



Optimal Designs for Prediction of Individual Effects in RCR Models

Maryna Prus*, Rainer Schwabe

Abstract: We propose optimal designs for the prediction of the individual response in random coefficient regression models with unknown population parameters for finite numbers of individuals.

Random Coefficient Regression

$$Y_{ij} = \mathbf{f}(x_{ij})^T \boldsymbol{\beta}_i + \varepsilon_{ij} \quad x_{ij} \in \mathcal{X}, j = 1, \dots, m_i, i = 1, \dots, n$$

$$\begin{aligned} E(\varepsilon_{ij}) &= 0, \text{Var}(\varepsilon_{ij}) = \sigma^2 \\ E(\boldsymbol{\beta}_i) &= \boldsymbol{\beta}, \text{Cov}(\boldsymbol{\beta}_i) = \sigma^2 \mathbf{D} \end{aligned} \quad \text{uncorrelated}$$

Equal individual settings $m_i = m$ & $x_{ij} = x_j$

$$\mathbf{Y}_i = \mathbf{F} \boldsymbol{\beta}_i + \boldsymbol{\varepsilon}_i$$

$$\mathbf{Y}_i = (\mathbf{Y}_{i1}, \dots, \mathbf{Y}_{im})^T, \quad \mathbf{F} = (\mathbf{f}(x_1), \dots, \mathbf{f}(x_m))^T$$

Best Linear Unbiased Predictor for individual parameters

$$\hat{\boldsymbol{\beta}}_i = \mathbf{D}((\mathbf{F}^T \mathbf{F})^{-1} + \mathbf{D})^{-1} \hat{\boldsymbol{\beta}}_{i,\text{ind}} + (\mathbf{F}^T \mathbf{F})^{-1}((\mathbf{F}^T \mathbf{F})^{-1} + \mathbf{D})^{-1} \hat{\boldsymbol{\beta}}$$

$$\hat{\boldsymbol{\beta}} = (\mathbf{F}^T \mathbf{F})^{-1} \mathbf{F}^T \bar{\mathbf{Y}} \quad \& \quad \hat{\boldsymbol{\beta}}_{i,\text{ind}} = (\mathbf{F}^T \mathbf{F})^{-1} \mathbf{F}^T \mathbf{Y}_i \quad \bar{\mathbf{Y}} = \frac{1}{n} \sum_{i=1}^n \mathbf{Y}_i$$

Mean Squared Error matrix for prediction

$$(\mathbf{I}_n - \frac{1}{n} \mathbf{1}_n \mathbf{1}_n^T) \otimes (\mathbf{F}^T \mathbf{F} + \mathbf{D}^{-1})^{-1} + \frac{1}{n} (\mathbf{1}_n \mathbf{1}_n^T) \otimes (\mathbf{F}^T \mathbf{F})^{-1}$$

Optimal design

distinct settings $x_1, \dots, x_k$
numbers of replications $m_1, \dots, m_k \quad \sum_{j=1}^k m_j = m$

Individual design

$$\xi = \begin{pmatrix} x_1 & \dots & x_k \\ m_1 & \dots & m_k \end{pmatrix}$$

Information (fixed effects model)

$$\mathbf{M}(\xi) = \sum_{j=1}^k m_j \mathbf{f}(x_j) \mathbf{f}(x_j)^T$$

Integrated Mean Squared Error criterion

$$\Phi(\xi) = \text{tr}(\mathbf{M}(\xi)^{-1} \mathbf{V}) + (n-1) \text{tr}((\mathbf{M}(\xi) + \mathbf{D}^{-1})^{-1} \mathbf{V})$$

$$\mathbf{V} = \int_{\mathcal{X}} \mathbf{f}(x) \mathbf{f}(x)^T \nu(dx)$$

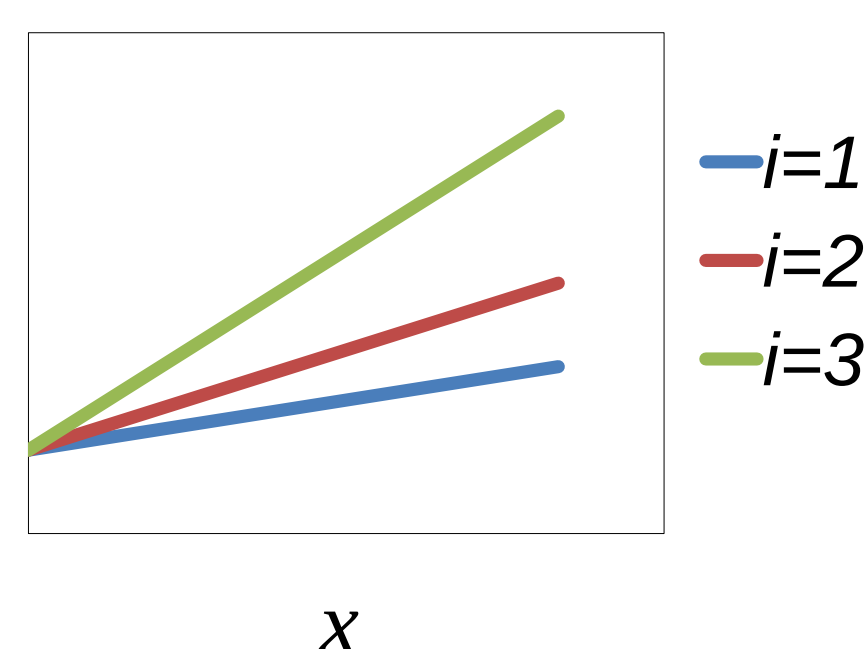
weighted sum of IMSE-criterion in fixed effects models and Bayesian IMSE-Criterion

Optimality can be checked for approximate designs by means of the general equivalence theorem

Example: straight line regression

$$Y_{ij} = \beta_{i1} + \beta_{i2} x_j + \varepsilon_{ij}, \quad x_{ij} \in [0, 1]$$

$$\mu_i(x) = \beta_{i1} + \beta_{i2} x$$



$$\mathbf{D} = \begin{pmatrix} d_1 & 0 \\ 0 & d_2 \end{pmatrix}, \quad n = 100, \quad m = 10, \quad d_1 = 0.01$$

Individual design $\xi = \begin{pmatrix} 0 & 1 \\ m - m_1 & m_1 \end{pmatrix}$

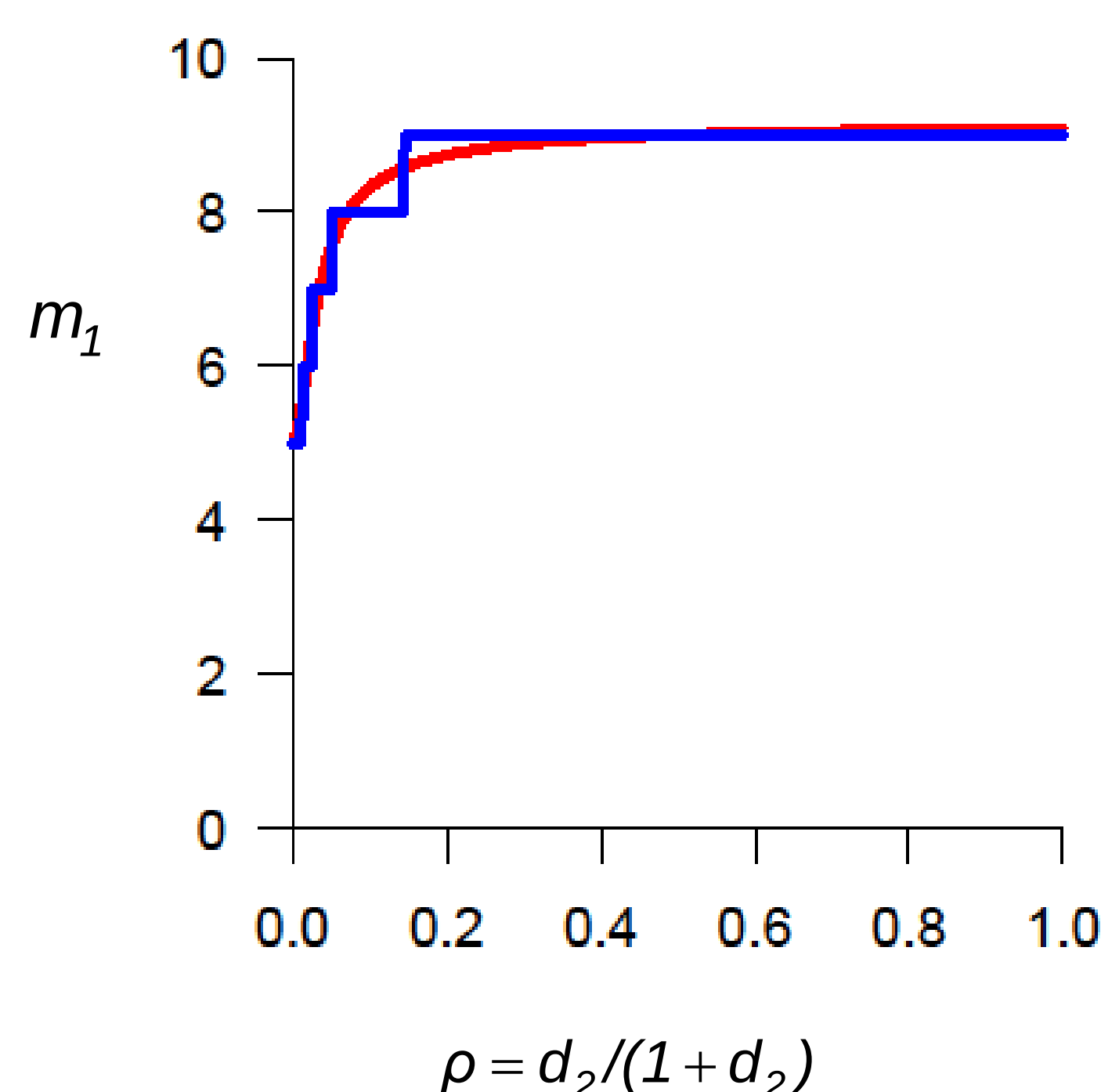


Fig.1: Optimal frequency (—) and the frequency assigned by the exact design (—) in dependence on the variance parameter ρ

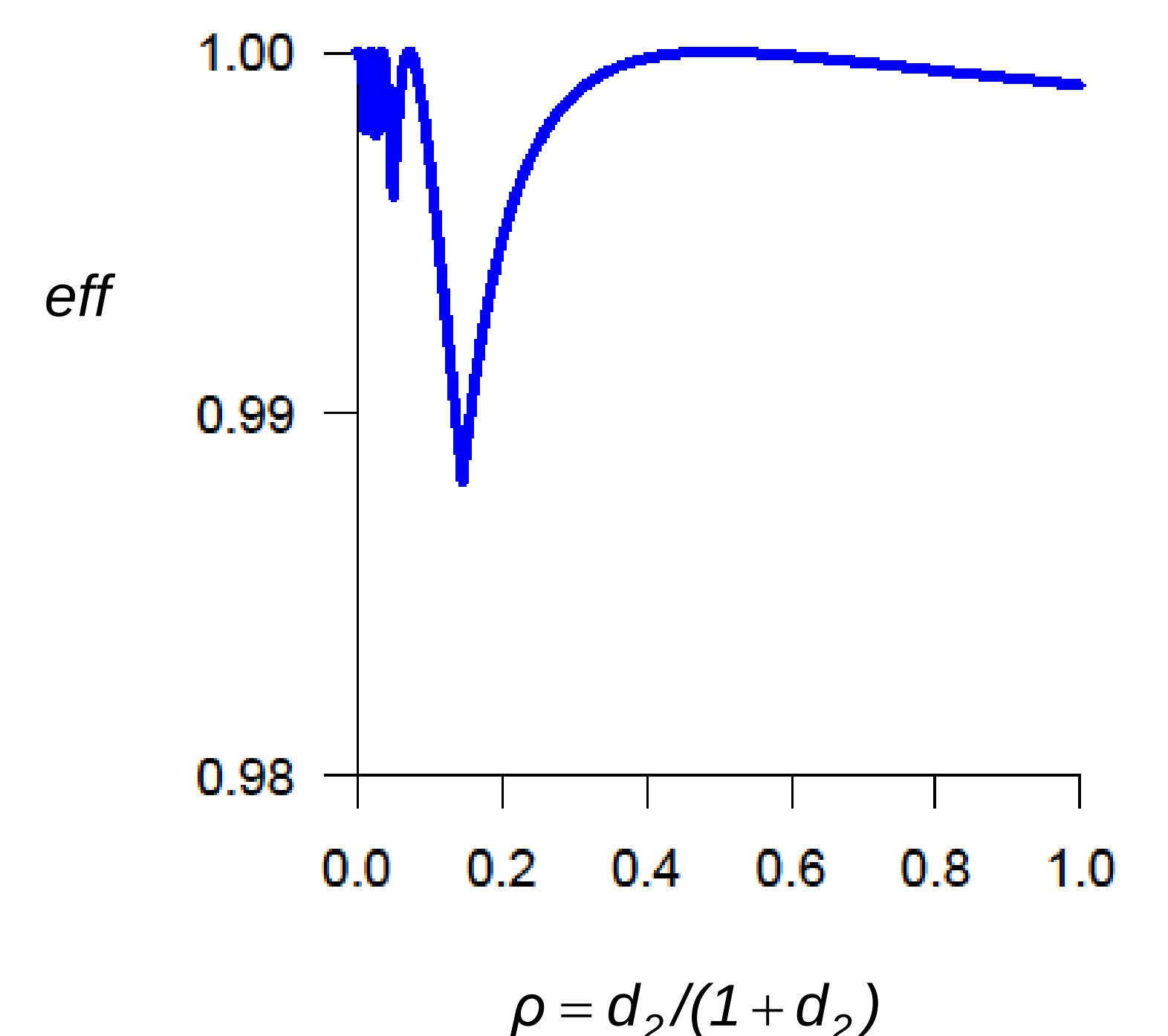


Fig.2: Efficiency of the exact design in dependence on the variance parameter ρ