**Supplementary Material 1**

***Bayesian quantile regression model***

Our statistical methodology relies on structured additive regression (STAR) model for conditional mean, an approach that allows for the influence of variables of different types to be simultaneously analysed in a framework([1](#_ENREF_1), [2](#_ENREF_2)). The model was extended to quantile regression by [Waldmann *et al.* (3](#_ENREF_3)).

Let

  (1)

be a linear model where  is the response variable  is a design matrix that contains all possible explanatory variables,  represents the quantile of interest with the quantile specific regression coefficient denoted by  and  is an unknown error term assigned a cumulative density function  and may depend on some additional parameter  ([4](#_ENREF_4)). Given a fixed and known quantile , the quantile of the error term is assumed to be zero, i.e., and  and are considered independent for . The quantile specific regression coefficients  are then estimated by minimizing an asymmetrically weighted sum of absolute deviations

 .

The check function

 

defines a suitable loss function for quantile regression. [Waldmann *et al.* (3](#_ENREF_3)), extended the linear quantile model in equation (1) through a semiparametric approach within a Bayesian framework such that

 

where are quantile specific non-linear smooth effects for continuous covariates,  accounts for spatial autocorrelation at a given quantile,.while  accounts for unstructured random effects. It is possible, within this framework, to include other types of variables beyond those considered in this study including possible arbitrary interaction terms among the variables of similar or different types.

The Bayesian formulation requires a specific distribution for the errors to be specified so that a likelihood needed for Markov chain Monte Carlo (MCMC) simulation can be set up. The Bayesian formulation therefore relies on asymmetric Laplace distribution as an auxiliary distribution such that  with location parameter , precision parameter , and asymmetry parameter . The probability density function is given by

 

The asymmetry Laplace distribution is suitable for quantile regression models because the minimization of the check function can be represented as maximizing the symmetric Laplace likelihood function

 

with respect to . To avoid the difficulties of maximizing the likelihood arising from the non-differentiability of the check function , [Yu & Moyeed(5](#_ENREF_5)) and [Yue & Rue(6](#_ENREF_6)) suggested that the ALD be represented as a location-scale mixture of normal distributions. Through this representation, the Bayesian quantile regression model can then be rewritten as a conditionally Gaussian regression model so that estimation procedures of Gaussian STAR models are available for geo-additive quantile regression models([3](#_ENREF_3)).

***Prior and Hyperprior***

For the smooth functions,  Bayesian P(enalized)-splines([7](#_ENREF_7), [8](#_ENREF_8)) originally proposed for the frequentist setting by [Eilers & Marx(9](#_ENREF_9)) was adopted. The prior assumes that the unknown smooth function  can be approximated by a polynomial spline of degree . The spline is then represented as a linear combination of  B-spline basis functions,  evaluated at equally spaced knots  within the domain of 

 

where are B-splines and the coefficients  are further defined to follow a first or second-order random work

 

 

where are Gaussian error terms. The variance parameter  controls the amount of smoothness and is considered as a random variable for which highly dispersed inverse Gamma hyper-prior  are assigned. For the initial values of first and second order random walks, flat hyper-priors, and  are assumed.

For the structured spatial effects, we relied on Markov random field prior which uses the concept of neighbourhood structure, that assumes that neighbouring districts would be more similar in their estimates than for any two arbitrary districts that may be farther apart ([10](#_ENREF_10)). Let denote the spatial index or in this case study, districts of the respondent. We assume  such that separate parameters  are estimated for each district. The Gaussian Markov random field prior for regression coefficients  is then defined by

 

where is the number of adjacent states of , and  denotes the districts that are neighbours of . The variance and the inverse of the number of neighbours  control how much the effect of state  is allowed to deviate from its prior expectation. The variance is again assigned an inverse Gamma hyper-prior. For the fixed parameters, diffuse priors were considered.

In order to avoid the difficulties of maximizing the likelihood arising from the non-differentiability of the check function , the ALD is represented as a location-scale mixture of normal distributions([3](#_ENREF_3), [5](#_ENREF_5)). Representing the ALD as a location-scale mixture allows the Bayesian quantile regression model to be formulated as a conditional Gaussian regression model so that Bayesian estimation procedures for Gaussian STAR models can be employed. Assuming the conditional Gaussian response, i.e., , the posterior distribution can be derived as:

 

where is the vector of all model parameters. Since the posterior is highly dimensional and analytically intractable MCMC simulation using Gibbs-sampling algorithm are employed to draw samples from the posterior from inference on the parameters are made. Details of the MCMC algorithm can be found in([3](#_ENREF_3), [11](#_ENREF_11)).

**References**

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