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Abstract

Empirical studies on farmland rental rates have predominantly concentrated on modelling conditional means using spatial autoregressive models, where a linear functional form between the response and the covariates is usually assumed. However, if it is in fact non-linear, misspecifying the functional form can adversely affect inference. While mean regression models only allow limited insights into the way covariates influence the response, extending the analysis to the modelling of conditional quantiles can give a more detailed picture of the conditional distribution. Based on data from the German agricultural census, this article contributes to the agricultural literature by modelling conditional quantiles of farmland rental rates semi-parametrically using Bayesian geoadditive quantile regression models. The flexibility of this model class overcomes the problems associated with functional form misspecifications and allows us to present a more detailed analysis. Our results stress the importance of making use of semi-parametric regression models as several covariates influence farmland rental rates in an explicit non-linear way.

Key words: *Bayesian Geoadditive Quantile Regression, Boosting, Farmland Rental Rates, Hedonic Pricing Models, P-splines.*

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Introduction

Farmland is one of the most important production factors in agriculture. Based on cash-flow considerations, farmers have to decide whether to buy or lease agricultural land. Amongst others, one advantage of leasing is that farmers can use their cash reserves to invest in new agricultural machinery and equipment, rather than to tie up capital in land purchases (Ciaian et al. 2012). This preference might explain why Germany is among European countries with a high share of rented farmland: in 2008, on average 70% of the total German agricultural farmland was leased, where the share of rented farmland was considerably higher in East Germany (80%) compared to West Germany (60%) (Ciaian et al. 2012; Ciaian, Kancs, and Swinnen 2010). Moreover, Ciaian, Kancs, and Swinnen (2010) report that German farmland rental rates exhibit substantial spatial variation with rental rates being almost twice as high in West Germany than in East Germany. These figures, and the fact that farmland rental rates have increased considerably over the last years, imply that the analysis of rental rates is of great importance in practice. Besides its relevance for farmers, the analysis of farmland rental rates and their determinants is an active field of research in agricultural economics. Herriges, Shogren, and Barickman (1992), Bierlen, Parsch, and Dixon (1999), Lence and Mishra (2003), as well as Roberts, Kirwan, and Hopkins (2003) and Kirwan (2009) analyse the determinants of price formations on agricultural rental markets in the United States. Fuchs (2002) analyses rental rates of farmland and their determinants in Belgium, Denmark, France, Germany and the Netherlands. Doll and Klare (1995), Drescher and McNamara (2000), Brümmer and Loy (2001), Breustedt and Habermann (2008), Margarian (2008), Breustedt and Habermann (2009) and Breustedt and Habermann (2011) investigate the determinants of rental rates in Germany. Kilian et al. (2008), as well as Breustedt and Habermann (2010) and Habermann and Ernst (2010) analyse the effects of increased land use for the production of bioenergy on German rental rates.

Most empirical studies that analyse farmland rental rates and their determinants make use of hedonic pricing models, as originally proposed by Court (1939) and popularized by Griliches (1961), Lancaster (1966) and Rosen (1974). According to hedonic pricing theory, farmland rental rates can be divided into the sum of its attributes‘ values which are then estimated using regression models. In order to avoid biased estimates and misleading inference resulting from spatial dependencies in the data, spatial autoregressive models have evolved as a standard tool in hedonic pricing studies of farmland rental rates. However, a remaining problem with hedonic pricing models is related to the choice of an appropriate functional form, since there is no theory that guides the researcher (Martins-Filho and Bin 2005). A common workaround is to use data transformations as proposed by Box and Cox (1964). The functional form chosen by the Box-Cox technique may, however, not adequately approximate the true relationship between covariates and the response. In spatial modelling, misspecifications of the dependence structure have particularly severe consequences; as an illustration, Kostov (2009) reanalyses the data of Patton and McErlean (2003) using semi-parametric regression models, and concludes that misspecifications regarding the functional form may be responsible for spuriously finding spatial dependencies when hedonic pricing models are used.[1] Consequently, hedonic models should be extended to semi-parametric regression models that allow for a broader class of functional relationships than parametric models (Ekeland, Heckman, and Nesheim 2004).

While empirical studies on farmland rental rates have predominantly concentrated on modelling conditional means, extending the analysis to the modelling of conditional quantiles can provide valuable insights into the price formation of farmland rental rates. It seems reasonable to assume that some covariates have an effect on the mean, while they may have no influence on more extreme quantiles; even if the same covariates are selected, the manner in which they affect rental rates may change across quantiles. Therefore, the analysis based on quantile regression models can provide a more detailed picture of the conditional distribution of the response variable. For this reason, linear spatial quantile regression models have recently been introduced within spatial econometrics (see McMillen (2013) for a recent overview). However, this model class cannot fully avoid the problems resulting from functional form misspecifications (Kostov 2013).

The purpose of this article is to extend the hedonic pricing literature of farmland rental rates by modelling conditional quantiles of German farmland rental rates semi-parametrically using Bayesian geoadditive quantile regression models. The flexibility of this model class frees the researcher from choosing the underlying functional form a-priori and allows for the modelling of a variety of covariates: linear effects of categorical covariates, smooth non-linear effects of continuous covariates, as well as spatial effects to account for spatial autocorrelation and unobserved heterogeneity. Our results indicate that linear spatial quantile regression models yield a misleading picture of the underlying functional form as some of the covariates clearly have a non-linear effect on rental rates. Consequently, Bayesian geoadditive quantile regression models overcome the problems of linear spatial quantile regression models and allow us to present a more detailed analysis of farmland rental rates and their determinants.

Structured Additive Regression Models

In recent years, statistical research on semi-parametric regression models that go beyond traditional linear regression has brought forward a powerful toolkit that allows for a more realistic treatment of a variety of real data problems. Structured Additive Regression Models (STAR), originally proposed by Fahrmeir, Kneib, and Lang (2004) and Brezger and Lang (2006), have turned out to be a very powerful model class as they cover the most prominent model extensions as special cases. STAR models include Generalized Additive Models (GAM) (Hastie and Tibshirani 1990), Varying Coefficient Models (VCM) (Hastie and Tibshirani 1993), Generalized Additive Mixed Models (GAMM) (Lin and Zhang 1999), Geoadditive Models (Kammann and Wand 2003), as well as Geographically Weighted Regression Models (Fotheringham, Brunsdon, and Charlton 2002). We present STAR models for the conditional mean first, since this model class forms the basis for geoadditive quantile regression models.

STAR Models: Getting the mean right

As with the usual linear regression framework, we assume that observations $(y_i, \boldsymbol{x}_i, \boldsymbol{z}_i), i = 1, \ldots, n$ are given, where y_i is a continuous response, $\boldsymbol{x}_i = (x_{i1}, \ldots, x_{iq})$ is a vector of categorical covariates and $\boldsymbol{z}_i = (z_{i1}, \ldots, z_{ip})$ is a vector of continuous covariates. In the Generalized Linear Model (GLM) framework of Nelder and Wedderburn (1972), the conditional mean of the response is modeled via

$$(1) \qquad \mathbb{E}(y_i|\boldsymbol{x}_i, \boldsymbol{z}_i) = h(\eta_i^{linear}) \quad , \quad \text{with} \quad \eta_i^{linear} = \boldsymbol{x}_i'\boldsymbol{\beta} + \boldsymbol{z}_i'\boldsymbol{\gamma}$$

where $h(\cdot)$ is a response function that links the conditional mean of y_i with the linear predictor η_i^{linear}. To allow the response to depend non-linearly on continuous covariates, GLMs can be extended to GAMs by replacing the strictly linear predictor in Equation (1) with a more flexible semi-parametric predictor

$$(2) \qquad \eta_i = \boldsymbol{x}_i'\boldsymbol{\beta} + f_1(z_{i1}) + \ldots + f_p(z_{ip})$$

where $f_1, \ldots, f_p$ are non-linear smooth effects of the continuous covariates and $\boldsymbol{x}_i'\boldsymbol{\beta}$ is the usual parametric part. For modelling the unknown functions f_j, we follow Lang and Brezger (2004) and Brezger and Lang (2006) who introduce a Bayesian analogue to P(enalized)-splines originally proposed from a frequentist point of view by Eilers and Marx (1996). In order to illustrate the basic principles of P-splines, we present the frequentist approach first, where it is assumed that the unknown function f_j can be approximated by a polynomial spline of degree l_j. The spline is then represented as a linear combination of $m_j = h_j + l_j - 1$ B-spline basis functions $B_{j,k}$ evaluated at pre-specified knots $z_{j,min} = \zeta_{j,1} < \zeta_{j,2} < \ldots < \zeta_{j,h_j} = z_{j,max}$

$$(3) \quad f_j(z_{ij}) = \sum_{k=1}^{m_j} \gamma_{j,k} B_{j,k}(z_{ij}) \quad , \quad i = 1, \ldots, n. \quad ; \quad j = 1, \ldots, p.$$

where the coefficients $\gamma_{j,k}$ can be interpreted as amplitudes that scale the basis functions $B_{j,k}$ accordingly to fit the data.[2] To ensure a good fit to the data, Eilers and Marx (1996) suggest using a sufficiently high number of equidistant knots (usually between 20 and 40), as well as to simultaneously impose a penalty $\lambda_j \sum_{k=d+1}^{m_j} (\Delta^d \gamma_{j,k})^2$ on adjacent B-spline coefficients $\gamma_{j,k}$ that prevents f_j from being too wiggly. The penalized least squares criterion can then be expressed as follows

$$(4) \quad \text{PLS}(\lambda_j) = \sum_{i=1}^{n} \left(y_i - \boldsymbol{x}_i' \boldsymbol{\beta} - \sum_{k=1}^{m_j} \gamma_{j,k} B_{j,k}(z_{ij}) \right)^2 + \lambda_j \sum_{k=d+1}^{m_j} \left(\Delta^d \gamma_{j,k} \right)^2 \quad , \quad j = 1, \ldots, p.$$

where Δ^d denotes the d-th order difference operator, i.e., $\Delta^1 = \gamma_{j,k} - \gamma_{j,k-1}$ for d=1. The penalty term, that balances the trade-off between a good fit to the data and the amount of smoothness of f_j, depends on the smoothing parameter λ_j: the greater the value of λ_j, the higher is the penalization and the smoother is f_j. A popular choice that has turned out to work well in many empirical applications are penalized cubic B-splines with a quadratic penalty term based on second order differences. Rewriting the smooth functions in matrix form $\boldsymbol{f}_j = (f_j(z_{1j}), \ldots, f_j(z_{nj}))' = \boldsymbol{Z}_j \boldsymbol{\gamma}_j$, where $\boldsymbol{\gamma}_j = (\gamma_{j,1}, \ldots, \gamma_{j,m_j})'$ is a vector of regression coefficients and $\boldsymbol{Z}_j$ is a $(n \times m_j)$ design matrix whose columns are given by the B-spline basis functions evaluated at the observed covariate values $\boldsymbol{Z}_j[i,k] = B_{j,k}(z_{ij})$, leads to the semi-parametric predictor $\boldsymbol{\eta} = \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{Z}_1\boldsymbol{\gamma}_1 + \ldots + \boldsymbol{Z}_p\boldsymbol{\gamma}_p$, with the penalized least squares criterion given by

$$(5) \quad \text{PLS}(\boldsymbol{\lambda}) = (\boldsymbol{y} - \boldsymbol{\eta})' (\boldsymbol{y} - \boldsymbol{\eta}) + \sum_{j=1}^{p} \lambda_j \boldsymbol{\gamma}_j' \boldsymbol{K}_d \boldsymbol{\gamma}_j$$

The penalty matrix $\boldsymbol{K}_d$ can be partitioned into $\boldsymbol{K}_d = \boldsymbol{D}_d' \boldsymbol{D}_d$, where $\boldsymbol{D}_d$ is a d-th order difference matrix. In the Bayesian framework, the vector of regression coefficients $\boldsymbol{\gamma}_j$ and $\boldsymbol{\beta}$ are considered to be random variables so that appropriate prior distributions have to be assigned. For the parameters $\boldsymbol{\beta}$ of the parametric part, non-informative priors are assumed, i.e.,

$p(\beta_r) \propto const, r = 1, \ldots, q$. Priors for the regression parameters $\boldsymbol{\gamma}_j$ of the smooth curves are defined by replacing the difference penalty by first or second order random walks

$$(6) \qquad \begin{aligned} RW_1 &: \gamma_{j,k} = \gamma_{j,k-1} + u_{j,k}, & k = 2, \ldots, m_j. \\ RW_2 &: \gamma_{j,k} = 2\gamma_{j,k-1} - \gamma_{j,k-2} + u_{j,k}, & k = 3, \ldots, m_j. \end{aligned}$$

where $u_{j,k} \sim N(0, \tau_j^2)$ are Gaussian error terms. The amount of smoothness is controlled by the variance parameter τ_j^2, that corresponds to the inverse of the smoothing parameter λ_j in the frequentist setting: the larger the variance τ_j^2, the more $\gamma_{j,k}$ is allowed to deviate from the preceding values and the more flexible is the fit. The unknown variance parameters τ_j^2 are also considered as random variables and highly dispersed inverse Gamma hyper-priors $p(\tau_j^2) \sim IG(a_j, b_j)$ are assigned that allow for the estimation of the amount of smoothing simultaneously with the regression coefficients. For initial values of first and second order random walks, flat hyper-priors $p(\gamma_{j,1}) \propto const$, and $p(\gamma_{j,1}, \gamma_{j,2}) \propto const, j = 1, \ldots, p$ are assigned. From the conditional distributions of first and second order randoms walks, it is possible to determine the joint multivariate prior distribution of the complete vector $\boldsymbol{\gamma}_j$ (Fahrmeir et al. 2013). From a Bayesian point of view, the quadratic penalty $\lambda_j \boldsymbol{\gamma}_j' \boldsymbol{K}_j \boldsymbol{\gamma}_j$ in Equation (5) can then be replaced with a Gaussian (improper) smoothing prior for the regression coefficients $\boldsymbol{\gamma}_j$

$$(7) \qquad p(\boldsymbol{\gamma}_j | \tau_j^2) \propto \frac{1}{(\tau_j^2)^{rank(\boldsymbol{K}_j)/2}} \exp\left(-\frac{1}{2\tau_j^2} \boldsymbol{\gamma}_j' \boldsymbol{K}_j \boldsymbol{\gamma}_j\right) \quad , \quad j = 1, \ldots, p.$$

Besides categorical and continuous covariates, spatially referenced data also contain information about the location where the observations have been collected. To include this information into the model, an additional spatial term f_{geo} is added to the predictor from Equation (2)

$$(8) \qquad \eta_i = \boldsymbol{x}_i' \boldsymbol{\beta} + f_1(z_{i1}) + \ldots + f_p(z_{ip}) + f_{geo}(s_i)$$

yielding a geoadditive model as proposed by Kammann and Wand (2003). The spatial effect f_{geo} acts as a surrogate for unobserved covariates that are not included in the model and also accounts for spatial autocorrelation (Fahrmeir and Kneib 2011). In the case that the spatial effect originates from both spatially correlated and uncorrelated unobserved covariates, it is advisable to split up the spatial effect $f_{geo} = f_{str} + f_{unstr}$ into a structured, correlated effect f_{str} and an unstructured, district specific effect f_{unstr}. This partition allows the researcher to assess the complete spatial information in the data. The estimation of the correlated spatial effect $\boldsymbol{f}_{str} = (f_{str}(s_1), \ldots, f_{str}(s_n))' = \boldsymbol{Z}_{str} \boldsymbol{\gamma}_{str}$ can be represented in a Bayesian framework; for each district $s \in \{1, \ldots, S\}$, a separate regression coefficient is estimated, where

$\boldsymbol{\gamma}_{str} = (\gamma_{str}(1), \ldots, \gamma_{str}(S))'$ is a vector of regression coefficients that collects all distinct spatial effects. The $(n \times S)$ design matrix $\boldsymbol{Z}_{str}$ connects an observation i with the corresponding spatial effect, i.e., $\boldsymbol{Z}_{str}[i, s] = 1$ if y_i was observed in district s and 0 otherwise. To ensure neighbouring districts to have similar effects, Gaussian Markov Random Field (GMRF) priors are assigned to the regression coefficients

$$(9) \qquad \gamma_{str}(s)|\boldsymbol{\gamma}_{str}(-s) \sim N\left(\frac{1}{|N(s)|}\sum_{r\in N(s)}\gamma_{str}(r), \frac{\tau^2_{str}}{|N(s)|}\right) \quad , \quad s = 1, \ldots, S.$$

where $\boldsymbol{\gamma}_{str}(-s)$ is the vector containing all spatial effects except the one for district s, and $|N(s)|$ denotes the total number of neighbours that share a common boundary with district s. GMRF assume that, given the effects of all other district, the expected value of $\gamma_{str}(s)$ is given by the average of the neighbouring districts. The variance τ^2_{str} and the inverse of the number of neighbours $|N(s)|$ control how much the effect of district s is allowed to deviate from its prior expectation. The joint prior of all spatial effects can be derived from the conditional distributions and can be represented as

$$(10) \quad p(\boldsymbol{\gamma}_{str}|\tau^2_{str}) \propto \frac{1}{(\tau^2_{str})^{rank(\boldsymbol{K}_{str})/2}}\exp\left(-\frac{1}{2\tau^2_{str}}\boldsymbol{\gamma}'_{str}\boldsymbol{K}_{str}\boldsymbol{\gamma}_{str}\right)$$

where the precision matrix $\boldsymbol{K}_{str}$ contains the neighbourhood information, i.e., $\boldsymbol{K}_{str}[s, r] = -1$ if districts s and r are neighbours, $\boldsymbol{K}_{str}[s, r] = |N(s)|$ if $s = r$ and $\boldsymbol{K}_{str}[s, r] = 0$ otherwise. The joint prior in Equation (10) induces a specific correlation structure and ensures spatial smoothness of the regression coefficients $\boldsymbol{\gamma}_{str}$, since parameters of neighbouring districts are not allowed to deviate too strongly from one another. If spatial heterogeneity exists only locally, it is not reasonable to assume that coefficients of neighbouring districts are spatially correlated and an uncorrelated spatial effect should be used instead. To model f_{unstr}, district specific i.i.d. Gaussian random effects $\gamma_{unstr}(s)|\tau^2_{unstr} \sim N(0, \tau^2_{unstr})$, $s = 1, \ldots, S$ are commonly used. In the Bayesian framework, the joint multivariate prior distribution of the unstructured effect can be represented as in Equation (10), with $\boldsymbol{K}_{unstr} = \boldsymbol{I}$.

Assuming a conditional Gaussian response, i.e., $\boldsymbol{y}|\boldsymbol{\eta}, \sigma^2 \sim N(\boldsymbol{\eta}, \sigma^2\boldsymbol{I})$, inference is based on full Bayesian MCMC simulation, with the posterior given as follows

$$(11) \quad \begin{aligned} p\left(\boldsymbol{\theta}|\boldsymbol{y}\right) \propto & \prod_{i=1}^{n} p\left(y_i|\eta_i, \sigma^2\right) \times \prod_{j=1}^{p}\left[p(\boldsymbol{\gamma}_j|\tau^2_j)p(\tau^2_j)\right] \times \\ & \times \left[p(\boldsymbol{\gamma}_{str}|\tau^2_{str})p(\tau^2_{str})p(\boldsymbol{\gamma}_{unstr}|\tau^2_{unstr})p(\tau^2_{unstr})\right]\prod_{r=1}^{q} p(\beta_r)p(\sigma^2) \end{aligned}$$

where $\boldsymbol{\theta}$ is the vector of all model parameters. For the variance of the residuals, highly dispersed inverse Gamma priors are assigned as well, i.e., $\sigma^2 \sim IG(a_\sigma, b_\sigma)$. Since conjugate priors are used, the full conditionals are known distributions and a Gibbs-sampling algorithm can be used to draw random numbers (we refer the interested reader to Fahrmeir and Kneib (2011) or Fahrmeir et al. (2013) for details on the estimation of STAR models).

Structured Additive Quantile Regression: Going beyond the mean

The regression models discussed so far focus on modelling conditional means. In order to provide a more detailed picture of the conditional distribution of the response variable, Waldmann et al. (2013) extend STAR models to semi-parametric additive quantile regression models, which are introduced in this section.

We start with the linear quantile regression model as proposed by Koenker and Bassett (1978)

$$(12)\quad y_i = \boldsymbol{x}_i'\boldsymbol{\beta}_\tau + \epsilon_{i_\tau}$$

where $\boldsymbol{x}$ is a design matrix that contains both categorical and continuous covariates, $\tau \in (0,1)$ indicates the quantile of interest, $\boldsymbol{\beta}_\tau$ is a vector of quantile specific regression coefficients and ϵ_{i_τ} is an unknown error term with cumulative density function F_{ϵ_τ} that depends on the quantile parameter τ. For linear quantile regression, no specific assumptions regarding the distribution of the error term are made apart from ϵ_{i_τ} and ϵ_{j_τ} being independent for $i \neq j$, as well as $F_{\epsilon_\tau}(0|\boldsymbol{x}) = \tau$, meaning that the τ-quantile of the error term conditional on $\boldsymbol{x}$ is zero. Given these assumptions, the quantile specific regression coefficients $\boldsymbol{\beta}_\tau$ are estimated by minimizing an asymmetrically weighted sum of absolute deviations

$$(13)\quad \boldsymbol{\beta}_\tau^* = \underset{\boldsymbol{\beta}_\tau}{\operatorname{argmin}} \sum_{i=1}^{n} \rho_\tau(y_i - \eta_{i_\tau}^{linear})$$

where $\eta_{i_\tau}^{linear} = \boldsymbol{x}_i'\boldsymbol{\beta}_\tau$ and

$$(14)\quad \rho_\tau(y_i - \eta_{i_\tau}^{linear}) = \begin{cases} \tau|y_i - \eta_{i_\tau}^{linear}| & \text{if} \quad y_i \geq \eta_{i_\tau}^{linear} \\ (1-\tau)|y_i - \eta_{i_\tau}^{linear}| & \text{if} \quad y_i < \eta_{i_\tau}^{linear} \end{cases}$$

is the check function that defines a suitable loss function for quantile regression. Hence, for a fixed quantile τ and observation $i = 1, \ldots, n$, the linear predictor $\eta_{\tau_i}^{linear}$ models the conditional quantile of the response y_i.

While in the frequentist setting of Koenker and Bassett (1978) no distributional assumptions regarding the error term have to be made, the Bayesian formulation of quantile regression relies on assuming an asymmetric Laplace distribution (ALD) as an auxiliary error distribution, as suggested by Koenker and Machado (1999) and Yu and Moyeed (2001). This assumption allows for the specification of a likelihood function that is needed for Markov chain Monte Carlo (MCMC) inference. The asymmetric Laplace distribution with location parameter $\eta_{i_\tau}^{linear}$, scale parameter σ^2 and asymmetry parameter τ is particularly suitable for quantile regression models, since the minimization of the check function in the frequentist setting can equivalently be represented as maximizing the asymmetric Laplace likelihood function

$$\text{(15)} \quad \prod_{i=1}^{n} p(y_i|\eta_{i_\tau}^{linear}, \sigma^2, \tau) \propto \exp\left(-\sum_{i=1}^{n} \rho_\tau \frac{(y_i - \eta_{i_\tau}^{linear})}{\sigma^2}\right)$$

with respect to $\eta_{i_\tau}^{linear}$. In the Bayesian framework of Waldmann et al. (2013), the strictly linear predictor $\eta_{i_\tau}^{linear}$ in Equation (15) is replaced with the more flexible geoadditive quantile predictor

$$\text{(16)} \quad \eta_{i_\tau} = \beta_{0_\tau} + \beta_{1_\tau} x_{i1} + \ldots + \beta_{q_\tau} x_{iq} + f_{1_\tau}(z_{i1}) + \ldots + f_{p_\tau}(z_{ip}) + f_{geo_\tau}(s_i)$$

that allows the researcher to analyze the influence of the covariates on the response variable semi-parametrically, for each quantile separately. In order to avoid the difficulties of maximizing the likelihood arising from the non-differentiability of the check function ρ_τ, Yu and Moyeed (2001) and Kozumi and Kobayashi (2011) suggest representing the ALD as a location-scale mixture of normal distributions. Using this representation, the Bayesian quantile regression model can then be rewritten as a conditionally Gaussian regression model so that Bayesian estimation procedures of Gaussian STAR models similar to Equation (11) are available for geoadditive quantile regression models (see Fahrmeir et al. (2013) and Waldmann et al. (2013) for the derivation of the full conditionals and the Gibbs sampling algorithm).

Data description and variable selection

Data description

For our analysis, we use farm-level data based on the 2010 German agricultural census (FDZ 2010). It is the most comprehensive survey since 1999 and gives a representative picture of the agricultural situation in Germany. The focus of the census is on questions regarding land use and livestock, property and leasing agreements, organic-farming, labor and employment. We use farmland rental rates for tenancies that are older than two years as the response which are transformed into farmland rental rates per hectare. This number can be interpreted more easily and farmers use this figure for guidance when determining appropriate rental agreements. We also exclude tenancies that were entered between family members to obtain a market based assessment of rental rates. Based on previous studies that analyse German farmland rental rates (see Breustedt and Habermann (2010) or Habermann and Ernst (2010) among others), we use the covariates presented in table 1 for the analysis.

[Table 1 about here.]

To account for differing soil qualities and varying precipitation levels, we use the share of rye in the cropping pattern as an approximation. Rye can be considered as being relatively resistant to drought and is predominantly grown on low quality agricultural land, which makes it a reasonable choice. Cattle and pig density, as well as the poultry density in livestock units per hectare of agricultural land serve as measures of the production intensity. To capture the local competition for farmland, we include both the average livestock densities of each district and the Herfindahl index as proxies. Field crops with high profit margins, such as the proportion of sugar beet, winter wheat and potato in the cropping pattern, are used as indicators of the farmers‘ willingness to pay. To take into account the potential effects of increased land use for the production of bioenergy on rental rates, we include the capacity of each farmers´ biogas plant in kWh in the model. This is an important issue for German farmers, since renewable energy sources have come to the centre of attention for German energy and climate policy in recent years. On the basis of the German Renewable Energy Act (EEG), which guarantees fixed feed-in tariffs for electricity gained from renewable sources, farmers have decided to use increasingly more arable land for the production of bioenergy. As a consequence, many farmers and landowners are driven by the question as to how the EEG affects farmland rental rates. To allow for structural differences in the rental market between East and West Germany, we include a dummy variable in our model. To adjust for unobserved spatial heterogeneity that is not accounted for by farm-level covariates, we also include socio-demographic covariates on the district level from the Regionaldatenbank (2010). The discrete spatial information that identifies each farmer and the municipality he operates in is provided by an 8-digit code. For ease of visualization and interpretation, the spatial effects are presented as average spatial effects on the district-level. The effects of the remaining covariates, however, are estimated and presented at the farm-level. After removing non-renting farmers, as well as outlying observations, we are left with 107,620 observations for the analysis.

Variable selection

Variable selection is a challenging task in geoadditive quantile regression. The researcher has to select a subset of covariates that he or she considers relevant for the analysis and has to decide whether the spatial information in the data is better described by an unstructured or structured effect. To make the task of variable selection more feasible, we use a systematic and fully data-driven approach based on componentwise functional gradient descent boosting for structured additive quantile regression, as proposed by Fenske, Kneib, and Hothorn (2011). Boosting is a machine learning approach that is aimed towards maximizing the prediction accuracy of the response by iteratively combining different model components, called base learners, where in each iteration step only the best-fitting base learner, i.e., the most informative covariate, is selected. For geoadditive quantile regression, boosting is particularly appealing since boosting decides for each quantile separately which covariates should enter the model.[3] Table 2 presents the selected variables and their selection frequencies for different quantiles. We choose to model conditional quantiles for $\tau = \{0.05, 0.50, 0.95\}$ to gain detailed insights into low, as well as into medium and expensive rental rates.

[Table 2 about here.]

Table 2 shows that the way in which covariates affect farmland rental rates varies across quantiles: while some covariates have an influence on low and median rates, they have no effect on more expensive ones. From table 2 it is also apparent that only f_{str} has been selected for the 5% and 95% quantiles in order to model the spatial information of the data. The spatial effect can therefore be assumed not to exist only locally, but to be correlated across districts for these quantiles. However, the unstructured spatial effect has also been selected for the 50% quantile indicating that there seems to be additional small scale, district specific spatial information in the data. Also note, that for expensive rents, mainly those covariates that reflect local competition for farmland, as well as field crops with high profit margins have been selected. Regarding the effect of increased land use for the production of bioenergy on rental rates, table 2 shows that boosting has decided to include it as an important covariate for median rents only.

Analysis of farmland rental rates

After having identified the relevant economic variables that determine farmland rental rates, we now present the estimation results of the Bayesian geoadditive quantile regression.[4]

Parametric and semi-parametric effects

Figure 1 shows posterior mean estimates for the semi-parametric effects together with 80% (dark grey) and 95% (light grey) pointwise credible intervals.[5]

[Figure 1 about here.]

According to figure 1, field crops with high profit margins, like sugar beets or potatoes, have a positive effect on rental rates. However, while the effect of sugar beet initially increases across all quantiles, it starts to decrease again for low rents if more than 30% of the farmland is used for the cultivation. We further investigate the decrease of sugar beets for the 5% quantile by forming the first derivative of the estimated effect and find that the sharp decrease is indeed significant at a nominal level of 5%. For medium and high rents, there seems to be a threshold effect as the effects level off above a share of 30%. Given the crop rotation, this seems to be reasonable. The effect of farm size for small and medium-sized farms is a positive one, as rental rates increase initially with growing farm size. Larger farms are more likely to realize economies of scale and are therefore able to pay higher rents. However, note that the size only has an increasing effect until a farm size of approximately 70 hectares. After this threshold, low rents remain almost constant with increasing farm size, while medium rents are negatively affected for farm sizes between 70 and 180 hectares. A possible explanation might be that, after a given threshold, farms may be so large that they may have a comparatively higher market power which allows them to keep rental rates low.

Similar to Drescher and McNamara (2000), Fuchs (2002) or Breustedt and Habermann (2011) we find that livestock densities have a major impact on rental rates, both at the farm and the district level. This positive influence might be explained by a statutory framework within which farmers are restricted in the amount of manure they are allowed to discharge on their land. Farmers with a livestock density that exceeds a certain threshold either have to rent additional acreage or have to register a trade. To avoid tax disadvantages, farmers prefer to rent additional farmland instead in order to reduce the livestock density. This effect is very pronounced for hog and poultry density at the farm level, and even more so for medium and high rents on the district level. The strong effects for regional livestock density also reflect the heavy competition for farmland in certain districts. From figure 1, it also appears that biogas increases medium rental rates, at least up to a plant capacity of approximately 380 kWh. As a result of the increased uncertainty attached to the estimation, which is reflected in the wide credible bands, reliable statements beyond this capacity cannot be made.

We now turn to the analysis of parametric effects that are summarized in table 3, showing posterior means, standard deviations and 95% credible intervals.

[Table 3 about here.]

Table 3 shows that differences exist between farmers and the rental rates they have to pay depending on whether they operate their farm full-time or part-time, since full-time farmers have to pay higher rents compared to their part-time counterparts. This difference may be attributed to several reasons. In order to earn a living, full-time farmers have to have a high production volume and a high production intensity. As a consequence, full-time farmers are on average larger than part-time farmers, with an average farm size of about 61 hectares. This is about the size until which rental rates increase with farm size (compare Panels (11)-(12) of figure 1). Another reason for the difference might be due to the fact that the proportion of full-time farmers is high in those districts where the principle income of the farmer is associated with livestock farming, and hence, in districts where rental rates are high (compare Panels (14)-(24) of figure 1). Due to the high demands with respect to capital intensity and the employment of labour, livestock farming on a larger scale can be operated successfully only as a full-time farmer.

Spatial effects

Our analysis of the spatial effects is motivated from a statistical point of view. In contrast to econometrics, where spatial autoregressive models are commonly used, we account for spatial correlation and non-observable farmland characteristics by adding a spatial term f_{geo_τ} to the additive predictor η_{i_τ}. As a consequence, we are mainly interested in investigating spatial patterns that emerge from spatial heterogeneities that are left unexplained after taking covariates into account. Plotting the estimated effects of f_{geo_τ} allows us to graphically investigate these spatial patterns and assists in identifying additional covariates that capture the remaining heterogeneity in the data. A careful visual inspection of the distribution of these spatial effects can also provide new insights into the data that were not previously considered. Significance maps shown in figure 2 enhance the detection of spatial patterns by classifying the estimated spatial effect into three categories; the spatial effect is classified as insignificant at the 80% level and the corresponding district is coloured in grey, if the credible interval includes zero. Districts with significant positive effects are coloured in white, whereas districts with significantly negative effects are coloured in black.[6]

[Figure 2 about here.]

Figure 2 shows that rental rates are considerably lower what can be explained with covariates in the southwest, as well as in large parts of East Germany across all quantiles (black districts). It is reasonable to assume that the pattern in East Germany results from structural differences between East and West German rental markets, and in particular from the way rental rates were set by the Bodenverwertungs- und -verwaltungs GmbH (BVVG), a company that managed state-owned land in East-Germany. In order to account for the differences between East and West German rental markets, we have included a dummy variable. However, as table 2 shows, the dummy variable leaves the structural differences between East and West German rental markets unexplained since boosting has never selected it during any of the iterations. Consequently, additional covariates other than the dummy variable have to be included in the model in order to account for the differences between East and West German rental markets. The patterns in the southwest of Germany may be attributed to the wine-growing districts. Since rental rates are grouped by the type of use of the agricultural land, rental rates of vineyards are recorded separately in the data. As a consequence, although winegrowers had to pay an average rent of approximately 828 EUR per hectare for vineyards in certain wine-growing districts, these high rents do not contribute to the estimation and the map only shows below average farmland rental rates.

Figure 2 also reveals that the covariates are better suited to explain expensive rental rates, as the covariates leave heterogeneities unexplained only in very few districts of Germany across all quantiles (white districts). While the pattern for the median and 95% quantile are similar with respect to high unexplained rents, the 5% quantile identifies some additional districts in the far north. In accordance with the literature and with the results from the semi-parametric effects, figure 2 shows that rental rates for farmland are more expensive in districts where livestock densities are high. Rental rates are also more expensive in districts in which high livestock densities and high biogas densities meet, such as in the southern part of Germany.

Conclusion

In this article we model and analyse conditional quantiles of farmland rental rates semi-parametrically using Bayesian geoadditive quantile regression models. The flexibility of this model class overcomes the problems of functional form misspecifications and allows us to present a more detailed analysis of farmland rental rates and their determinants. This is of interest, both for practitioners and academics, since hedonic pricing studies in the agricultural literature have primarily concentrated on modelling conditional means, where a linear relationship between covariates and the response is usually assumed. Our results stress the importance of making use of flexible, semi-parametric models as some of the covariates clearly have a non-linear influence on farmland rental rates. By explicitly modelling and plotting the spatial effects, we account for spatial autocorrelation and are able to detect spatial patterns in the data that can be used in future studies in order to identify additional covariates that capture the remaining spatial heterogeneity.

There are several ways to extend the current analysis. From an agricultural point of view, it would be interesting to investigate whether the increased investment in agricultural land by both agricultural and non-agricultural investors has an effect on farmland rental rates. Furthermore, our analysis could be extended by using farmland rental rates of more recent data or by using tenancies that have been signed or for which the terms have been adjusted within the last two years, as they might be better suited for analysing the effect of bioenergy on the recent mark-up of German farmland rental rates. From a statistical point of view, it would be interesting to allow the effect of one or more covariates to vary across space. When modelling the covariate effects, we have implicitly assumed that the way in which the covariates act on the response is homogeneous across all districts. However, the effect of one or more covariates may vary both in size and in their functional form from district to district. Geographically Weighted Regression models allow regression coefficients to differ regionally from their global values and assume that the spatial heterogeneity is explained solely by the space varying regression parameters. Generalized Additive Models for Location, Scale and Shape (GAMLSS), originally proposed by Rigby and Stasinopoulos (2005) and extended to Bayesian Structured Additive Distributional Regression by Klein, Kneib, and Lang (2013), also provide an interesting extension of the analysis, as they allow for the modelling of all parameters of an assumed response distribution as additive functions of covariates. This is important in the case of (spatial) heteroscedasticity, where interest does not lie with farmland rental rates themselves, but with their (spatial) variation.

Notes

[1]McMillen (2003) and Maddison (2004) also note that functional form misspecifications can falsely lead researchers to fit a spatial model to the data, even if spatial dependencies are not present.

[2]Each B-spline consists of polynomial pieces of degree l_j that are joined together smoothly at points known as knots. Regression splines, specifically B-splines with penalties, are usually known as P-splines.

[3]Componentwise functional gradient descent boosting for structured additive quantile regression is a method that solves the following optimization problem

$$\boldsymbol{\eta}_\tau^* = \underset{\boldsymbol{\eta}_\tau}{\operatorname{argmin}}\, \mathbb{E}\left[L(\boldsymbol{y}, \boldsymbol{\eta}_\tau)\right]$$

where $\boldsymbol{y}$ is the response, $\boldsymbol{\eta}_\tau$ is the geoadditive quantile predictor and $L(\cdot,\cdot)$ is a suitable loss function. In practical applications, the expected loss $\mathbb{E}\left[L(\boldsymbol{y}, \boldsymbol{\eta}_\tau)\right]$ is replaced with the empirical risk $n^{-1}\sum_{i=1}^{n}\rho_\tau(y_i - \eta_{i_\tau})$ which is minimized with respect to η_{i_τ}. The following steps illustrate the basic principle of componentwise functional gradient descent boosting:

Step 1: Specify a corresponding base learner b_d for each component $d = 1, \ldots, D$ in the additive quantile predictor $\boldsymbol{\eta}_\tau$.

Step 2: Initialize all D base learners, as well as the additive predictor $\hat{\boldsymbol{\eta}}_\tau^{[\mathbf{0}]}$ and set the iteration index to $m = 1$.

Step 3: Calculate the negative gradient residuals of the loss function that will serve as a working response for the base learning procedure:

$$u_i^{[m]} = -\frac{\delta}{\delta \eta_{i_\tau}} L(y_i, \eta_{i_\tau})\bigg|_{\eta_{i_\tau} = \hat{\eta}_{i_\tau}^{[m-1]}} \quad \text{for } i = 1, \ldots, n.$$

Step 4: Fit each of the D base learners separately to the negative residuals to obtain $\hat{b}_d^{[m]}$.

Step 5: Select the best fitting base learner $\hat{b}_{d^*}^{[m]}$ and add a fraction of its fitted value to $\hat{\eta}_{d_\tau^*}^{[m-1]}$:

$$\hat{\eta}_{d_\tau^*}^{[m]} = \hat{\eta}_{d_\tau^*}^{[m-1]} + \nu \cdot \hat{b}_{d^*}^{[m]}, \qquad \text{where } 0 < \nu \leq 1 \text{ is a given step length.}$$

Step 6: Keep all other effects constant, i.e., set $\hat{\eta}_{d_\tau}^{[m]} = \hat{\eta}_{d_\tau}^{[m-1]}$ for $d \neq d^*$.

Step 7: Unless $m = m_{stop}$, increase m by one and go back to Step 3.

The algorithm shows that the final estimate for the d-th component of the predictor $\boldsymbol{\eta}_\tau$ can be expressed as a weighted sum of fitted base learners

$$\hat{\eta}_{d_\tau}^{[m_{stop}]} = \sum_{m=1}^{m_{stop}} \nu \cdot \hat{b}_d^{[m]}$$

where $\hat{b}_d^{[m]} = 0$ if the d-th base learner was not selected in iteration m. By stopping the algorithm after a fixed number of iterations $m = m_{stop}$, boosting implicitly performs variable selection; typically, the important covariates (in terms of prediction accuracy) with a high influence on the response will be selected first, while covariates with a limited influence will be selected, if at all, only in very late boosting iterations. Hence, early stopping excludes those covariates from the model that are not considered to have any explanatory power. The optimal number of iterations m_{stop} is determined by k-fold cross-validation. For the estimation of the effects presented in table 2, we have set k=5. For the starting model of the boosting algorithm, we have include all covariates presented in table 1. Variable selection is performed using the R-package *mboost* of Hothorn et al. (2013).

[4]The results are obtained via full Bayesian MCMC simulation based on 22,000 iterations, a burn-in period of 2,000 iterations and a thinning parameter of 20 resulting in a sample of 1,000 samples from the posterior. The smooth effects of continuous covariates are estimated via cubic penalized B-splines based on second order random walk priors. To avoid very rough estimates for the extreme quantiles, we use 10 equidistant inner knots for all model specifications. Hyper-parameters for the smoothing variances τ_j^2 are set to $a_j = b_j = 0.001$ as a default. The structured spatial effect is estimated based on a Markov Random Field prior, whereas for the estimation of the unstructured effect district specific i.i.d. Gaussian random effects are used. The estimation is performed using the R-packages *BayesXsrc* of Adler et al. (2013) and *R2BayesX* of Lang et al. (2013), which is an R interface to the standalone software *BayesX* of Belitz et al. (2013).

[5]Since the parametric part of the geoadditive quantile predictor includes an intercept term, each function is centered around zero, i.e., $\sum_{i=1}^n f_1(z_{i1}) = \ldots = \sum_{i=1}^n f_p(z_{ip}) = 0$ in order to guarantee the identification of the estimated semi-parametric effects. The estimated functions in figure 1 are plotted in this way.

[6]Figure 2 presents the estimation results for the structured spatial effects only, as the unstructured spatial effect of the 50% quantile is less important in terms of its magnitude.

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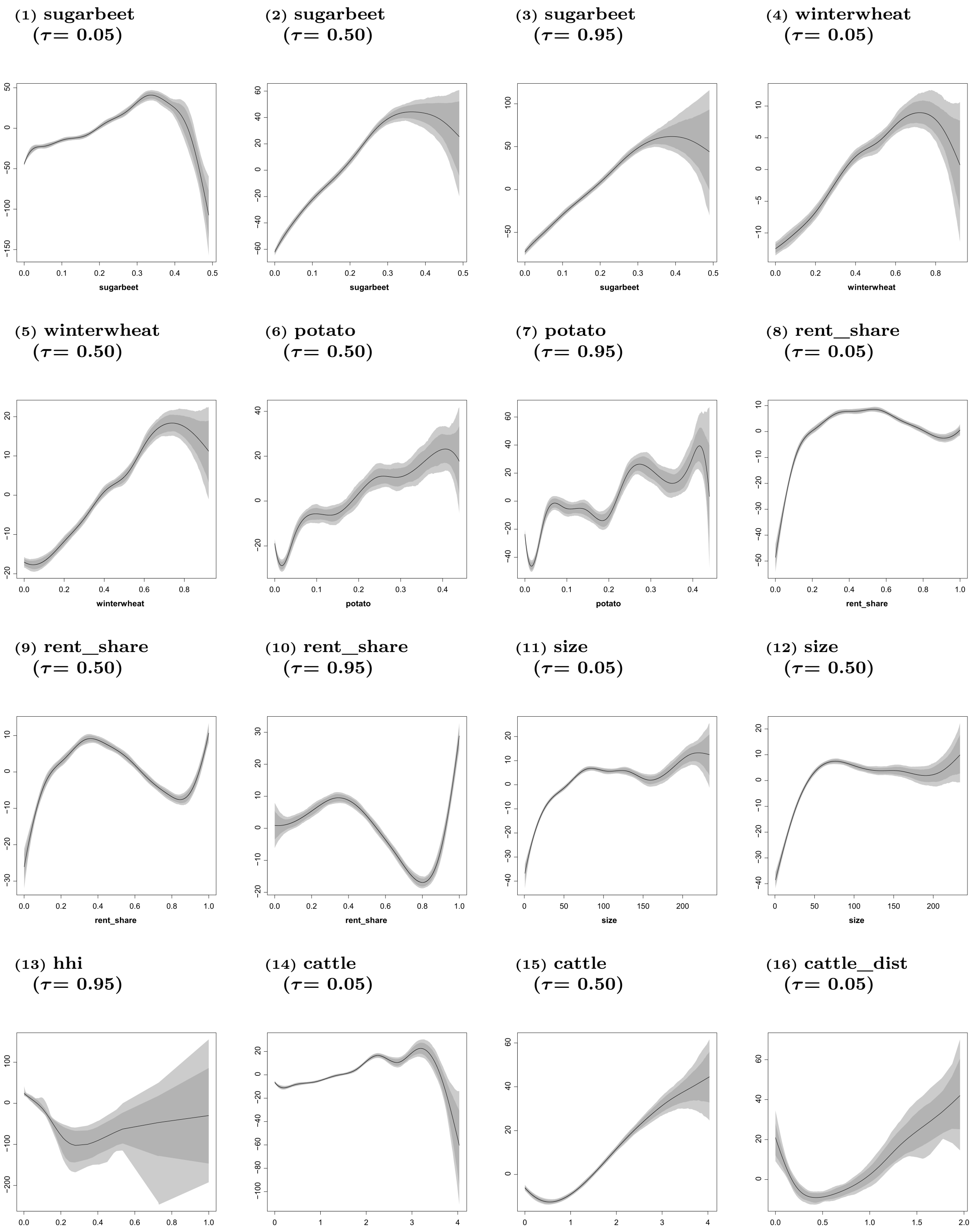
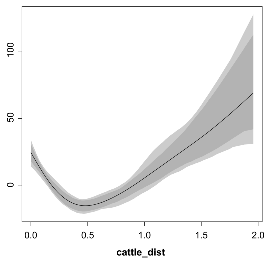
Figures



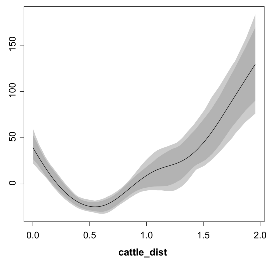
Source: own calculations based on data from the 2010 German agricultural census and from the Regionaldatenbank.

Figure 1. Semi-parametric effects with 80% and 95% pointwise credible intervals.

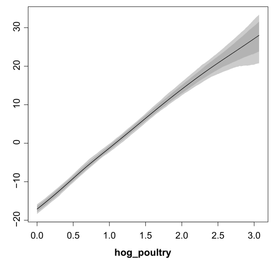
(17) **cattle_dist (τ= 0.50)**



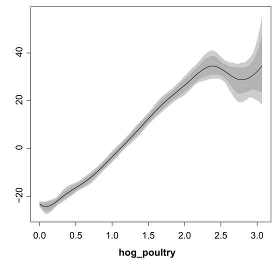
(18) **cattle_dist (τ= 0.95)**



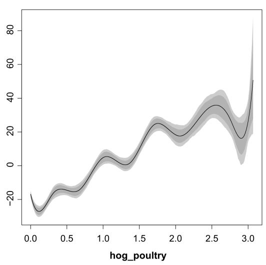
(19) **hog_poultry (τ= 0.05)**



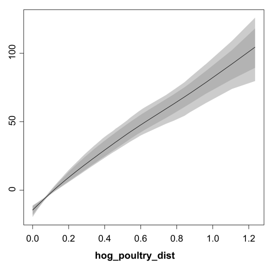
(20) **hog_poultry (τ= 0.50)**



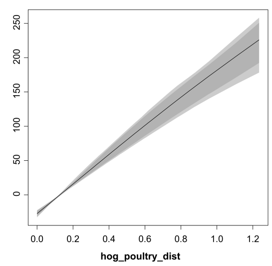
(21) **hog_poultry (τ= 0.95)**



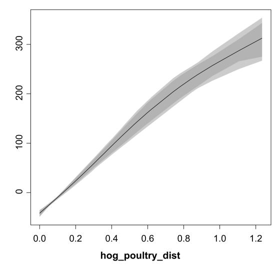
(22) **hog_poultry_dist (τ= 0.05)**



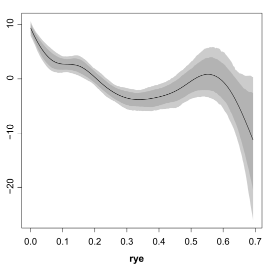
(23) **hog_poultry_dist (τ= 0.50)**



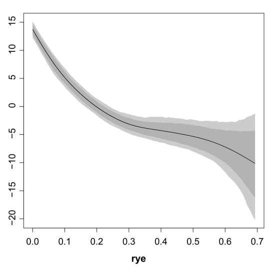
(24) **hog_poultry_dist (τ= 0.95)**



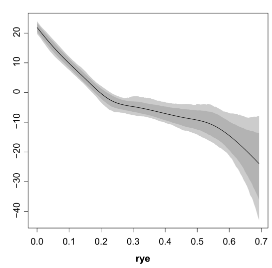
(25) **rye (τ= 0.05)**



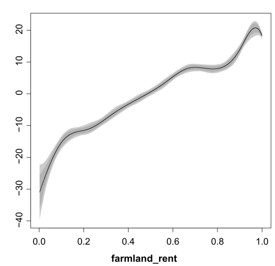
(26) **rye (τ= 0.50)**



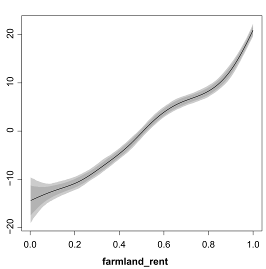
(27) **rye (τ= 0.95)**



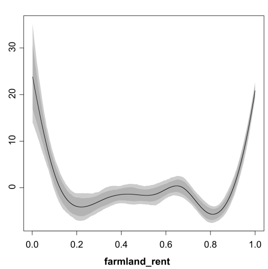
(28) **farmland_rent (τ= 0.05)**



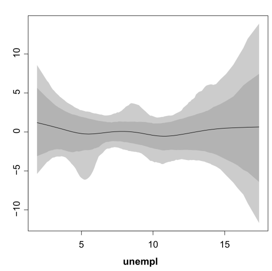
(29) **farmland_rent (τ= 0.50)**



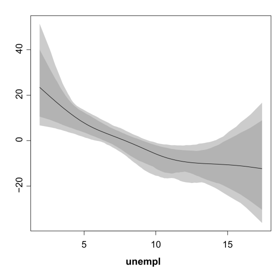
(30) **farmland_rent (τ= 0.95)**



(31) **unempl (τ= 0.05)**



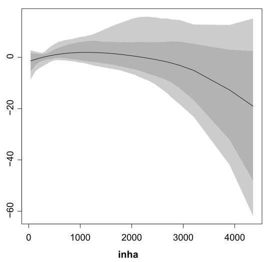
(32) **unempl (τ= 0.50)**



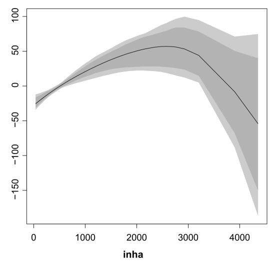
Source: own calculations based on data from the 2010 German agricultural census and from the Regionaldatenbank.

Figure 1 continued.

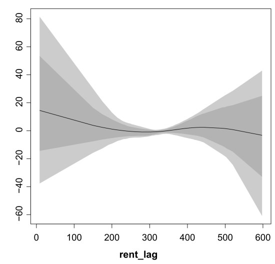
(33) **inha**
(τ= 0.50)



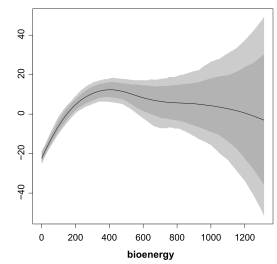
(34) **inha**
(τ= 0.95)



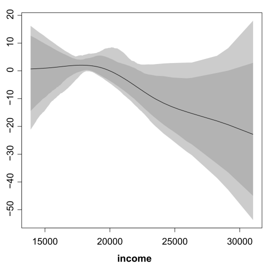
(35) **rent_lag**
(τ= 0.50)



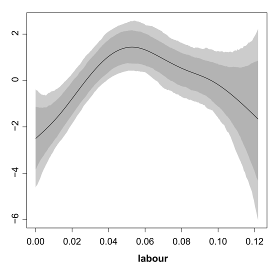
(36) **bioenergy**
(τ= 0.50)



(37) **income**
(τ= 0.50)



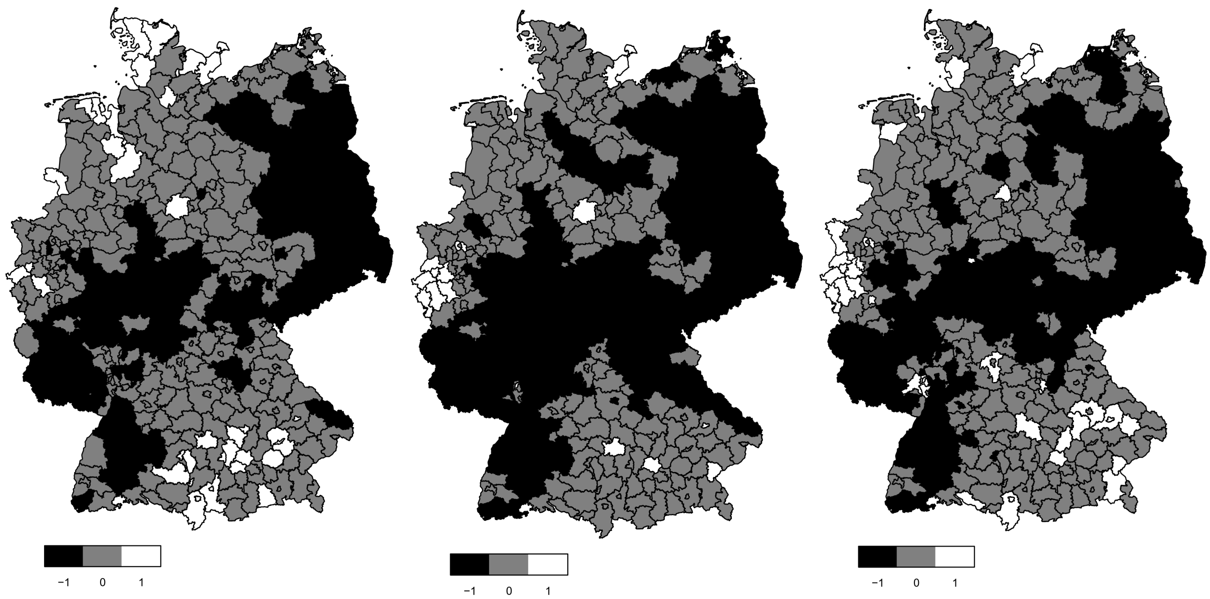
(38) **labour**
(τ= 0.50)



Source: own calculations based on data from the 2010 German agricultural census and from the Regionaldatenbank.

Figure 1 continued.

(1) **Posterior probabilities of f_{str} (τ= 0.05)** (2) **Posterior probabilities of f_{str} (τ= 0.50)** (3) **Posterior probabilities of f_{str} (τ= 0.95)**



Source: own calculations based on data from the 2010 German agricultural census and from the Regionaldatenbank.

Figure 2. Posterior probabilities of the structured spatial effect f_{str} based on a nominal level of 80%.

Tables

Table 1. Description of Covariates

Covariate (farm-level)	Description
farm_succ	Farm succession (categorical: 1=yes, 2=no, 3=unsettled)
east	Dummy Variable for East Germany (categorical: 1=West Germany, 2=East Germany)
organic	Dummy Variable for organic farming (categorical: 1=yes, 2=no)
fulltime	Dummy Variable indicating whether the farmer operates his business in full-time or part-time (categorical: 1=no individual enterprise as legal form, 2=full-time, 3=part-time)
rent_share	Share of rented agricultural land to total agricultural land (continuous)
farmland_rent	Share of rented farmland to total rented agricultural land (continuous)
cattle	Farm-level cattle density in animal unit (AU) per hectare (continuous)
hog_poultry	Farm-level hog and poultry density in animal unit (AU) per hectare (continuous)
bioenergy	Capacity of biogas plant in kWh (continuous)
winterwheat	Share of winter wheat in cropping pattern (continuous)
sugarbeet	Share of sugar beet in cropping pattern (continuous)
potato	Share of potato in cropping pattern (continuous)
rye	Share of rye in cropping pattern (continuous)
labour	Labour force per hectare (continuous)
irrigation	Share of agricultural land that could have been irrigated (continuous)
size	Total agricultural land of the farmer in hectare (continuous)
Covariate (district-level)	**Description**
hhi	Herfindahl-Hirschman index based on the share of rented agricultural land to total agricultural land in each district (continuous)
inha	Inhabitants per square kilometre (continuous)
unempl	Unemployment rate (continuous)
income	Average income per inhabitant (continuous)
rent_lag	Spatially lagged farmland rental rate (continuous)
dist2cc	Distance to next city center in kilometres (continuous)
cattle_dist	Average district-level cattle density in animal unit (AU) per hectare (continuous)
hog_poultry_dist	Average district-level hog and poultry density in animal unit (AU) per hectare (continuous)

Source: own calculations based on data from the 2010 German agricultural census and from the Regionaldatenbank.

Table 2. Covariates and their Selection Frequencies during Boosting Iterations

$\tau = 0.05$		$\tau = 0.50$		$\tau = 0.95$	
Covariate	Freq.	Covariate	Freq.	Covariate	Freq.
f_{str}	0.3998	f_{str}	0.7162	f_{str}	0.3208
$f(cattle\_dist)$	0.1453	$f(cattle\_dist)$	0.0735	$f(hog\_poultry\_dist)$	0.1239
$f(size)$	0.0711	$f(cattle)$	0.0422	$f(sugarbeet)$	0.1103
$fulltime$	0.0675	$f(rent\_share)$	0.0222	$f(cattle\_dist)$	0.1056
$f(farmland\_rent)$	0.0564	f_{unstr}	0.0217	$fulltime$	0.0762
$f(rent\_share)$	0.0547	$f(size)$	0.0216	$f(farmland\_rent)$	0.0752
$f(hog\_poultry\_dist)$	0.0398	$f(hog\_poultry\_dist)$	0.0199	$intercept$	0.0414
$f(sugarbeet)$	0.0395	$f(sugarbeet)$	0.0149	$f(potato)$	0.0334
$f(winterwheat)$	0.0347	$f(farmland\_rent)$	0.0107	$f(inha)$	0.0313
$f(unempl)$	0.0239	$fulltime$	0.0083	$f(rye)$	0.0281
$f(cattle)$	0.0234	$f(winterwheat)$	0.0078	$f(hhi)$	0.0213
$f(hog\_poultry)$	0.0179	$f(unempl)$	0.0076	$f(hog\_poultry)$	0.0196
$intercept$	0.0152	$f(hog\_poultry)$	0.0068	$f(rent\_share)$	0.0130
$f(rye)$	0.0108	$f(potato)$	0.0053		
		$f(rye)$	0.0053		
		$f(bioenergy)$	0.0048		
		$f(income)$	0.0040		
		$f(rent\_lag)$	0.0032		
		$f(labour)$	0.0022		
		$f(inha)$	0.0019		
$\sum$	1.0000	$\sum$	1.0000	$\sum$	1.0000

Source: own calculations based on data from the 2010 German agricultural census and from the Regionaldatenbank.

Table 3. Parametric Effects

	$\tau = 0.05$			
	Mean	Std.	2.5%	97.5%
Intercept	167.3150	1.5635	164.3530	170.2770
full-time	-4.4783	0.7025	-5.8641	-3.0617
part-time	-9.0094	0.8166	-10.5819	-7.4320
	$\tau = 0.50$			
	Mean	Std.	2.5%	97.5%
Intercept	324.0170	3.0758	317.5430	329.7030
full-time	-5.3913	0.9449	-7.2346	-3.5716
part-time	-12.1409	1.0729	-14.2923	-10.1269
	$\tau = 0.95$			
	Mean	Std.	2.5%	97.5%
Intercept	445.6230	4.8821	436.3380	455.0340
full-time	-11.3771	1.4211	-14.1269	-8.6229
part-time	-29.8125	1.4229	-32.5452	-27.0207

Source: own calculations based on data from the 2010 German agricultural census and from the Regionaldatenbank.

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Die Wurzeln der **Fakultät für Agrarwissenschaften** reichen in das 19. Jahrhundert zurück. Mit Ausgang des Wintersemesters 1951/52 wurde sie als siebente Fakultät an der Georgia-Augusta-Universität durch Ausgliederung bereits existierender landwirtschaftlicher Disziplinen aus der Mathematisch-Naturwissenschaftlichen Fakultät etabliert.

1969/70 wurde durch Zusammenschluss mehrerer bis dahin selbständiger Institute das **Institut für Agrarökonomie** gegründet. Im Jahr 2006 wurden das Institut für Agrarökonomie und das Institut für Rurale Entwicklung zum heutigen **Department für Agrarökonomie und Rurale Entwicklung** zusammengeführt.

Das Department für Agrarökonomie und Rurale Entwicklung besteht aus insgesamt neun Lehrstühlen zu den folgenden Themenschwerpunkten:

- Agrarpolitik
- Betriebswirtschaftslehre des Agribusiness
- Internationale Agrarökonomie
- Landwirtschaftliche Betriebslehre
- Landwirtschaftliche Marktlehre
- Marketing für Lebensmittel und Agrarprodukte
- Soziologie Ländlicher Räume
- Umwelt- und Ressourcenökonomik
- Welternährung und rurale Entwicklung

In der Lehre ist das Department für Agrarökonomie und Rurale Entwicklung führend für die Studienrichtung Wirtschafts- und Sozialwissenschaften des Landbaus sowie maßgeblich eingebunden in die Studienrichtungen Agribusiness und Ressourcenmanagement. Das Forschungsspektrum des Departments ist breit gefächert. Schwerpunkte liegen sowohl in der Grundlagenforschung als auch in angewandten Forschungsbereichen. Das Department bildet heute eine schlagkräftige Einheit mit international beachteten Forschungsleistungen.

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