

```
logLik.bamlss <- function(object, ..., optimizer = FALSE, samples = FALSE)
{
  Call <- match.call()
  Call <- Call[!(names(Call) %in% c("optimizer", "samples"))]
  mn <- as.character(Call)[-1L]
  object <- list(object, ...)
  mstop <- object$mstop
  if(any(names(object) != "") {
    i <- names(object) == ""
    object <- object[i]
    mn <- mn[i]
  }
  object <- object[mn != "mstop"]
}
```

Distributional Modelling in R

Case Studies I – Continuous Distributions

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<https://nikum.org/dmr.html>

Normal Location-Scale Model

- The normal location-scale model

$$y_i | \mathbf{x}_i \sim N(\mu(\mathbf{x}_i), \sigma^2(\mathbf{x}_i))$$

with

$$\begin{aligned}\mu(\mathbf{x}_i) &= \eta_\mu(\mathbf{x}_i) \\ \sigma^2(\mathbf{x}_i) &= \exp(\eta_{\sigma^2}(\mathbf{x}_i))\end{aligned}$$

is the most commonly known distributional regression model for continuous responses.

- However, there is a huge variety of distributions to pick from!

Example: Income Inequality

- Utilise information from the German Socio-Economic Panel to study real gross annual personal labour income in Germany for the years 2001 to 2010.
- Specific focus on changes in spatial differences in income inequality.
- Response: income of males in full time employment in the age range 20–60.
- Information available on 7,216 individuals with a total of $n = 40,965$ observations.
- Potential response distributions:
 - Log-normal $\text{LN}(\mu, \sigma^2)$.
 - Gamma $\text{Ga}(\mu, \sigma)$.
 - Inverse Gaussian $\text{IG}(\mu, \sigma^2)$.
 - Dagum $\text{Da}(a, b, c)$.

with covariate effects on potentially all distributional parameters.

Covariates

- `educ`: Educational level measured as a binary indicator for completed higher education (according to the UNESCO International Standard Classification of Education 1997).
- `age`: age in years.
- `lmexp`: previous labour market experience in years.
- `t`: calendar time.
- `r`: area of residence in terms of geographical district (*Raumordnungsregion*).
- `east`: indicator in effect coding for districts belonging to the eastern part of Germany.

Model Specification

- Hierarchical predictor structure:

$$\eta_i = \beta_0 + \text{educ}_i \beta_1 + s_1(\text{age}_i) + \text{educ}_i s_2(\text{age}_i) + s_3(\text{lmexp}_i) + s_{\text{spat}}(r_i) + s_{\text{time}}(\mathbf{t}_i)$$

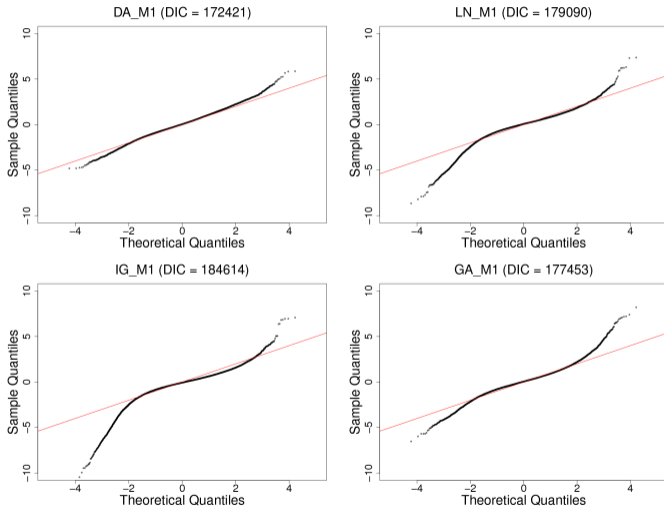
where the spatial effects is decomposed as

$$s_{\text{spat}}(\mathbf{r}) = \text{east}_r \gamma_1 + s_{\text{str}}(\mathbf{r}) + s_{\text{unstr}}(\mathbf{r})$$

Model Comparison by DIC and Scoring Rules

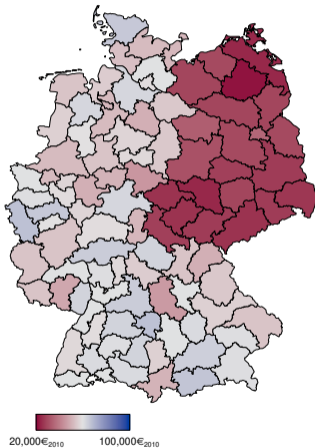
| Distribution | DIC | Quadratic | Logarithmic | Spherical | CRPS |
|--------------|----------------|---------------|----------------|---------------|----------------|
| LN | 179,090 | 0.1304 | -2.4363 | 0.3621 | -2.1581 |
| IG | 184,614 | 0.1464 | -2.2741 | 0.3777 | -1.6195 |
| GA | 177,453 | 0.1609 | -2.1715 | 0.3963 | -1.2735 |
| DA | 172,421 | 0.1684 | -2.1034 | 0.4053 | -1.2662 |

Quantile Residuals (after some model selection)

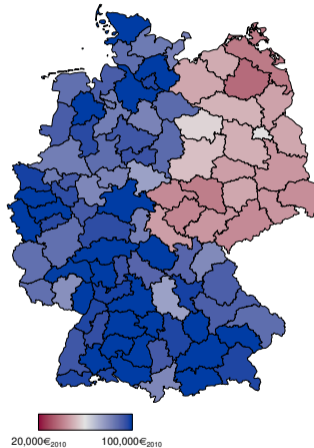


Expected Income for an “Average Man”

Without Higher Education

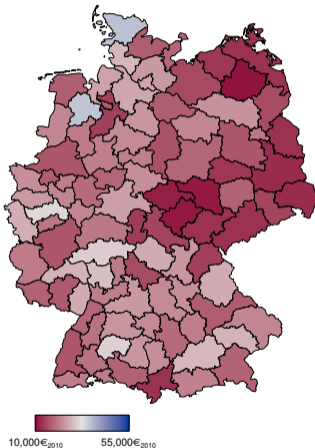


With Higher Education

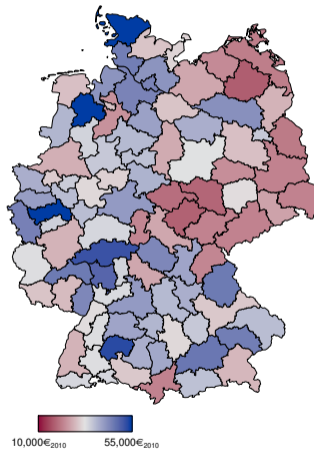


Income Standard Deviation for an “Average Man”

Without Higher Education

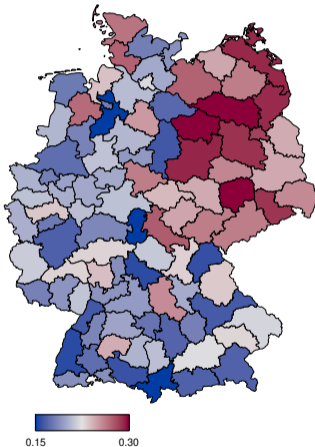


With Higher Education



Gini Coefficient for an “Average Man”

Without Higher Education



With Higher Education

