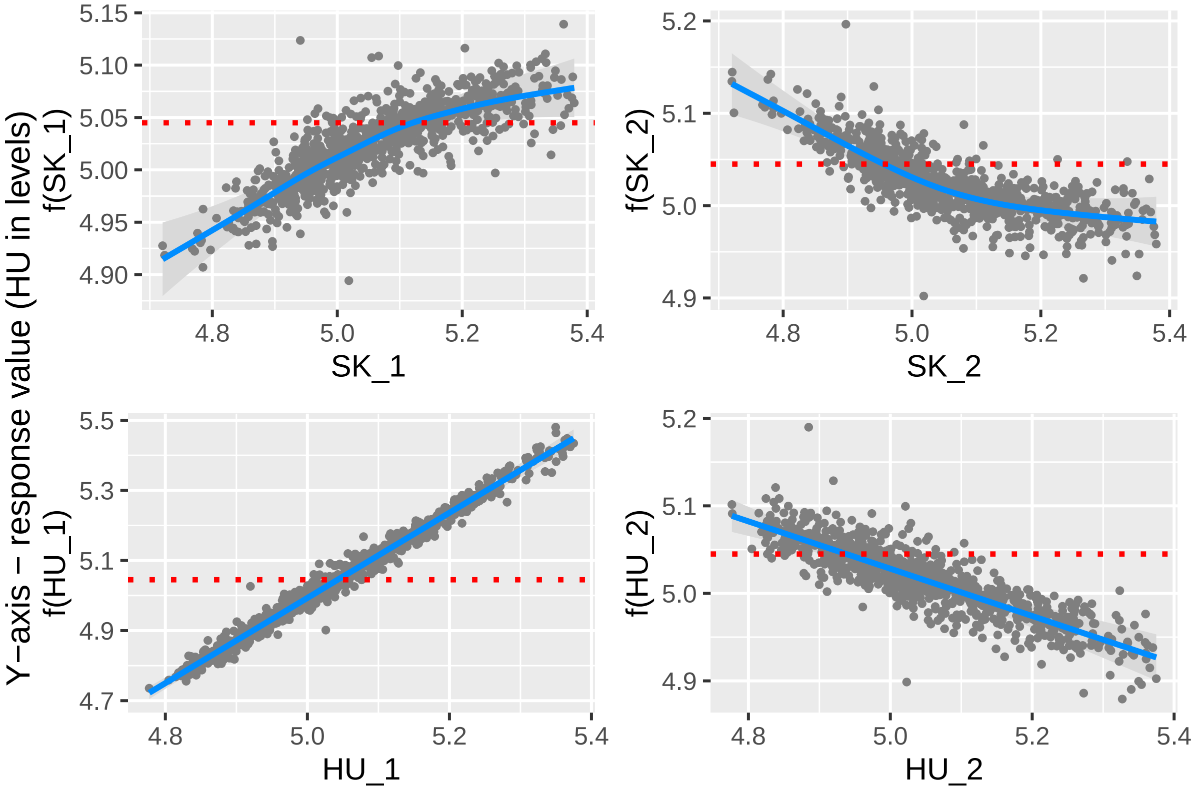


GAM (VAR representation PL∼HU, 3 lags)

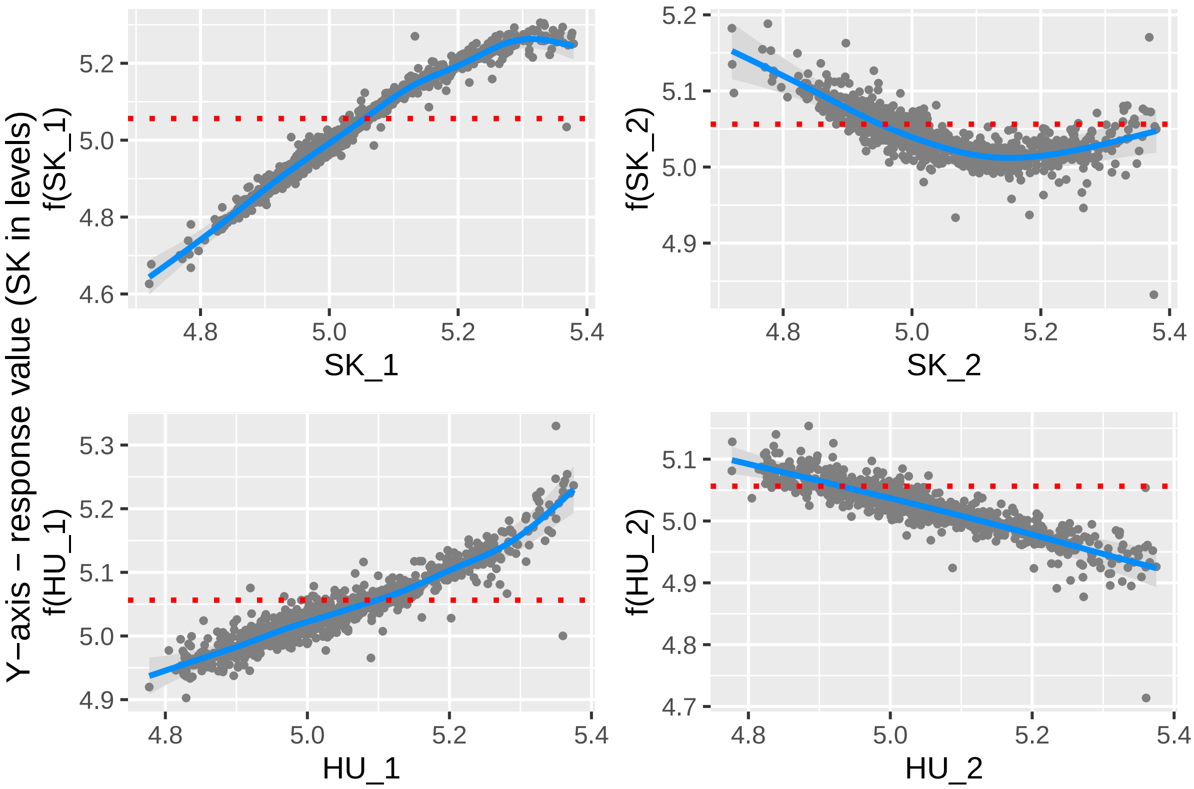


A.5 Hungary & Slovakia

GAM (VAR representation HU~SK, 2 lags)

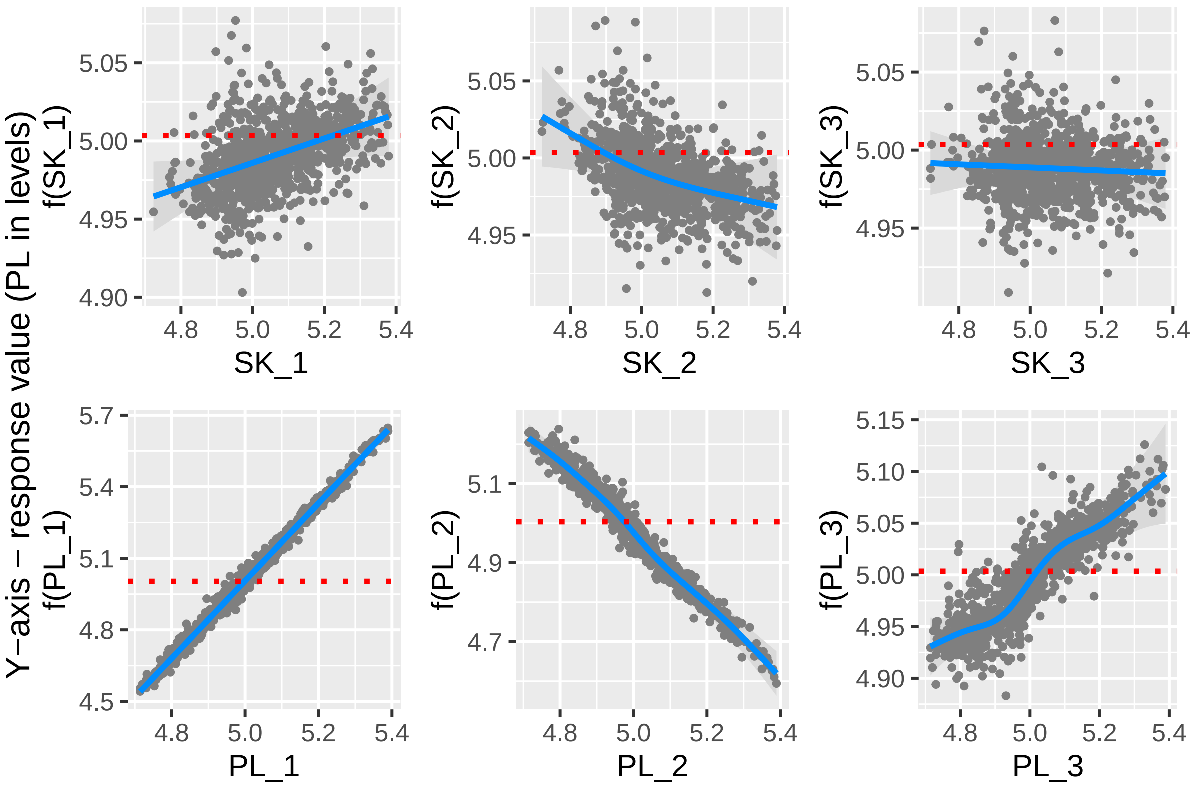


GAM (VAR representation SK~HU, 2 lags)

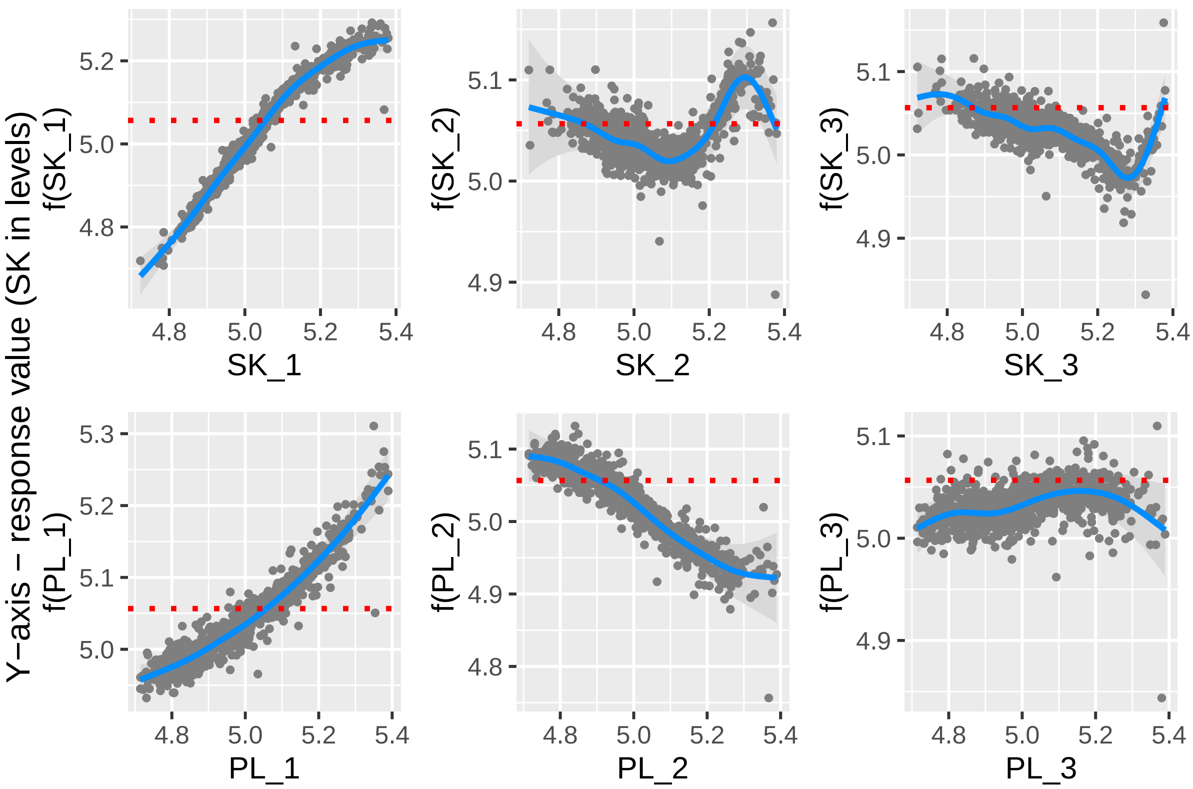


A.6 Poland & Slovakia

GAM (VAR representation PL∼SK, 3 lags)



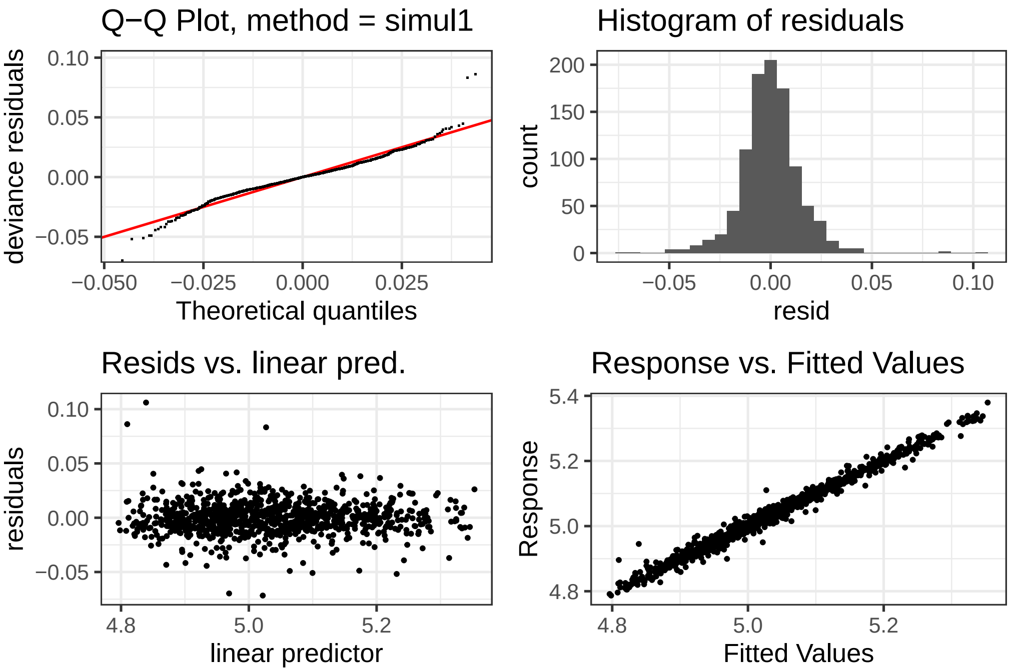
GAM (VAR representation SK∼PL, 3 lags)



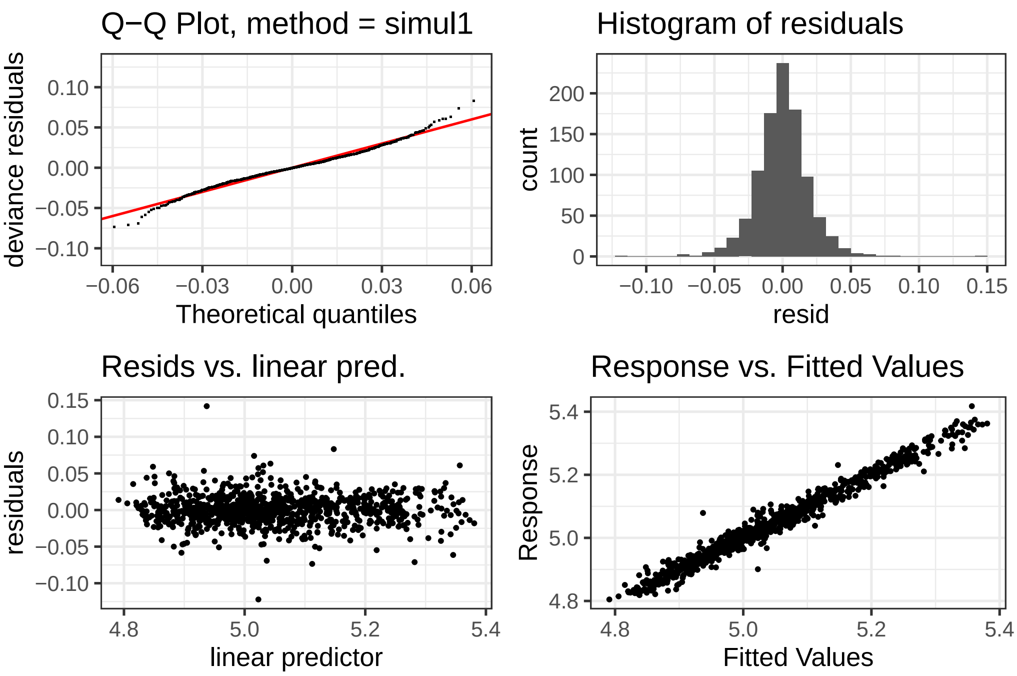
B Some diagnostics for the fitted GAMs

B.1 Czechia & Hungary

Robustness checking for the GAM (CZ∼HU)

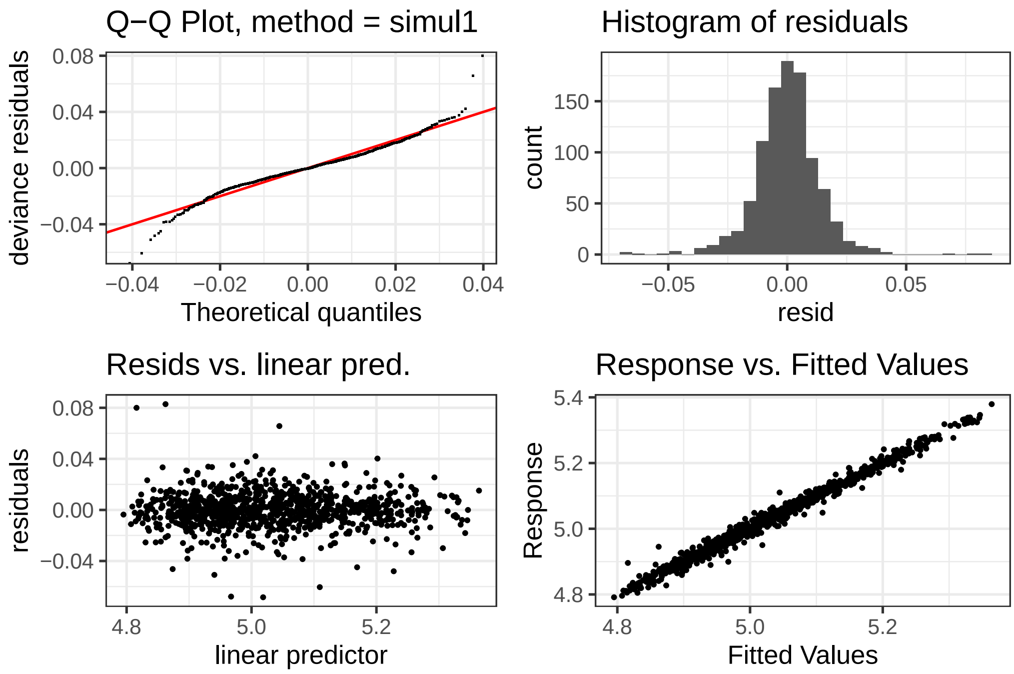


Robustness checking for the GAM (HU∼CZ)

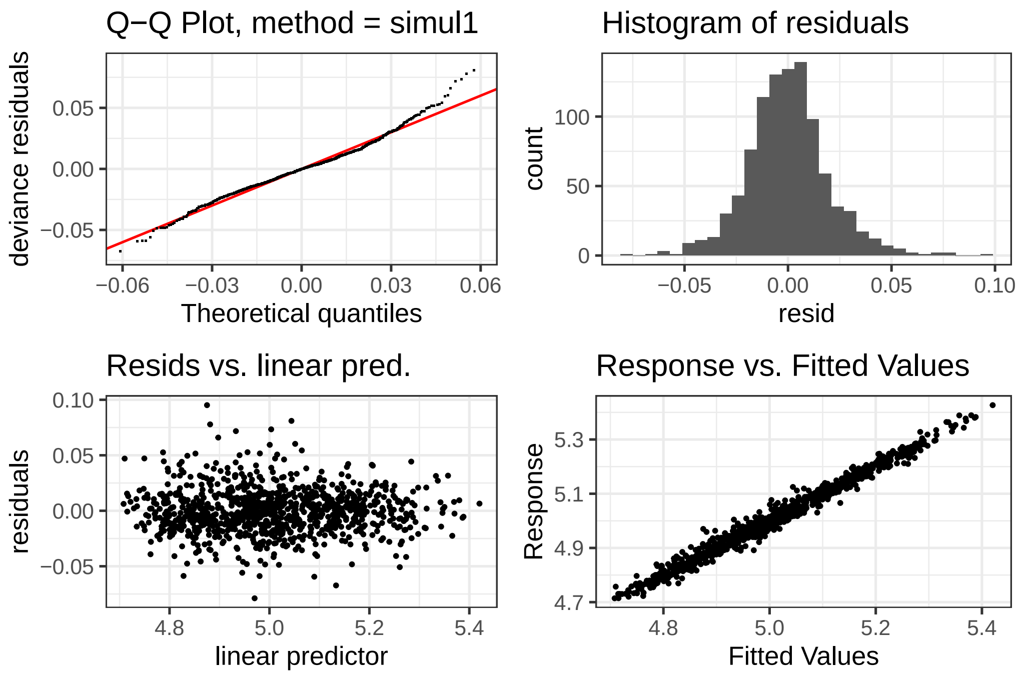


B.2 Czechia & Poland

Robustness checking for the GAM (CZ~PL)

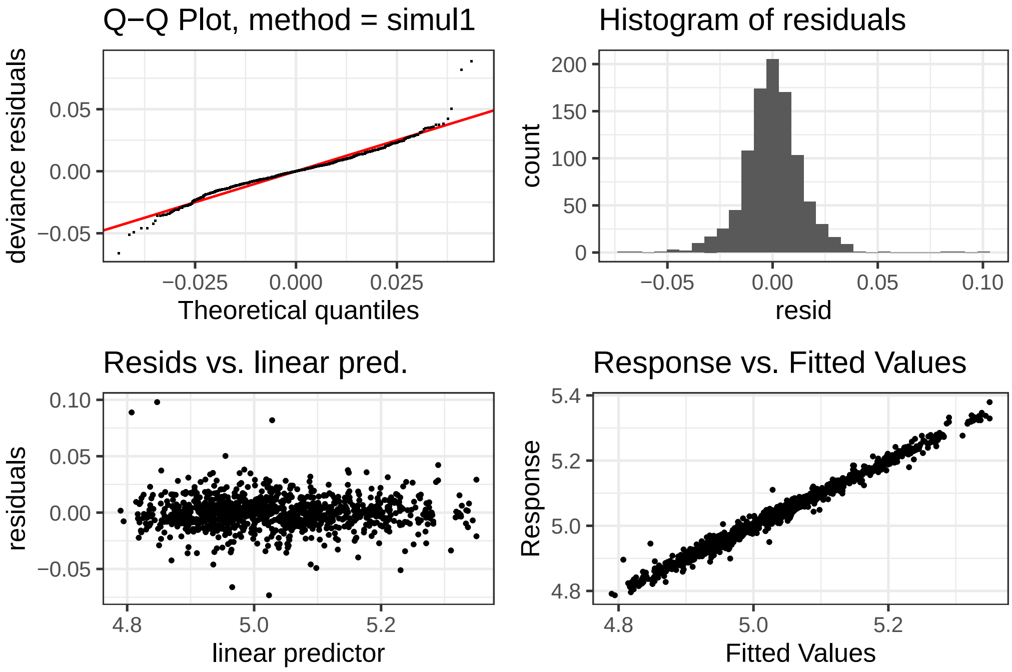


Robustness checking for the GAM (PL~CZ)

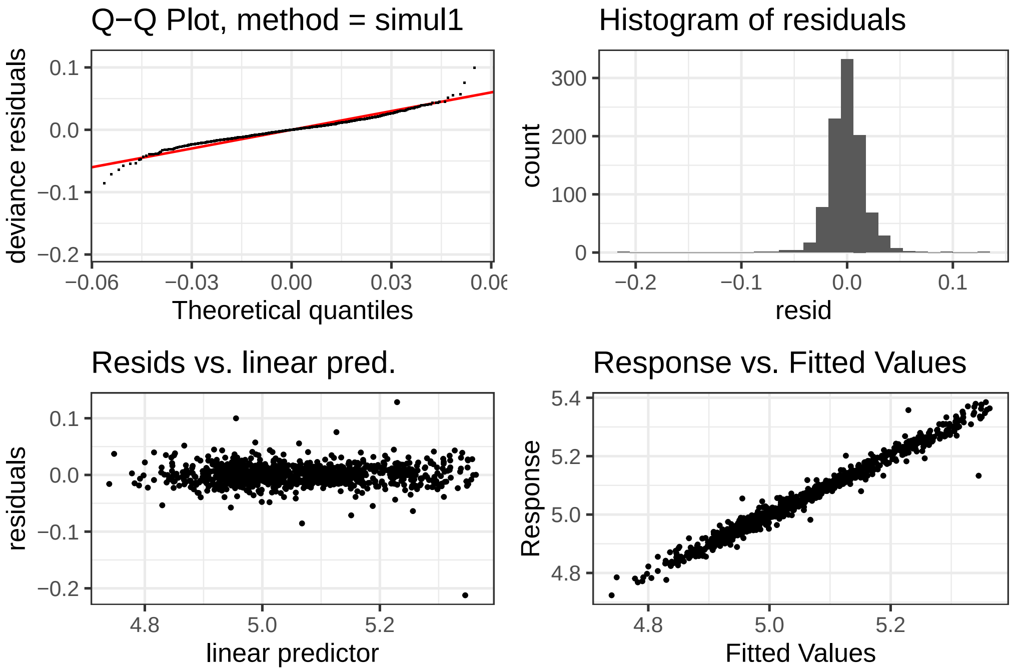


B.3 Czechia & Slovakia

Robustness checking for the GAM (CZ~SK)

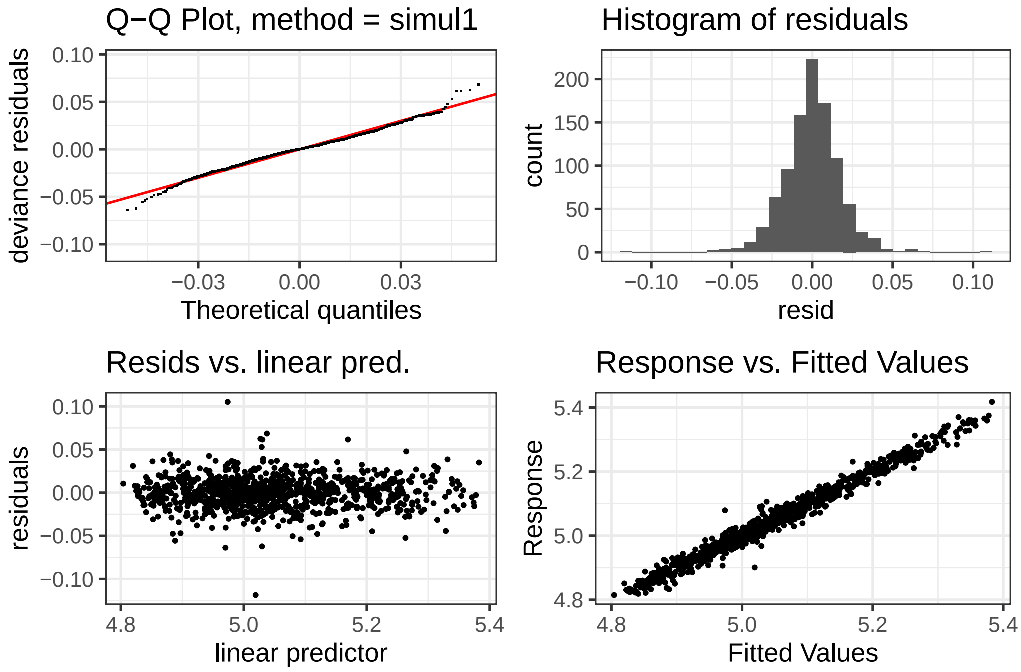


Robustness checking for the GAM (SK~CZ)

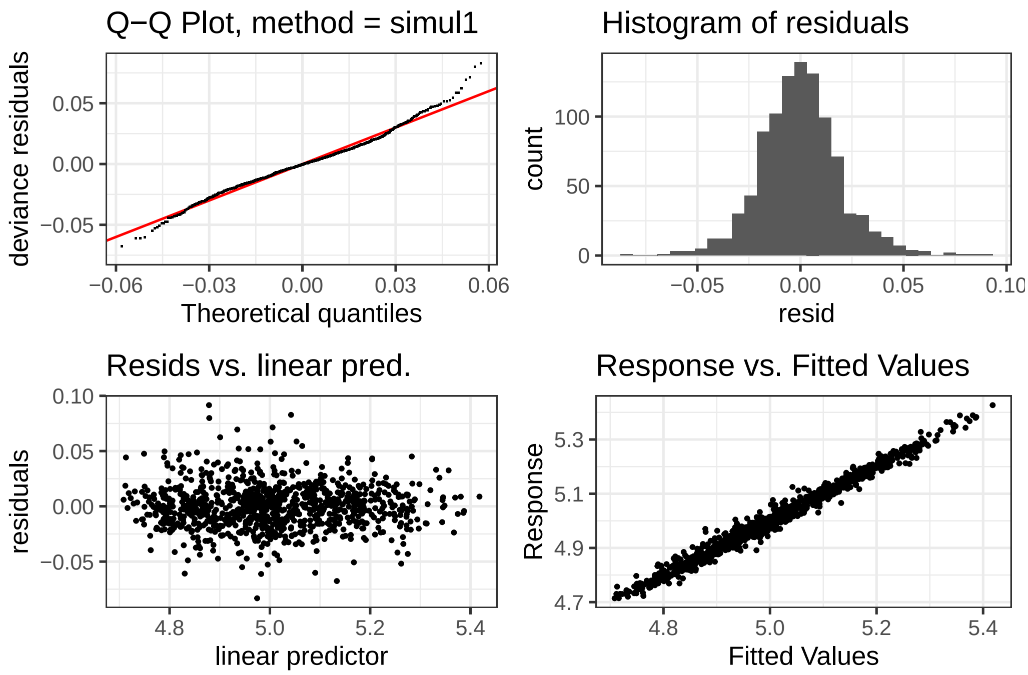


B.4 Hungary & Poland

Robustness checking for the GAM (HU∼PL)

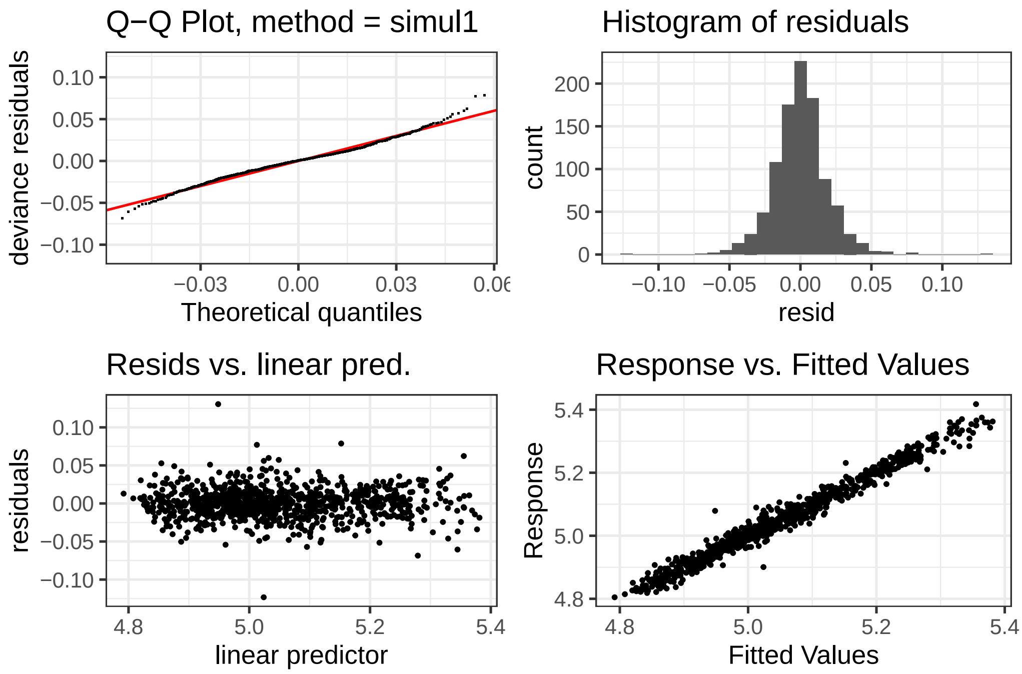


Robustness checking for the GAM (PL∼HU)

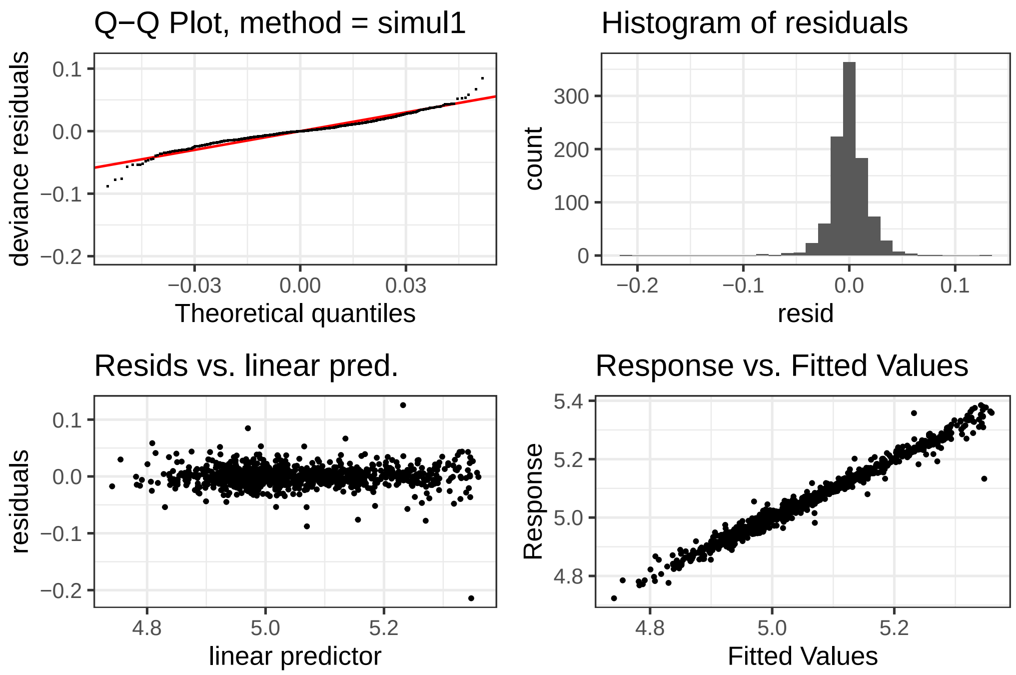


B.5 Hungary & Slovakia

Robustness checking for the GAM (HU∼SK)

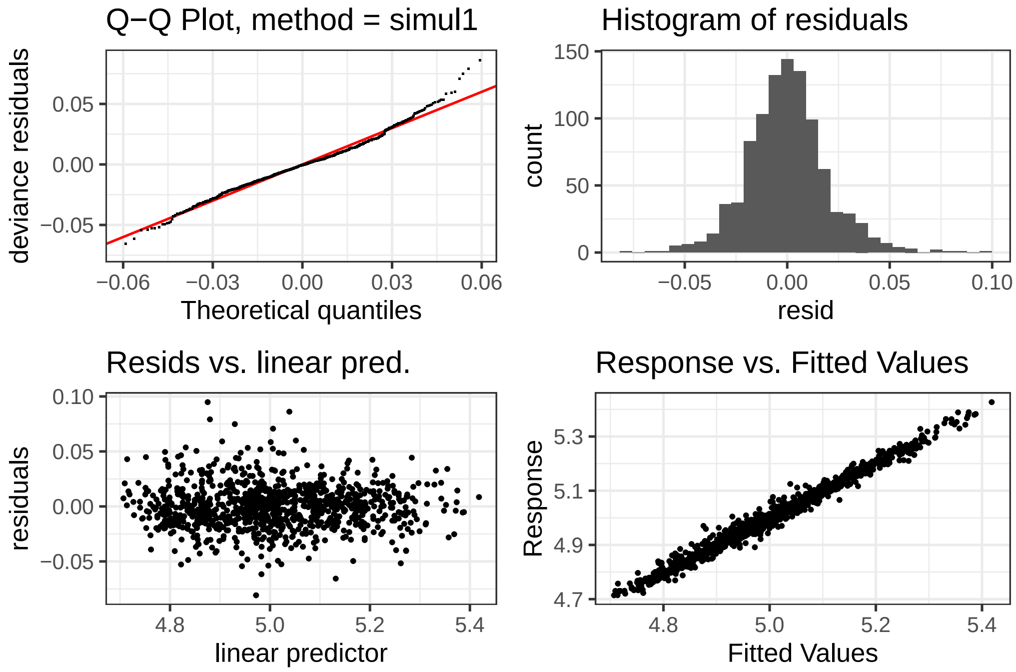


Robustness checking for the GAM (PL∼HU)



B.6 Poland & Slovakia

Robustness checking for the GAM (PL∼SK)



Robustness checking for the GAM (SK∼PL)