SMOOTH TRANSITION FROM FIXED EFFECTS TO MIXED EFFECTS MODELS IN MULTI-LEVEL REGRESSION MODELS

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FUNDACIÓN DE LAS CAJAS DE AHORROS
DOCUMENTO DE TRABAJO
Nº 374/2008

De conformidad con la base quinta de la convocatoria del Programa de Estímulo a la Investigación, este trabajo ha sido sometido a evaluación externa anónima de especialistas cualificados a fin de contrastar su nivel técnico.

Smooth Transition from Fixed Effects to Mixed Effects Models in Multi-level regression Models

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Abstract

We introduce a semiparametric extension of multi-level regression models that includes mixed and fixed effects models as its two extreme cases. In some practical cases, one could consider the fixed effects model as an over parametrized model without modeling but just plugging in dummies. In other words, it suffers from "too many parameters but too little model". The mixed effects model tries to overcome this by using just random effects and therefore has "too few parameters but too much model", where "too much model" refers to the necessary assumptions made. We propose including a nonparametric term that allows the practitioner to shift the model smoothly between these extremes, depending on its data and underlying problem. Thereby, the smoothing parameter serves as its switcher. We will show that so we can filter out possible dependency between covariates and random effects. We further provide consistent bootstrap procedures for possible inference and to analyze prediction power. The positive implications of using this model are highlighted in particular for small area statistics and econometrics. This is underlined by simulation studies and a real data application.[1]

Keywords and Phrases: Mixed effects models, semiparametric multilevel models, small area statistics, bootstrap inference, partial linear models.

[1] The authors gratefully acknowledge the financial supported of the Spanish "Direccíón General de Investigación del Ministerio de Ciencia y Tecnología", MTM2005-00820, FUNCAS, and of the Xunta de Galicia PGIDIT06PXIB207009R.

1 Introduction and Motivation

Mixed effects models are quite popular in many areas of statistics with panel data analysis being maybe the most popular one. More recently they have also attracted a good amount of attention in small area statistics, see Ghosh and Rao (1994), Rao (2003), Jiang and Lahiri (2006) for reviews of small-area techniques. The same holds still for the analysis of any kind of panel data, see e.g. Laird and Ware (1982) and Diggle, Heagerty, Liang and Zeger (2002) as typical examples. We can find these methods now equally well in biomedical, forestal or agricultural, economic and social science studies. Although the different research areas favor different names like small area statistics, multi-level (regression) models or simply mixed effects models, the statistical problems of modelling, estimation and testing are basically the same; the differences arise mainly in the subsequent inferences. For example, in panel data analysis they are often just a remedy to account for the heterogeneity over the cross sectional samples when the data is short in time; in small area statistics they shall improve the prediction of area level parameters, or in econometrics improve the prediction of macro indices from micro-data; and finally they have become popular in economics for doing data matching, i.e. to impute a certain factor for the individuals in the sample of interest with the aid of a different (auxiliary) sample.

More recently now, they have entered the nonparametric world, see Ruppert, Wand and Carroll (2003), Wand (2003), Hamilton (2001), Opsomer, Claeskens, Ranalli, Kauermann and Breidt (2005), Tutz (2001), and Tutz and Reithinger (2007). In applied statistics, semiparametric Bayesian approaches are often used in combination with (penalized) splines, series or MCMC (random field) estimators, see Fahrmeir, Kneib, and Lang (2004), Kneib and Fahrmeir (2006) and Fahrmeir and Lang (2001) among others. In maybe most of the literature on semiparametric models, the idea has always been to separate the nonparametric function into a deterministic (fixed effects) and a random part (random effects) so that the smoothing parameter of a spline estimator could be written in terms of the variances of the random effects and the error term. Considerations of additional random effects have mainly been limited to Bayesian approaches and/or computational questions. However, until recently, asymptotic theory has been missing for estimation in semiparametric mixed models. Lombardía and Sperlich (2006) introduced an estimation procedure for generalized partial linear mixed effects models, a semiparametric model specification test with a bootstrap procedure, and provided asymptotic theory for all these methods.

For response $Y_d \in \Re$ with covariates $\boldsymbol{X}_{dj} \in \Re^p$ including the intercept, the classical generalized linear Mixed Effects Model (MEM) with known link g(·) can be written as

$$E\left[Y_{dj}|\boldsymbol{u}_d, \boldsymbol{X}_{dj}\right] = g\left\{\boldsymbol{X}_{dj}^t\boldsymbol{\beta} + \boldsymbol{Z}_{dj}^t\boldsymbol{u}_d\right\}, \quad d = 1, \ldots, D;\ j = 1, \ldots, n_d, \qquad (1)$$

with $\boldsymbol{Z}_{dj} \subseteq \boldsymbol{X}_{dj}$ of dimension ρ, $\beta \in \Re^p$ the fixed effect, and $\boldsymbol{u}_d \in \Re^\rho$ the i.i.d. unobservable random effect with mean zero and unknown variances-covariance matrix σ_u^2. This has to be estimated. We have sample size $n = \sum_{d=1}^{D} n_d$, where D is the number of areas (domains or groups) with the typical assumption of $D \to \infty$ at rate $O(n)$. An essential but crucial assumption for the existing ethodology is that $\boldsymbol{u}_d$ is independent from $\boldsymbol{X}_{dj}$ and that $g(\cdot)$ is known. Note that, if g is the identity, model (1) includes the nested-error ($\boldsymbol{Z}_{dj} = 1$ and $\boldsymbol{u}_d \in \Re$), the random regression coefficient ($\boldsymbol{Z}_{dj} = \boldsymbol{X}_{dj}$), and the Fay-Herriot model (only area specific information), see Prasad & Rao (1990) for a summary. Let us concentrate on the nested error model, which is very popular in practice.

For this response and covariates, the corresponding Fixed Effects Model (FEM) is

$$E\left[Y_{dj}|\boldsymbol{X}_{dj}\right] \;=\; g\left\{\boldsymbol{X}_{dj}^{t}\boldsymbol{\beta}+c_{d}\right\}, \quad d=1,\ldots,D;\; j=1,\ldots,n_{d}, \tag{2}$$

with c_d being an area (domain or group) specific fixed effect without the assumption of independence from the individual effects $\boldsymbol{X}_{dj}$.

For a better understanding of the main idea, recall first two striking facts. The MEM is often motivated as follows: for not over parameterizing one models the area effect by random effects. This seems to beat any other parametric model when predicting. This is often due to the fact that in the moment of prediction one adds the predicted random effect to the total prediction. The additional variance of the prediction caused by assuming this effect to be random, is only slightly larger than the variance of a fixed effect estimate based on small samples. Additionally, the modelling of the new variance structure allows for a more efficient estimation of $\boldsymbol{\beta}$ using a feasible generalized least squares estimator. However, this gain can easily be a self-deception because it might improve prediction in the mean but under the quite unrealistic assumption of independence between area effects and the covariates as well as the individual (i.e. error) effects. Thus, even if MEM leads to a better sample fit, it does at the cost of biased estimates. Furthermore, it does not at all contribute to a better understanding of the underlying process. Finally, a method to do valid inference is not available. Indeed, all available methods for testing or prediction intervals are clearly inconsistent if the assumption of independence is violated.

We studied about 25 applications from the mixed-models literature where the random effect $\boldsymbol{u}_d$ represented the effect of either a region, a climate type, a socio-economic group or the proband group (in biostatistics). In almost all cases the independence assumption was little credible. Clearly, this causes endogeneity giving inconsistent estimates for $\boldsymbol{\beta}$ and awful performance for out of sample predictors. In other words, it does not satisfy neither the needs of econometric (or other) modelling nor of small area prediction.

We therefore propose to use a flexible modelling of area effects that allows the practitioner (or its model, respectively) to move smoothly from a MEM (1) without area specific covariates over a Semiparametric Mixed Effects Model (SMEM) with area specific effects (3) to a FEM (2). In order to illustrate the ideas and comments before said, we will study an example with interest in economy and small area prediction. We consider the tourist expenditures in each county of Galicia (which is divided in 53 counties). Galicia is a region in the Northwest of Spain, and as with the rest of the country, tourism is one of the most important economic factors. This survey of tourism contains information about at least 10 tourists per county including average expenditure per day and several characteristics of the individuals. Note that our dependent variable *expenditure* means total expenditure including accommodation, food, purchases, travel, leisure activities, and other miscellaneous.

The rest of the paper is organized as follows. In Section 2 we develop the flexible modelling of area effects. The smooth transition is achieved by relaxing more and more the smoothness assumption on the semiparametric (area specific) impact: we start with the highest smoothness (a constant) giving a random effects model, and end up in no smoothness (interpolation of the area effects) giving a fixed effects model. This way we resolve all problems at once: we model and thus explain the area or group effect, can dispose of the "independence-assumption" problem, this way obtaining consistent estimates and valid inference; all this without losing the advantages of MEM and without running into the problems we would face in a FEM. Our method can be seen as an extension of Partial Linear Models (PLM); including random effects we are able to more efficiently estimate both the parametric and the nonparametric part. We will see why this approach can always be used to filter out possible dependence between the individual covariates and the random effects. Additionally, Lombardía and Sperlich (2006) provide methods of statistical inference which can be applied to this model. We introduce and compare the different models together with possible estimation and bootstrap procedures. We also discuss model extensions and how we overcome the (in)dependence problem. In Section 3 we illustrate with a simulation study the use of our method highlighting also the arguments which motivate our modelling idea. Finally, in Section 4 we come back to the real data example.

2 The Semiparametric Transition Model

2.1 The Model

In the following, area (specific) effects refer to random and/or fixed effects, respectively. We start from model (1) considering the nested-error model (i.e. $\boldsymbol{Z}_{dj} = 1$ and $\boldsymbol{u}_d \in \Re$). Let now $\boldsymbol{W} \in \Re^q$ denote the specific area covariates. Then, if any information $\boldsymbol{W}$ about the areas is available, we suggest using the following semiparametric mixed effects model (SMEM):

$$E\left[Y_{dj}|\boldsymbol{X}_{dj}, \boldsymbol{W}_d, u_d\right] \;=\; g\left\{\boldsymbol{X}_{dj}^t\boldsymbol{\beta} + \eta_v(\boldsymbol{W}_d) + u_d\right\} \;, \qquad (3)$$

where $\eta_v : \Re^q \to \Re$ is an unknown nonparametric function with a given a "switcher" v. We introduce the condition $E[\eta_v(\boldsymbol{W})] = 0$ for identification. Let us think of v as a smoothness parameter so that, for example, for kernel estimates we set the bandwidth to $h = v \cdot n^{-2/(4+q)}$. Then, for one extreme we have $\eta_0(\boldsymbol{W_d}) = c_d$ with $\sum_{d=1}^{D} c_d = 0$ and on the other extreme $\eta_\infty(\boldsymbol{W}_l) = 0$. In the first case η_0 catches the area effect completely so that we get $u_d = 0$ for all d and we indeed have a FEM (2), whereas for $h = \infty$ we obtain a MEM (1). Then, v is indeed a switcher between the models:

$$v = 0 : \;\; E\left[Y_{dj}|\boldsymbol{X}_{dj}\right] = g\left\{\boldsymbol{X}_{dj}^t\boldsymbol{\beta} + c_d\right\} \;\;\leftrightarrow\;\; v = \infty : \;\; E\left[Y_{dj}|u_d, \boldsymbol{X}_{dj}\right] = g\left\{\boldsymbol{X}_{dj}^t\boldsymbol{\beta} + u_d\right\}$$

and for $0 < v < \infty$

$$E\left[Y_{dj}|\boldsymbol{X}_{dj}, \boldsymbol{W}_d, u_d\right] = g\left\{\boldsymbol{X}_{dj}^t\boldsymbol{\beta} + \eta(\boldsymbol{W}_d) + u_d\right\} .$$

For ease of presentation we set $\boldsymbol{\theta}$ for the variance components and $\boldsymbol{\delta} = (\boldsymbol{\beta}, \boldsymbol{\theta})$ for the unknown parameters of the model. Set $Var[Y_{dj}| \boldsymbol{X}_{dj}, W_d, u_d] = \sigma_e^2$ and $\sigma_u^2 = Var[u_d]$ for all $d = 1,\ldots,D$, $j = 1,\ldots, n_d$, and $\boldsymbol{\theta} = (\sigma_e^2, \sigma_u^2)$.

Note that this is not a data adaptive approach in the common sense because the smoothness is given by the practitioner. On the other hand, if for example inference or prediction intervals are the objective, to fix v in advance is not a restriction in practice, as for pre-estimated smoothness parameter valid inference is unfeasible anyway. Certainly, bandwidth selection procedures for kernel smoother are thinkable also for model (3) but would follow an idea of modelling different from what we focus on.

In practice, often some of the $\boldsymbol{X}$ are not independent of the area effects. Imagine they are correlated with some of the $\boldsymbol{W}$. It is clear then that estimation and prediction from model (1) gives biased results whereas those from model (3) will be unbiased. One may argue that, in order to handle this problem, model

$$E\left[Y_{dj}|\boldsymbol{X}_{dj},\boldsymbol{W}_d,u_d\right] \;=\; g\left\{\boldsymbol{X}_{dj}^t\boldsymbol{\beta}+\boldsymbol{W}_d^t\boldsymbol{\delta}+u_d\right\}\ , \tag{4}$$

would work as well.

Unfortunately, the dependence structure between $\boldsymbol{X}$ and the area is usually much more complex and not limited to a simple linear relation with the available area information $\boldsymbol{W}$. However, in practice the relation can indeed always be described sufficiently via $\psi(\boldsymbol{W})$ for a particular, though unknown function ψ as long as $\boldsymbol{W}$ varies continuously over the different areas. For illustration, imagine the relation between $\boldsymbol{X}_{dj}$ and the area d is summarized in $\boldsymbol{J}_d$, i.e. $\boldsymbol{X}_{dj} = \boldsymbol{J}_d + \widetilde{\boldsymbol{X}}_{dj}$ with $\widetilde{\boldsymbol{X}}_{dj}$ being independent of any area effect. Our claim is that we can always find an artificial function ψ so that $\psi(\boldsymbol{W_d}) = \boldsymbol{J}_d + \boldsymbol{V}_d$ with $\boldsymbol{V}_d$ defined implicitly as the residual. A particular boundary case is $\boldsymbol{W_d} \equiv \boldsymbol{J}_d$ with ψ the identity. Another particular is when ψ simply assigns $\boldsymbol{J}_d$ to $\boldsymbol{W_d}$ for each $d = 1,\ldots,D$, i.e. interpolation. Such an assignment is possible as long as $\boldsymbol{W}$ moves continuously over the D areas. Recall that η_v is a nonparametric function with appropriate smoothness v. Then, for an implicitly defined φ_ω we get

$$\begin{aligned}
E\left[Y_{dj}|\boldsymbol{X}_{dj},\boldsymbol{W}_d,u_d\right] &= g\left[\boldsymbol{X}_{dj}^t\boldsymbol{\beta}+\eta_v(\boldsymbol{W}_d)+u_d\right] \\
&= g\left[\boldsymbol{X}_{dj}^t\boldsymbol{\beta}+\varphi_\omega\left\{\psi(\boldsymbol{W}_d)\right\}+u_d\right] \\
&= g\left[\boldsymbol{X}_{dj}^t\boldsymbol{\beta}+\varphi_\omega\left\{\boldsymbol{J}_d+\boldsymbol{V}_d\right\}+u_d\right]\ ,
\end{aligned} \tag{5}$$

where φ_ω is again a nonparametric function with a smoothness parameter ω which depends on v and the smoothness of ψ or, vice verse, v depends on ω and ψ. From (5) we see clearly that this model does not suffer from dependency between $\boldsymbol{X}_{dj}$ and u_d , i.e. endogeneity of $\boldsymbol{X}_{dj}$. Consequently, in practice where we only face finite samples, η_v can perfectly filter out the endogeneity.

Now it is clear why in the SMEM we can always filter out possible dependence between the covariates and the random effect: it just depends on the choice of $\boldsymbol{W}$ and v. In econometric words, $\psi(\boldsymbol{W}_d)$ can serve here as a proxy. For example, in the "worst case", $\boldsymbol{W} \perp \boldsymbol{J}$, we need to set $v = 0$ as ψ cannot feature any smoothness. What then actually happens is that the SMEM becomes a FEM without random effect and thus without any independence problem.

2.2 Estimation

There exist plenty of estimation procedures for MEM, and more recently some for mixed effects models allowing for a semiparametric impact of $\boldsymbol{X}$ when g is the identity. Most of them are Bayesian methods, some combined with penalized splines, some with MCMC methods, see references in the Introduction. For the estimation of our model (3) many alternatives are possible. Lombardía and Sperlich (2006) propose a smoothed maximum likelihood based on the so called integral approach and describe also the so called penalized quasi likelihood method for maximizing the posterior mode of density $f(\boldsymbol{\beta}, \boldsymbol{u}|Y, \boldsymbol{W}, \boldsymbol{X}\,;\, \eta, \boldsymbol{\theta})$, see for example Breslow and Clayton (1993). The first method is easier to tackle from a conceptual point of view (asymptotic theory is straight forward for this one), whereas the second one is more popular in practice. Note that the implementation is combined with ideas of Vilar-Fernández and Francisco-Fernández (2002). When we apply the integral approach we concentrate on the following marginal density

$$f(Y_{dj}|\boldsymbol{W}_d, \boldsymbol{X}_{dj}; \eta, \boldsymbol{\delta}) \;=\; \int f(Y_{dj}|\boldsymbol{u}, \boldsymbol{W}_d, \boldsymbol{X}_{dj}; \eta, \boldsymbol{\beta}, \sigma_e^2) p(\boldsymbol{u}; \boldsymbol{\sigma}_u) d\boldsymbol{u}. \tag{6}$$

To estimate the parametric part we take directly the logarithm and get the (unsmoothed) likelihood

$$l(\boldsymbol{Y}; \eta, \boldsymbol{\delta}) \;=\; \sum_{d=1}^{D}\sum_{j=1}^{n_d} \log f(Y_{dj}|\boldsymbol{W}_d, \boldsymbol{X}_{dj}; \eta, \boldsymbol{\delta}) \ . \tag{7}$$

For estimating the nonparametric function, fix a point $\boldsymbol{w}_0$ and construct an empirical counterpart of $E[\log f(Y \mid \boldsymbol{W}, \boldsymbol{X}; \eta, \boldsymbol{\delta})| \boldsymbol{W} = \boldsymbol{w}_0]$ which, in terms of kernel function $K_{\boldsymbol{h}}(\cdot)$, could be

$$l_s(\boldsymbol{Y}; \eta, \boldsymbol{\delta}) = \sum_{d=1}^{D}\sum_{j=1}^{n_d} K_{\boldsymbol{h}}\left(\boldsymbol{w}_0 - \boldsymbol{W}_d\right) \log f(Y_{dj}|\boldsymbol{W}_d, \boldsymbol{X}_{dj}; \eta(\boldsymbol{w}_0), \boldsymbol{\delta}) \ . \tag{8}$$

Here, $K_{\boldsymbol{h}}(\cdot)$, is a q-dimensional product kernel, and $\boldsymbol{h} = (h_1,...,h_q)$ the corresponding bandwidth vector. Often, l_s is called the smoothed likelihood function.

Applying now (twice - as the variance components are unknown, too) the idea of profiled likelihood estimation one gets from Lombardía and Sperlich (2006), compare also with Lin and Carroll (2006), that under some rather common smoothness conditions we have

a) $\sqrt{n}(\hat{\boldsymbol{\delta}} - \boldsymbol{\delta}) \xrightarrow{d} N(0, I_{\boldsymbol{\delta}}^{-1})$, where $I_{\boldsymbol{\delta}}$ is the marginal Fisher information of $l(\cdot)$.

b) defining $h_{\text{prod}} = \prod_{j=1}^{q} h_j$ and $h_{\max} = \max_{1 \le j \le q} h_j$, $\boldsymbol{w}_0$ being from the interior of the support of $\boldsymbol{W}$, and $p_W(\cdot)$ its density function, then

$$\sqrt{nh_{prod}}\left(\hat{\eta}_v(\boldsymbol{w}_0) - \eta_v(\boldsymbol{w}_0) - B_\eta(\boldsymbol{w}_0)\right) \xrightarrow{d} \mathrm{N}\left(0, Var_\eta(\boldsymbol{w}_0)\right)$$

with bias $B_\eta(\boldsymbol{w}_0) = O(h_{\max}^2)$

and variance $Var_\eta(\boldsymbol{w}_0) = \dfrac{\int K(\boldsymbol{w})^2 d\boldsymbol{w}}{p_W(\boldsymbol{w}_0)\ E\left[\frac{\partial}{\partial \eta_v} l\left(Y; \eta_v, \boldsymbol{\delta}_0\right)^2 | \boldsymbol{W} = \boldsymbol{w}_0\right]}$.

From Maity, Ma, and Carroll (2007) we even conclude that using these estimates will produce efficient predictors for forecasting area-specific means.

2.3 Extensions

When $\boldsymbol{W}$ is of higher dimension ($q > 3$), in practice one usually would like to break down the dimension by modelling η_v in a separable, maybe additive way

$$\eta_v(\boldsymbol{W}_d) = \sum_{k=1}^{q} \eta_v^k(W_{d,k}), \qquad \eta_v^k : I\!R \to I\!R \quad \forall\ k \tag{9}$$

or as a single index function $\eta_v\ (\boldsymbol{W}_d^t \boldsymbol{\delta})$, $\boldsymbol{\delta} \in \Re^q$ an unknown parameter vector. These extensions are mostly straightforward (concerning both implementation and asymptotic theory) when using the approach of Härdle, Huet, Mammen, and Sperlich (2004), respectively of Carroll, Fan, Gijbels, and Wand (1997).

In this context, we would like to recall the discussion in the Introduction. There, we referred e.g. to Fahrmeir et al. (2001,2004) and Tutz (2001) which combined Bayesian approaches with splines to estimate nonparametric additive mixed effects models in different applied problems. Although one could implement estimators for the above introduced models also with P-splines and additivity as in (9), we have disregard that possibility in this article for two reasons. Firstly, asymptotic theory for P-splines is not well developed, and especially not for $q > 1$. Secondly, while for kernel based estimators it is clear how to put into practice $v \to 0$, for P-splines we have to move both, the penalizing coefficient (usually denoted as λ) and the number of knots K. To guarantee a *smooth transition* one would also need additional information about the proper proportion of λ and K. In practice this makes a smooth transition from FEM to MEM much less convenient than it is for kernels.

Another extension is to allow for a nonparametric impact of $\boldsymbol{X}$, i.e.

$$E\left[Y_{dj}|\boldsymbol{X}_{dj}, \boldsymbol{W}_d, u_d\right] \;=\; g\left\{m(\boldsymbol{X}_{dj}) + \eta_v(\boldsymbol{W}_d) + u_d\right\} \;, \tag{10}$$

where $m(\cdot)$ is a nonparametric unknown function. In practice, one could model $m(\cdot)$ additively as a sum of p one-dimensional nonparametric functions, maybe with interactions, compare Sperlich, Tjøstheim, and Yang (2002). In case one would model both m and η_v additively we get a generalized additive mixed effects model. For g = identity, i.e. with $\boldsymbol{X}_{dj} = (X_{dj,1}, \ldots, X_{dj,p})^t$, $\boldsymbol{W}_d = (W_{d,1}, \ldots, W_{d,q})^t$, m^l and η_v^k being one dimensional nonparametric functions for all $l = 1, \ldots, p$ and $k = 1, \ldots, q$;

$$E\left[Y_{dj}|\boldsymbol{X}_{dj}, \boldsymbol{W}_d, u_d\right] \;=\; \sum_{l=1}^{p} m^l(X_{dj}^l) + \sum_{k=1}^{q} \eta_v^k(W_d^k) + u_d. \tag{11}$$

There exists a good set of applied research using Bayesian methods for the estimation, compare discussion in the Introduction. Quite recently, Roca Pardiñas and Sperlich (2007) introduced a weighted smooth backfitting estimator which can handle - at least from a computational point of view – the estimation of different kind of generalized structured models like (11) with m and η_v having additive, single index, interaction or other forms. For more semiparametric models to which extensions are thinkable, see Härdle, Müller, Sperlich, and Werwatz (2004).

2.4 Bootstrap Inference

We propose here a parametric bootstrap method for further inference. The algorithm is as follows. Assuming that the distribution of $Y_{dj}|(\boldsymbol{X}_{dj}, \boldsymbol{W}_d, u_d) \sim F(\mu_{dj}, \sigma_e^2)$ and the distribution of the random effects $u_d \sim G(0, \sigma_u^2)$ are both known, then:

Step 1: From sample, calculate the estimator $\hat{\boldsymbol{\delta}} = (\hat{\boldsymbol{\beta}}, \hat{\sigma}_u^2, \hat{\sigma}_e^2)$.

Step 2: Take a pilot bandwidth g, and calculate $\hat{\eta}_g(\cdot)$. This is done in order to try to reproduce the same bias incurred in the real world.

Step 3: Generate u_d^* from $G(0, \hat{\sigma}_u^2)$, $d = 1, \ldots, D$.

Step 4: Given the auxiliar variables $\boldsymbol{X}_{dj}$, $\boldsymbol{W}_d$ and the bootstrap random effect u_d^*, draw Y_{dj}^* from F($\mu_{dj}^*, \hat{\sigma}_e^2$), with $\mu_{dj}^* = g\{\boldsymbol{X}_{dj}^t\hat{\boldsymbol{\beta}} + \hat{\eta}_g(\boldsymbol{W}_d) + u_d^*\}$.

Step 5: From the bootstrap sample $\{Y_{dj}^{*}, \boldsymbol{X}_{dj}, \boldsymbol{W}_{d}\}$ and the estimation algorithm before, we can get the bootstrap estimators $\hat{\boldsymbol{\delta}}^{*} = (\hat{\boldsymbol{\beta}}^{*}, \sigma_{u}^{*2}, \sigma_{e}^{*2})$ and $\hat{\eta}_{v}^{*}$.

The consistency can be concluded from Lombardía and Sperlich (2006) where a similar procedure has been proposed for a different model. It is based on the consistency of the estimators of the model parameters and the behaviour of $\hat{\eta}_{g}$ (see Härdle and Marron, 1991). To the assessment of uncertainty about parameter values $\boldsymbol{\delta} = (\boldsymbol{\beta}, \sigma_{u}^{2}, \sigma_{e}^{2})$ and the nonparametric functions we can then derive confidence intervals and construct also prediction intervals.

Finally, note that the impact of η_v can be tested for significance with the statistics introduced in Lombardía and Sperlich (2006). It is easy to see that the asymptotic theory developed there carries over to our model.

3 Simulation Studies

In this section we show the results of a large simulation study, which studies all points made in the motivation of this work. We consider a data generating process such as the independence assumption of the MEM is violated. And in this context we compare the estimation of the model parameters in the MEM versus SMEM, the (expected) mean squared errors of $\hat{\eta}_{v}$ and $\hat{\boldsymbol{\beta}}$ resulting from SMEM and PLM, the prediction power of MEM versus SMEM for in-sample and out-of-sample individuals, and the prediction power for the area-level parameters. Finally, we check the proposed bootstrap procedure.

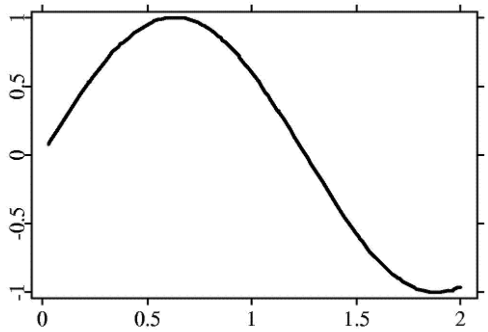
3.1 The Data Generating Process

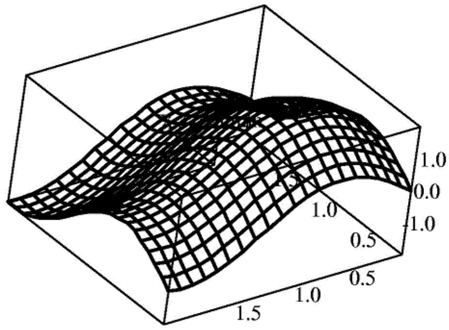
Consider the data generating process

$$Y_{dj} = \beta_0 + \boldsymbol{X}_{dj}^{t}\boldsymbol{\beta} + \sum_{k=1}^{q} \sin(2.5W_{d,k}) + u_d + \epsilon_{dj} \ , \tag{12}$$

where $(X_{dj,1}, X_{dj,2})^{t} = \boldsymbol{X}_{dj} \in \Re^{2}$. For all k is $W_{d,k} \sim U[0, 2]$ i.i.d., $u_d \sim N(0, \sigma_{u}^{2})$ i.i.d, and $\varepsilon \sim N(0, \sigma_{e}^{2})$ i.i.d. For $i = 1, 2$ we have created $X_{dj,i} = 0.8 \cdot O_{\mathrm{dj,i}} + 0.5 \sum_{k=1}^{q} W_{d,k}^{2}$ with $O_{dj,i} \sim N(0, 1)$ i.i.d. Further, $\beta_0 = 1.5$, $\beta_1 = 1.5$, and $\beta_2 = 1$. We will study the performance of our method for $q = 1$ and $q = 2$. This gives $Var[X_{dj,i}] \approx 1$ with $Corr[X_{dj,i}, W_d] \approx 0.29$ for $q = 1$, and $Var[X_{dj,i}] \approx 1.35$ with $Corr[X_{dj,i}, W_{d,k}] \approx 0.25$ for $q = 2$; $i, k = 1, 2$. In Figure 1 are plotted the impacts of the systematic area effect $\sum_{k=1}^{q} \sin(2.5W_{d,k})$ for $q = 1, 2$. Note that for the sake of illustration we have concentrated here on the canonical link for the normal distribution, i.e. g = *identity*.

Figure 1: The systematic area effect η for q=1 (left) and q=2 (right).



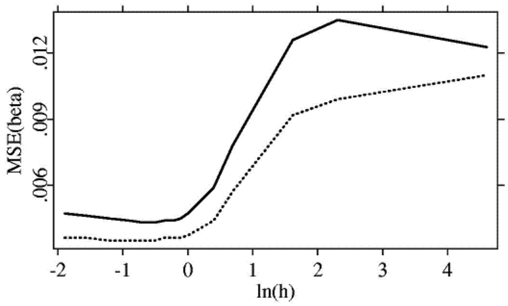


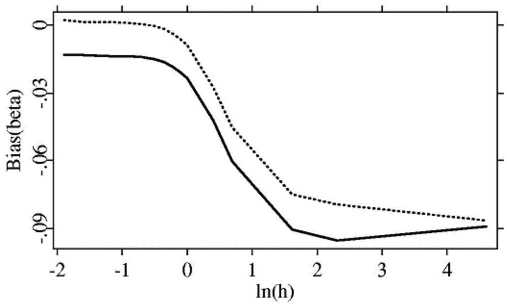
In the following we present simulation results for n = 250, d = 50, where data was generated from model (12) with different $\boldsymbol{\theta}$ = (σ_e^2, σ_u^2). All results shown here are based on 250 simulation runs. The procedures are implemented in FORTRAN90. Actually, the implementations of FMEM, MEM, SMEM and PLM are in a way so that they are nested algorithms to guarantee a fair comparison.

3.2 Results

Due to the data generating process (12) the independence assumption of the MEM is violated, therefore the estimator $\hat{\boldsymbol{\beta}}$ will be inconsistent, but it is not clear how the mean squared error (MSE) and bias will change with the bandwidth $0 \leq h \leq \infty$. Our first simulation has been performed to study MSE and bias of $\hat{\boldsymbol{\beta}}$ as a function of v, respectively ln(h), see Figure 2. The underlying data generating process is (12) with q = 1 and $\boldsymbol{\theta}$ = (0.5, 0.25). The figure may make one believe that v = 0, i.e. the FEM, would be a good choice. Notice that, this could be a delusion as this choice implicates the admissibility of a fixed effects model, a conclusion that can only be drawn from the practical context.

Figure 2: MSE and Bias of **β** estimates for β_1 and β_2 as functions of bandwidth h when q=1 and **θ**=(0,5,0.25).





Next, we compare the results of our SMEM

$$E\left[Y_{dj}|\boldsymbol{X}_{dj}, \boldsymbol{W}_d, u_d\right] = \beta_0 + \boldsymbol{X}_{dj}^t\boldsymbol{\beta} + \eta_v(\boldsymbol{W}_d) + u_d$$

for a fixed bandwidth h = 0.5, with the classical MEM ($h = \infty$ and $\sigma_u^2 \neq 0$)

$$E\left[Y_{dj}|\boldsymbol{X}_{dj}, u_d\right] = \beta_0 + \boldsymbol{X}_{dj}^t\boldsymbol{\beta} + u_d,$$

and with the PLM ($0 < h < \infty$ and $\sigma_u^2 = 0$)

$$E[Y_{dj}|\boldsymbol{X}_{dj}, \boldsymbol{W}_d] = \boldsymbol{X}_{dj}^t\boldsymbol{\beta} + \beta_0 + \eta_v(\boldsymbol{W}_d) .$$

The bias and variance for $\hat{\boldsymbol{\beta}}$ are compared in Table 1. Results are given for models with different $\boldsymbol{\theta}$ and q. We see that the bias can become quite serious when the independence assumption does not hold - something that happens quite often in practice, recall the discussion in the Introduction. At the same time the variance is not larger (even somewhat smaller) in the SMEM despite the nonparametric estimate applied in this model. Before studying this point more in detail recall that we make use of the variance estimates $\hat{\boldsymbol{\theta}}$ in both models, MEM and SMEM. Therefore, we also will have a look at the estimates of $\boldsymbol{\theta}$, see Table 2 where we give biases and mean squared errors (MSE) for σ_e^2 and σ_u^2. Note that $Var[\eta(\boldsymbol{W})] \approx 0.5067$ for $q = 1$, and 1.013 for $q = 2$. Here, a fair comparison is not really possible because in the MEM, part of the variation due to η will be assigned to σ_u^2 erroneously.

Table 1: Bias and variances of β-estimates. The SMES refers to h=0,5.

Model	σ_e^2	σ_u^2	$q=1$ bias($\hat\beta_1$)	bias($\hat\beta_2$)	var($\hat\beta_1$)	var($\hat\beta_2$)	$q=2$ bias($\hat\beta_1$)	bias($\hat\beta_2$)	var($\hat\beta_1$)	var($\hat\beta_2$)
	.1	.0	-.0315	-.0305	.0009	.0008	-.0327	-.0294	.0008	.0008
		.25	-.0215	-.0203	.0008	.0007	-.0263	-.0230	.0008	.0007
M		.5	-.0166	-.0154	.0008	.0007	-.0221	-.0189	.0008	.0007
E	.5	.0	-.1336	-.1311	.0046	.0040	-.1617	-.1533	.0051	.0050
M		.25	-.0893	-.0864	.0043	.0036	-.1206	-.1124	.0043	.0042
		.5	-.0690	-.0662	.0042	.0035	-.0987	-.0908	.0041	.0040
	.1	.0	-.0045	-.0033	.0007	.0007	-.0072	-.0046	.0007	.0007
S		.25	-.0028	-.0015	.0008	.0007	-.0036	-.0008	.0008	.0007
M		.5	-.0025	-.0013	.0008	.0007	-.0030	-.0002	.0008	.0007
E	.5	.0	-.0084	-.0057	.0032	.0033	-.0136	-.0093	.0032	.0031
M		.25	-.0074	-.0042	.0038	.0035	-.0104	-.0049	.0037	.0034
		.5	-.0067	-.0035	.0040	.0036	-.0086	-.0028	.0038	.0034

Table 2: Bias and MSEs of σ^2-estimates. The SMES refers to h=0,5.

Model	σ_e^2	σ_u^2	$q=1$ bias($\hat\sigma_e^2$)	bias($\hat\sigma_u^2$)	MSE($\hat\sigma_e^2$)	MSE($\hat\sigma_u^2$)	$q=2$ bias($\hat\sigma_e^2$)	bias($\hat\sigma_u^2$)	MSE($\hat\sigma_e^2$)	MSE($\hat\sigma_u^2$)
	.1	.0	.0003	.4470	.0001	.2038	-.0001	.8946	.0001	.8259
		.25	-.0003	.4574	.0001	.2256	-.0005	.9088	.0001	.8771
M		.5	-.0005	.4606	.0001	.2457	-.0008	.9161	.0001	.9209
E	.5	.0	.0177	.3174	.0027	.1087	.0257	.5807	.0042	.3687
M		.25	.0055	.3636	.0022	.1534	.0111	.6659	.0031	.4971
		.5	.0016	.3845	.0021	.1875	.0051	.7131	.0028	.5925
	.1	.0	-.0207	.0156	.0006	.0003	-.0272	.0220	.0010	.0005
S		.25	-.0036	-.0144	.0001	.0026	-.0062	-.0754	.0002	.0078
M		.5	-.0022	-.0390	.0001	.0104	-.0030	-.1691	.0001	.0361
E	.5	.0	-.0511	.0297	.0045	.0010	-.0762	.0244	.0089	.0007
M		.25	-.0150	-.0223	.0024	.0043	-.0235	-.0987	.0038	.0129
		.5	-.0097	-.0490	.0022	.0138	-.0112	-.1953	.0031	.0479

Although Vilar Fernández and Francisco Fernández (2002) considered a different context in their paper, it is clear from their theorems that our SMEM (3) will also be more efficient than common PLM estimators when estimating η_v (and, in our context, $\hat{\beta}$). For the numerical (not the asymptotic) performance this might even be true if the random effects are zero, since when estimating model (3), $\hat{\sigma}_u^2$ will correct for a possible over- or undersmoothing of the impact of $\mathbf{W}$ and vice versa. In Table 3 are compared the (expected) mean squared errors of $\hat{\eta}_v$ and $\hat{\beta}$ resulting from SMEM and PLM for h = 0.5. The *Expected Mean Squared Error* (EMSE) of $\hat{\eta}_v$ is defined by $E[\{\eta_v(\mathbf{W}) - \hat{\eta}_v(\mathbf{W})\}^2]$. The results are supporting our expectations: the SMEM clearly outperforms the PLM.

Table 3: EMSEs of and $\hat{\eta}_v$ and $\hat{\beta}$ for PLM and SMEM when the bandwidth is h=0.5.

Model	σ_e^2	σ_u^2	$q=1$ EMSE($\hat{\eta}_v$)	$q=1$ MSE($\hat{\beta}_1$)	$q=1$ MSE($\hat{\beta}_2$)	$q=2$ EMSE($\hat{\eta}_v$)	$q=2$ MSE($\hat{\beta}_1$)	$q=2$ MSE($\hat{\beta}_2$)
	.1	.0	.0150	.0007	.0007	.0344	.0009	.0008
		.25	.0340	.0022	.0021	.0933	.0021	.0018
P		.5	.0529	.0037	.0035	.1520	.0033	.0028
L	.5	.0	.0247	.0033	.0034	.0640	.0035	.0032
M		.25	.0440	.0048	.0046	.1231	.0048	.0043
		.5	.0630	.0063	.0060	.1818	.0060	.0053
	.1	.0	.0148	.0007	.0007	.0320	.0007	.0007
S		.25	.0311	.0008	.0007	.0842	.0008	.0007
M		.5	.0474	.0008	.0007	.1371	.0008	.0007
E	.5	.0	.0246	.0033	.0033	.0630	.0034	.0032
M		.25	.0419	.0039	.0035	.1159	.0038	.0034
		.5	.0585	.0040	.0036	.1681	.0038	.0034

Another argument used in favor of MEM is their presumable prediction power, important for data matching when imputing factors for individuals and in small area statistics to predict area-, or say macro-, level parameters. Therefore, the next simulation study (see Table 4) compares the prediction power of MEM versus SMEM for all: in-sample prediction, out-of-sample prediction, for individuals, and for area-levels.

Here the used in-sample prediction risk measure is simply the average over the 250 simulations runs of the mean squared error, we denote this measure by ASE for *Averaged Squared Errors*

$$ASE = \frac{1}{250}\sum_{repl=1}^{250} MSE^{repl}$$

where $MSE = \frac{1}{n}\sum_{d=1}^{D}\sum_{j=1}^{n_d}(Y_{dj} - \hat{Y}_{dj})^2$, with $\hat{Y}_{dj} = \hat{\boldsymbol{\beta}}^t \boldsymbol{X}_{dj} + \hat{\beta}_0 + \hat{u}_d$, the so called feasible EBLUP for the MEM, and $Y_{dj} = \hat{\beta}^t \mathbf{X}_{dj} + \hat{\beta}_0 + \hat{\eta}_v(\mathbf{W}_d) + \hat{u}_d$ for the SMEM. Note that $\hat{\beta}$ and $\hat{u}$ are certainly different for the two models.

Now, our first out-of-sample risk is the *Mean Squared Prediction Error* for two particular $\mathbf{x}$, called $MSE(\hat{Y}_l, \hat{Y}_s)$ for $\mathbf{X}_l = \left(\frac{2q}{3} + 2.5, \frac{2q}{3} + 2.5\right)$, respectively $\mathbf{X}_s = \left(\frac{2q}{3} - 2.5, \frac{2q}{3} - 2.5\right)$, each in a different but fixed area.

Due to the nature of the MEM which basically fits the area effect with random coefficients, it is clear that an in-sample prediction will always do a good job with respect to the mean squared error. In contrast, for small and moderate sample size nonparametric methods like we use them for the estimation of η in our SMEM can have an awful numerical performance. Nevertheless, the results in Table 4 show that our model clearly outperforms the MEM, surprisingly even in the ASE, and by far in the out-of-sample prediction. Note additionally that valid inference with the MEM is hardly possible for our data generating processes as the so far available methods are typically model based and therefore ``model biased".

Table 4: The average mean squared error (ASE) of the inside-sample predictors, and the $MSE(\hat{Y}_l, \hat{Y}_s)$ when SMEM is estimated with h=0.5.

Model			$q=1$			$q=2$		
	σ_e^2	σ_u^2	ASE	MSE$(\hat{Y}_l, \hat{Y}_s)$		ASE	MSE$(\hat{Y}_l, \hat{Y}_s)$	
	.1	.0	.0208	.0780	.1286	.0214	.0995	.1806
		.25	.0205	.0562	.0816	.0211	.0775	.1360
M		.5	.0205	.0486	.0652	.0210	.0663	.1126
E	.5	.0	.1004	.7701	1.659	.1179	1.625	3.344
M		.25	.0987	.4634	.8589	.1093	.9843	1.966
		.5	.0988	.3540	.5947	.1063	.7199	1.406
	.1	.0	.0103	.0368	.0261	.0154	.0393	.0576
S		.25	.0194	.0352	.0409	.0198	.0424	.0566
M		.5	.0200	.0363	.0413	.0203	.0426	.0557
E	.5	.0	.0251	.1152	.1012	.0461	.1565	.2294
M		.25	.0797	.1515	.1829	.0862	.1976	.2785
		.5	.0894	.1651	.1958	.0936	.2056	.2810

When predicting area-level parameter, MEM is expected to perform reasonably well compared to SMEM regardless of possible violation of the independence assumption. In the next simulation study we predict the mean parameter for each area $d = 1,\dots,50$. Two slightly different parameters at the area level: (i) $\mu_d = E\left[\overline{Y}_{d\bullet} \mid X, W\right]$, this is assuming that the number of population units in the dth area is large; and (ii) $\overline{Y}_{d\bullet} = \sum_{j=1}^{N_d} y_{dj} / N_d$, assuming a superpopulation regression model of the form (12) for the N_d population units in the dth area. When considering (ii), the best linear unbiased estimator of $\overline{Y}_{d\bullet}$ is given by

$$\hat{\overline{Y}}_{d\bullet} = f_d \overline{y}_s + (1 - f_d)\hat{\mu}_{dr},$$

where $f_d = n_d / N_d$, $\overline{y}_s$ is the average of the in-sample values and $\hat{\mu}_{dr}$ is the estimator of μ_d with the mean of the $\mathbf{X}_{dj}$ for the $(N_d - n_d)$ non sampled units. Therefore we only concentrate here on the situation when we need to predict *Y* for some individuals of which *X* is available.

We performed two simulation runs, each with 250 replications. In both cases data was generated from the model (12) with q=2 but with 10 observations X_{dj} for each area whereas Y_{dj} was observed only for the first 5 individuals j in each area. In the first case all X_{dj} were randomly drawn (d = 1,...,50 and j = 1,...,10) and in the second we set

$$X_{d6} = (-1, -1),\ X_{d7} = (0.16, 0.16),\ X_{d8} = (1.33, 1.33), \qquad (13)$$
$$X_{d9} = (2.5, 2.5),\ \text{and}\ X_{d10} = (3.67, 3.67).$$

Note that (-1,0.16,1.33,2.5,3.67) are approximately

$$(E[X] - 2\sigma_X,\ E[X] - \sigma_X,\ E[X],\ E[X] + \sigma_X,\ E[X] + 2\sigma_X)$$

for each element X of $\mathbf{X}$, with σ_X denoting its standard deviation unconditionally from the area. The values Y_{dj} were generated with its corresponding X_{dj} (j = 1,...,5). As before, we show only results with bandwidth h = 0.5 throughout, although in simulation studies not shown here the SMEM with somewhat larger bandwidths $h \approx 0.7$ outperformed the MEM even more, depending on the model.

The results are given in form of box-plots which show the distributions of the D = 50 mean squared errors for different (σ_e^2, σ_u^2) in the data generating process. In each plot the box-1 and box-2 are refered to SMEM and MEM respectively, with X_{d6} to X_{d10} taken randomly; box-3 and box-4 are refered to SMEM and MEM respectively, with X_{d6} to X_{d10} as in (13). For better illustration we skipped the extreme large mean squared errors for the MEM (about 2 to 5% of the data).

Given the particular simulation model, the mean squared errors are generally quite small, especially when predicting (ii) $\overline{Y}_{d\bullet}$, where half of the information (Y_{d1} to Y_{d5}) is given. There, the differences between the prediction based on MEM compared to the prediction based on SMEM is restricted to the out-of-sample prediction. Consequently, as can be seen in all graphs of Figure 3, the SMEM outperforms MEM by far. When turning to the prediction of (i) $\mu_d = E[\overline{Y}_{d\bullet} \mid \mathbf{X}, \mathbf{W}]$, then the mean squared errors have to increase significantly, representing half in-sample and half out-of-sample prediction errors. We already have discussed and seen in Table 4, compare the ASE, that the advantage of the SMEM over the MEM for in-sample prediction can become fairly small though always visible. When now looking at the box-plots given in Figure 4, recalling that we always have to compare box-plot 1 with 2 and box-plot 3 with 4, the superiority of the SMEM over MEM even in this exercise is surprisingly strong. For the prediction of both parameters, $\overline{Y}_{d\bullet}$ and μ_d, we see that the most area effects can be captured by instruments $\mathbf{W}$.

Figure 3: Mean squared error distributions over the 50 predicted area level parameter $\overline{Y}_{d\bullet}$ for different data generating (σ_e^2, σ_u^2). Boxes 1 and 2 refer to MEM and SMEM respectively, with X_{d6} to X_{d10} random; Boxes 3 and 4 refer to MEM and SMEM respectively, with X_{d6} to X_{d10} fixed.

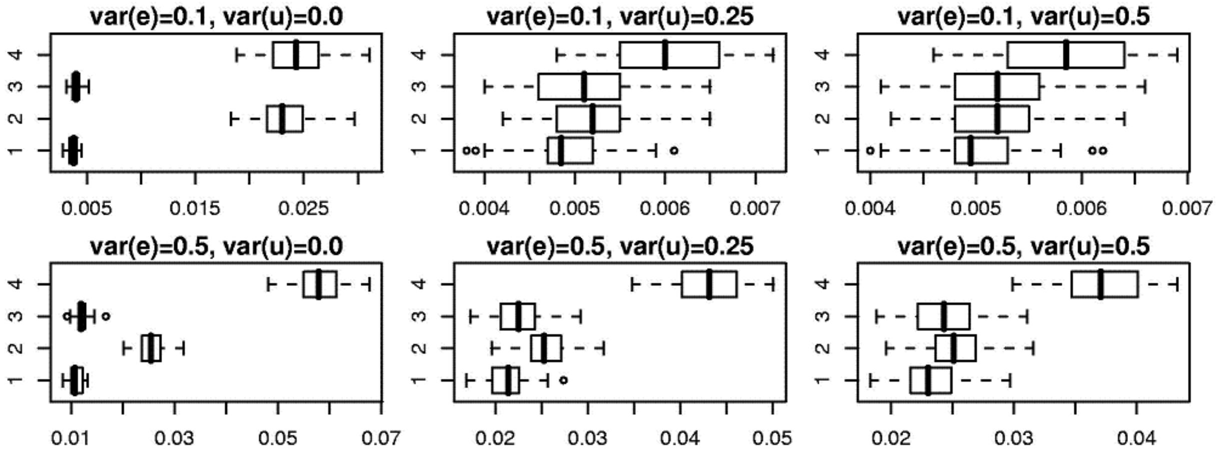
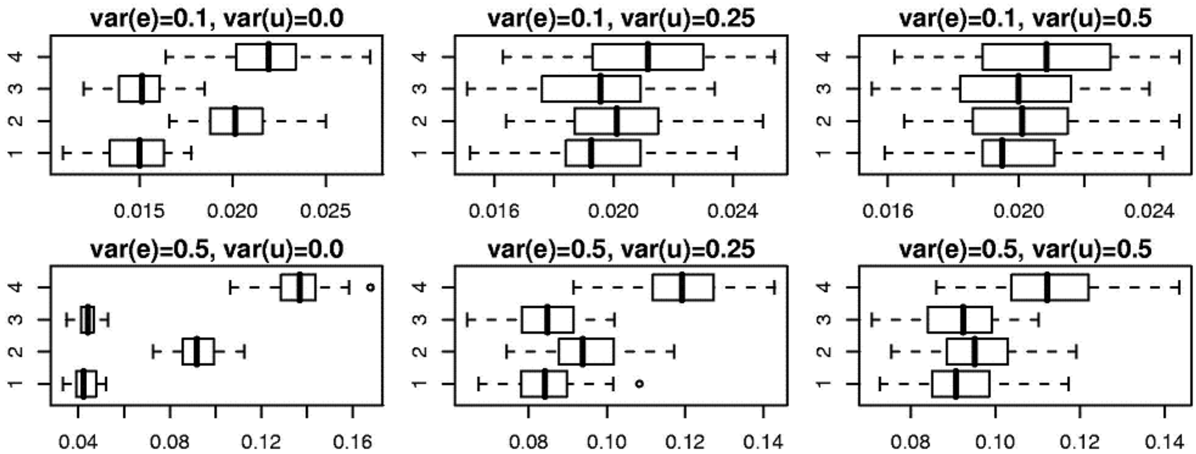


Figure 4: Mean squared error distributions over the 50 predicted area level parameter μ_d for different data generating (σ_e^2, σ_u^2). Boxes 1 and 2 refer to MEM and SMEM respectively, with X_{d6} to X_{d10} random; Boxes 3 and 4 refer to MEM and SMEM respectively, with X_{d6} to X_{d10} fixed.



Finally, we would like to check in a small simulation study whether the proposed bootstrap procedure works. We consider the data generating process as in Section 3.1 with $q = 1$. We have done only 100 simulation runs with 200 bootstrap replicates being aware that this will give only a rough approximation. The results are given in Table 5. Following the recommendation of Härdle and Marron (1991), the bootstrap model was constructed using a pilot bandwidth g greater than h; concretely, all bootstrap samples were generated with a bandwidth $g = 1.1\ h$. We also tried other values for g obtaining rather similar results. As can be seen, the results confirm that the bootstrap procedure can serve as a reasonable tool for doing inference in our SMEM. Further simulations not shown here revealed that the bootstrap does a quite good job for estimating the variance but sometimes, i.e. not for all cases, problems to catch the bias, a not surprising but rather expected finding. We therefore admit that further research on improving the bootstrap performance might be desirable, e.g. to give better bias estimates, but this is beyond the scope of this paper.

Table 5: Bootstrap approximations (B) of actual mean squared errors (O) for β, θ, and our individual predictors. Estimates and predictions are calculated in the SMEM, dimension q = 1, with bandwidth h = 0,5.

	σ_e^2	σ_u^2	MSE($\hat{\beta}_1, \hat{\beta}_2$)		MSE($\hat{\sigma}_e^2, \hat{\sigma}_u^2$)		MSE($\hat{Y}_l, \hat{Y}_s$)	
O	.1	.25	.0008	.0007	.0001	.0026	.0352	.0409
B	.1	.25	.0007	.0007	.0001	.0030	.0337	.0388
O	.5	.25	.0039	.0035	.0024	.0043	.1515	.1829
B	.5	.25	.0035	.0036	.0025	.0050	.1455	.1684

3.3. Concluding Remarks

The simulation study has confirmed all the points made in the introduction and the motivation of our procedure. Firstly, our SMEM allows for a smooth transformation from FEM to MEM. Secondly, under the wrong assumption of independence the parameter vector β is estimated with a clear bias in the MEM. Also the variance of $\hat{\beta}$ is larger than the one in our semiparametric alternative. Similar statements certainly hold true for $\hat{\theta} = (\hat{\sigma}_e^2, \hat{\sigma}_u^2)$. Thirdly, our proposal also clearly outperforms FEM and PLM. However, recall that - asymptotically - such a conclusion is not surprising as our model nests FEM, PLM and MEM. This is exactly the strength of our innovation.

Fourthly, due to the nature and the construction of the MEM made rather for prediction of area parameters then for estimating individual effects, one might have expected strong biases for the model parameters, see Tables 1 and 2. However, the simulations show that even for prediction of area parameters the results are better for the SMEM in both out-of-sample and in-sample prediction.

Finally, the proposed bootstrap arms us with a valid and feasible procedure to do statistical inference. However, applying bootstrap in MEM when the independence assumption is violated is inconsistent, or more clearly said, simply wrong as it is based on a wrong model and therefore leads to wrong conclusions. In contrast, FEM and PLM based bootstrap will suffer from a large variance in practice, whereas the SMEM is consistent and has small variance.

4 A Real Data Example

4.1 Application to a Tourism Survey in Galicia

For Galicia like for the rest of Spain, tourism is one of the most important economic factors. Therefore, official statistics and politics have a strong interest in acquiring information about the expenditure behavior of tourists. Presently, the Galician Statistical Institute (IGE) is focusing its efforts on extending their statistics to county level, in particular the level of the so-called *comarcas* of which 53 exist in Galicia. Obviously, to receive reliable information about a tourists expenditure is cumbersome and expensive, and one is happy with observing, i.e. interviewing in detail maybe 10 individuals per comarca. A peculiarity of Galicia is the famous pilgrim trails to Santiago de Compostela, in particular the so-called *French trail*. For example, in the *holy year* of 2004 about 180000 pilgrims visited Galicia, and in particular

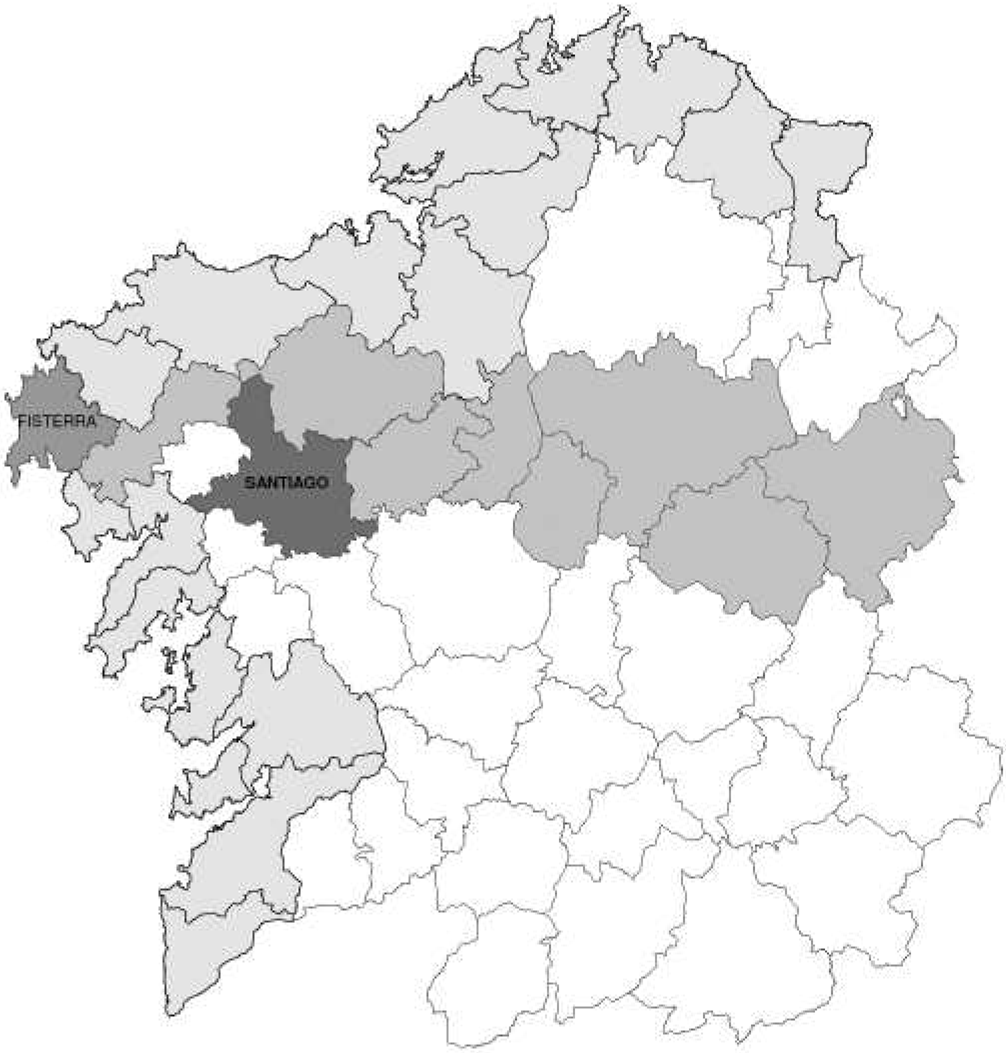
Santiago[2]. Another tourist attraction is certainly the coast. Figure 5 shows the map of the comarcas of Galicia; with all comarcas having coast in light grey and the comarcas that the French trail passes through in grey. The comarca with name *Fisterra* has both peculiarities, and *Santiago* is the pilgrim center and capital. Finally, rural tourism is growing in the sparsely populated areas.

We make use of a survey organized by the University of Santiago de Compostela in 2004. This survey contains information of 10 tourists per comarca including average expenditure per day and several characteristics of the individuals. Note that our dependent variable expenditure means total expenditure including accommodation, food, purchases, travel, leisure activities, and other miscellaneous. We have selected the set of variables described in Table 6.

Other variables of the comarcas which at first glimpse should be important like the index of tourism, the index of bars and restaurants, and the index of economic activity (all the three being monetary quantities) have been studied but finally excluded from the model. This has various reasons. Firstly, all three indices have two sources for endogeneity: measurement error and simultaneity. In some regions of Spain bars and restaurants claim sales of about the same amount tourists report to consume in bars and restaurants. So either the restaurants and bars under-report or the tourists over-report or residents do not consume in bars and restaurants. Similar problems occur for the economic activity, e.g. in Spain the construction branch has an important impact on the Gross Product but it is commonly believed that alone in this sector more than 30% of the real turnover is {paid cash in hand}, that is without VAT (value-added tax). The simultaneity is evident. The exclusion is also justified by problems of multicollinearity: all three indices are strongly correlated (up to 99.4%) between each other and with population density (up to 98.8%). At the same time, this indicates that lpopd is a good instrument for the indices ``tourism" and ``bars and restaurants".

Figure 5: Map of Galicia, with all comarcas having coast are in light grey, comarcas the French trail passes through in grey. Fisterra has both, and Santiago is the pilgrim center and the capital.

[2] For details see statistics at www.santiago-today.com/santiago_article.cfm?art_id=302.



The inclusion of dummies in the nonparametric function η_v is not a problem but alternatively a partial linear modelling could be considered. However, we observed interaction between lpopd, ftrail so that we preferred to disregard that alternative. Next we performed a simple linear regression of each covariate of the comarcas on the individual characteristics to study the dependence structure. For lpobd we got $R^2 = .063$, for ftrail $R^2 = .179$, and for coast $R^2 = .076$. This indicates dependence so that the independence assumption necessary for MEM is violated.

Table 6: Descriptive statistics: mean, standard deviation, and median.

The dependent variable				
lexp	ln of total expenditure per day & cap.	4.064	.6464	4.086
Variables of the individuals				
sex	= 1 if male	.4774	.4995	.0000
age1	= 1 if strictly younger than 29	.2340	.4233	.0000
age2	= 1 if 29 ≤ age ≤ 65	.7057	.4557	1.000
single	= 1 if single	.4094	.4917	.0000
child	= 1 if children ≤ 16 years old	.2792	.4486	.0000
ngal	= 1 if not from Galicia	.7453	.4357	1.000
educ	= 1 if academic	.4981	.5000	.0000
stud	= 1 if student	.1226	.3280	.0000
self	= 1 if self-employed	.1000	.3000	.0000
pilgr	= 1 if pilgrim	.1189	.3236	.0000
family	= 1 visit family, friends, etc.	.3868	.4870	.0000
stay	measured in days	16.74	17.71	10.00
Variables of the comarca				
lpopd	ln of population density	3.276	.8068	3.156
ftrail	= 1 if French pilgrim trail	.0440	.0913	.0000
coast	= 1 if coast	.0839	.1122	.0000

Firstly we give the coefficient estimates for five different smoothing parameter, including 0 and 1000, together with the bootstrap estimates of the standard errors, see Table 7. The bandwidths have been $h = h_c \sigma_W$ with $h_c = 0$ (giving a FEM), 0.2, 0.4, 0.8, and 1000 (giving a MEM); where σ_W is the vector of standard deviations for the comarca covariates. In the bootstrap we used g = 1.1h as the pilot bandwidth for the pre-estimation, and 400 bootstrap replications.

Table 7: Coefficient and variance estimates with their bootstrap standard errors.

$h_c =$	0.0		0.2		0.4		0.8		1000	
Var.	$\hat{\beta}$	S.E.	$\hat{\beta}$	S.E.	$\hat{\beta}$	S.E.	$\hat{\beta}$	S.E.	$\hat{\beta}$	S.E.
sex	-.0284	.0447	-.0147	.0437	-.0242	.0448	-.0264	.0399	-.0327	.0409
age1	.2428	.1199	.2201	.1196	.2249	.1188	.2226	.1047	.2271	.1017
age2	.2665	.1080	.1916	.0972	.1978	.0966	.2069	.0857	.2145	.0879
single	-.0402	.0613	-.0877	.0609	-.0745	.0568	-.0667	.0548	-.0543	.0526
child	.0003	.0565	-.0190	.0565	-.0166	.0501	-.0103	.0475	-.0164	.0486
ngal	.2288	.0560	.2237	.0582	.2377	.0565	.2428	.0468	.2474	.0471
educ	.0648	.0487	.0514	.0509	.0481	.0454	.0514	.0404	.0517	.0410
stud	-.2219	.1011	-.2134	.1045	-.2212	.0963	-.2173	.0816	-.2312	.0829
self	.0809	.0786	.1316	.0825	.1288	.0740	.1173	.0719	.1131	.0721
pilgr	-.7004	.0910	-.7188	.0936	-.6926	.0752	-.6802	.0654	-.6918	.0683
family	-.1798	.0544	-.1304	.0527	-.1478	.0487	-.1565	.0466	-.1689	.0443
stay	-.0047	.0014	-.0042	.0015	-.0045	.0014	-.0045	.0012	-.0044	.0011
$\hat{\sigma}_u^2$	.0001	.0141	.0108	.0165	.0297	.0171	.0424	.0133	.0650	.0123
$\hat{\sigma}_e^2$	.2545	.0000	.2763	.0016	.2937	.0067	.2770	.0042	.2830	.0050

Table 8: For FEM, the parametric estimates (parametric orthogonal least squares regression) of the standard errors (O) and the bootstrap approximation (B).

	sex	age1	age2	single	child	ngal	educ	stud	self	pilgr	family	stay
O	.0447	.1199	.1080	.0613	.0565	.0560	.0487	.1011	.0786	.0910	.0544	.0014
B	.0461	.1207	.1022	.0623	.0579	.0591	.0510	.0989	.0812	.0893	.0564	.0015

For the FEM, see the columns refer to $h_c = 0.0$ in Table 7, we can compare the results with a parametric orthogonal least squares regression to check the robustness of our implementation when applying it to real data. The coefficient estimates coincide perfectly with the numbers given in Table 7 and we get an $R^2 = .3908$. The parametric estimates of the standard errors deviate only slightly from the bootstrap analogs, see Table 8 which is organized like Table 7. We conclude once more that the bootstrap approximation seems to work reasonable well. However, have in mind that also the bootstrap estimates certainly are model based estimates. So if it is used for example to approximate the mean squared error of a predictor in the MEM although the independence assumption is violated, then it is clear that the bootstrap will strongly under estimate the true mean squared error.

Next, the aim is to predict

$$\bar{Y}_{d\bullet} := \beta_0 + \frac{1}{n_d}\sum_{j=1}^{n_d} \boldsymbol{X}_{dj}^t \boldsymbol{\beta} + \eta_v(\boldsymbol{W}_d) + u_d \quad \text{for all } d = 1, \ldots, D.$$

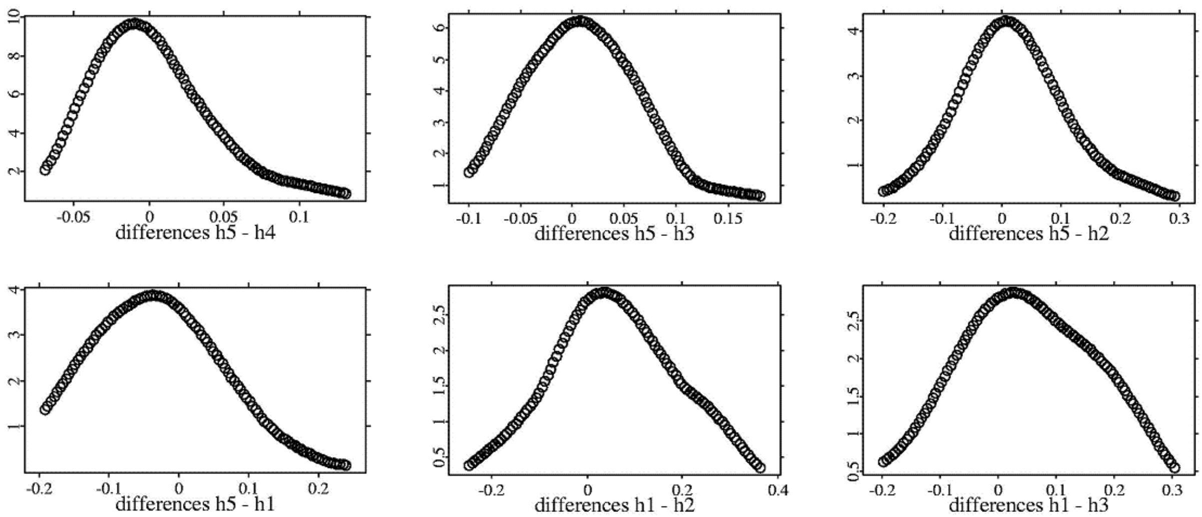
or $\widetilde{Y}_{d\bullet} := \bar{Y}_{d\bullet} - \bar{Y}_{\bullet\bullet}$. We have done this with the same bandwidth and the same bootstrap as above. While the coefficient estimates in Table 7 seem not to change a lot with the chosen model, the estimation of these parameters do. For half of the comarcas *d*, their $\widetilde{Y}_{d\bullet}$ is changing significantly with the chosen model; some of the values tripled when changing from one model to the other, others changed signs, etc. For illustration issues let us denote by $0 = h_1 < h_2 < \ldots < h_5 = 1000$ the five different smoothing parameter. We are interested in differences between the MEM h_5 and the SMEM (h_2, h_3, h_4), respectively the FEM (h_1), and between the FEM and the most flexible SMEM (h_2). First, note that for $\bar{Y}_{\bullet\bullet}$ we have

	h_1	h_2	h_3	h_4	h_5
$\widehat{\bar{Y}_{\bullet\bullet}}$	3.8166	3.8076	3.7993	3.7825	3.6922

For an easier comparison of the different predictions of $\widetilde{Y}_{d\bullet}$ we have plotted in Figure 6 the differences between predictors based on different models, i.e. based on the different h_j. We can see from these graphs that the differences are quite serious and the bootstrap estimates of the standard deviations (not shown them here) reveal that many changes are significant.

Finally, let us simply look at he number of sign changes of $\widetilde{Y}_{d\bullet}$ when switching from model to model. When we express the models simply in terms of h_l (l = 1,2,3,4,5), we observe the following number of sign changes ($\widetilde{Y}_{d\bullet} < 0$ to $\widetilde{Y}_{d\bullet} > 0$ or vice versa) for the 53 comarcas:

Figure 6: Densities of the differences $\widetilde{Y}_{d\bullet}(h_j) - \widetilde{Y}_{d\bullet}(h_k)$ for different j,k=1,2,3,4,5



h_5 to h_4	h_5 to h_3	h_5 to h_2	h_5 to h_1	h_1 to h_2
4	6	6	4	8

This brings to evidence once again that possible dependence between X and the area effect matters a great deal. Conclusions like political decisions, which are based on $\widetilde{Y}_{d\bullet}$ can therefore be strongly misleading if they rely on simple mixed effects models, or highly vague if based on simple fixed effects models (due to the large variance).

4.2 Concluding Remarks

Summarizing, we have got an idea that the model choice not only matters, an inappropriate choice can give rather misleading estimates and predictions. The bootstrap estimates of the standard error decrease clearly with increasing bandwidth giving the smallest values for the MEM. Unfortunately, we know that for the MEM the model bias is the most serious problem but is not captured by the parametric bootstrap. Not surprisingly, we conclude that our SMEM arms the practitioner with a powerful tool but cannot overcome the bias-variance trade-off inherit in all statistical problems. Further research will be directed into studying a possible data adaptive choice of the switcher. However, in practice this choice will often be - at least to some extent - subject to the empirical researchers aims and interests, and it is not clear what would be the most opportune objective function for such a bandwidth choice.

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