

---

# Supporting information for: “Regression type models for extremal dependence”

L. Mhalla<sup>1</sup> | M. de Carvalho<sup>2</sup> | V. Chavez-Demoulin<sup>3</sup>

<sup>1</sup>Geneva School of Economics and Management, Université de Genève, Genève, Switzerland

<sup>2</sup>School of Mathematics, University of Edinburgh, Edinburgh, UK

<sup>3</sup>HEC Lausanne, Université de Lausanne, Lausanne, Switzerland

## 1 | AUXILIARY LEMMAS AND PROOFS

Recall the following notations

$$\begin{aligned}\ell(\beta) &= \sum_{i=1}^{n_r} c_i + \log\{h(\mathbf{w}; \beta)\}, \\ \mathbf{m}(\beta) &= \frac{\partial \ell(\beta)}{\partial \beta}, \\ \mathbf{m}(\mathbf{w}, \beta) &= \frac{\partial \log\{h(\mathbf{w}; \beta)\}}{\partial \beta},\end{aligned}$$

where  $c_i$  is a constant independent of  $\beta$ , for  $i = 1, \dots, n_r$ .

As mentioned in the paper, the penalized log-likelihood estimator (PMLE)  $\hat{\beta}$  satisfies the following score equation

$$\mathbf{m}(\hat{\beta}) - \mathbf{P}(\gamma)\hat{\beta} = \mathbf{0}_{p(1+q\bar{d})}. \quad (1)$$

We now define

$$\boldsymbol{\phi}(\beta) = \frac{\partial^2 \ell(\beta)}{\partial \beta \partial \beta^\top}, \quad \boldsymbol{\phi}(\mathbf{w}, \beta) = \frac{\partial^2 \log\{h(\mathbf{w}; \beta)\}}{\partial \beta \partial \beta^\top}.$$

Based on Assumption (A2), we prove the following two lemmas that will streamline the proof of the first part of Theorem 1, i.e., the weak consistency of  $\hat{\beta}$ .

**Lemma 1** *Let  $h(\mathbf{w}; \beta)$  be continuously differentiable a.e. for  $\beta \in \mathbf{B}$ . If  $\int \sup_{\beta \in \mathbf{B}} \|\partial h(\mathbf{w}; \beta) / \partial \beta\| d\mathbf{w} < \infty$ , then for  $\beta \in \mathbf{B}$ :*

1.  $\int h(\mathbf{w}; \beta) d\mathbf{w}$  is continuously differentiable.
2.  $\int \partial h(\mathbf{w}; \beta) / \partial \beta d\mathbf{w} = \partial \int h(\mathbf{w}; \beta) d\mathbf{w} / \partial \beta$ .

**Proof** See Newey and McFadden (1994, Lemma 3.6).

**Lemma 2** If (A2) holds, then

$$E \{ \mathbf{m}(\mathbf{W}, \beta_0) \} = 0, \quad -E \{ \boldsymbol{\phi}(\mathbf{W}, \beta_0) \} = \mathbf{i}(\beta_0).$$

**Proof** By Lemma 1, it follows that

$$E \{ \mathbf{m}(\mathbf{W}, \beta_0) \} = \int \mathbf{m}(\mathbf{w}, \beta_0) h(\mathbf{w}; \beta_0) d\mathbf{w} = \int \left. \frac{\partial h(\mathbf{w}; \beta)}{\partial \beta} \right|_{\beta=\beta_0} d\mathbf{w} = \left. \frac{\partial \int h(\mathbf{w}; \beta) d\mathbf{w}}{\partial \beta} \right|_{\beta=\beta_0} = 0.$$

Now, using (A2) (parts 3 and 4) we have that

$$\begin{aligned} E \{ \boldsymbol{\phi}(\mathbf{W}, \beta_0) \} &= \int \boldsymbol{\phi}(\mathbf{w}, \beta_0) h(\mathbf{w}; \beta_0) d\mathbf{w} \\ &= \int \left. \frac{\partial \mathbf{m}(\mathbf{w}, \beta) h(\mathbf{w}; \beta)}{\partial \beta^\top} \right|_{\beta=\beta_0} h(\mathbf{w}; \beta_0) d\mathbf{w} - \int \mathbf{m}(\mathbf{w}, \beta_0) \mathbf{m}(\mathbf{w}, \beta_0)^\top h(\mathbf{w}; \beta_0) d\mathbf{w} \\ &= - \int \mathbf{m}(\mathbf{w}, \beta_0) \mathbf{m}(\mathbf{w}, \beta_0)^\top h(\mathbf{w}; \beta_0) d\mathbf{w}. \end{aligned}$$

We now prove the first part of Theorem 1 by proving the following lemma.

**Lemma 3** Let  $Q_a = \{ \beta \in \mathbf{B} : \beta = \beta_0 + n_r^{-1/2} \mathbf{a} \}$  be the surface of the sphere around  $\beta_0$  with radius  $n_r^{-1/2} \|\mathbf{a}\|$ . Then, for every  $\varepsilon > 0$ , there exists  $\mathbf{a}$  such that

$$\Pr \left\{ \sup_{\beta \in Q_a} \ell(\beta, \boldsymbol{\gamma}) < \ell(\beta_0, \boldsymbol{\gamma}) \right\} \geq 1 - \varepsilon,$$

for  $n_r$  large enough.

**Proof** Let  $\beta \in Q_a$ , i.e., there exists  $\mathbf{a}$  such that  $\beta = \beta_0 + n_r^{-1/2} \mathbf{a}$ . Applying a second-order Taylor expansion around  $\beta_0$  of the penalized log-likelihood  $\ell(\beta, \boldsymbol{\gamma})$ , we have

$$\begin{aligned} \ell(\beta, \boldsymbol{\gamma}) - \ell(\beta_0, \boldsymbol{\gamma}) &= \ell(\beta) - \ell(\beta_0) - \frac{1}{2} \{ \beta^\top \mathbf{P}(\boldsymbol{\gamma}) \beta - \beta_0^\top \mathbf{P}(\boldsymbol{\gamma}) \beta_0 \} \\ &= n_r^{-1/2} \mathbf{m}(\beta_0)^\top \mathbf{a} + \frac{n_r^{-1}}{2} \mathbf{a}^\top \boldsymbol{\phi}(\beta_0) \mathbf{a} - \frac{n_r^{-1}}{2} \mathbf{a}^\top \mathbf{P}(\boldsymbol{\gamma}) \mathbf{a} - n_r^{-1/2} \beta_0^\top \mathbf{P}(\boldsymbol{\gamma}) \mathbf{a} \\ &\quad + \frac{n_r^{-3/2}}{2} \sum_q \sum_r \sum_s a_q a_r a_s \left. \frac{\partial^3 \ell(\beta)}{\partial \beta_{qrs}} \right|_{\beta=\beta^*}, \end{aligned} \tag{2}$$

with  $\beta^*$  in the interior of  $Q_a$ . The terms involving the penalty matrix  $\mathbf{P}(\boldsymbol{\gamma})$  converge in probability to 0 due to the vanishing penalty from (A1). By the central limit theorem (based on a Lindeberg-type condition), Lemma 2, and (A2), we have that  $n_r^{-1/2} \mathbf{m}(\beta_0) \xrightarrow{d} N(0, \mathbf{i}(\beta_0))$  implying that  $|n_r^{-1/2} \mathbf{m}(\beta_0)^\top \mathbf{a}| = O_p(1) \|\mathbf{a}\|$ . By the law of large numbers and Lemma 2, we have that  $n_r^{-1} \boldsymbol{\phi}(\beta_0) \xrightarrow{p} -\mathbf{i}(\beta_0)$ . Hence, applying the continuous mapping theorem, we end up with  $\mathbf{a}^\top n_r^{-1} \boldsymbol{\phi}(\beta_0) \mathbf{a} / 2 \xrightarrow{p} -\mathbf{a}^\top \mathbf{i}(\beta_0) \mathbf{a} / 2 \leq \|\mathbf{a}\|^2 \lambda_{\min} / 2$ , where  $\lambda_{\min} > 0$  is the smallest eigenvalue of  $\mathbf{i}(\beta_0)$ . Finally, Assumption (A2) (last part) implies that the terms  $\partial^3 \ell(\beta) / \partial \beta_{qrs} |_{\beta=\beta^*} < \infty$  and that, by Cauchy-Schwartz inequality, the remainder

term in (2) vanishes in probability (is  $O_p(n_r^{-1/2})$ ). Leaving out the terms vanishing in probability, (2) yields

$$\ell(\beta, \gamma) - \ell(\beta_0, \gamma) \leq O_p(1)\|\mathbf{a}\| - \|\mathbf{a}\|^2 \lambda_{\min}/2 = T, \quad \beta \in Q_a,$$

for  $n_r$  large enough. Thus,

$$\Pr \left\{ \sup_{\beta \in Q_a} \ell(\beta, \gamma) < \ell(\beta_0, \gamma) \right\} \geq \Pr(T < 0),$$

implying that for every  $\varepsilon > 0$ , there exists an  $a$  such that  $\Pr\{\sup_{\beta \in Q_a} \ell(\beta, \gamma) < \ell(\beta_0, \gamma)\} \geq 1 - \varepsilon$ . Hence, with probability tending to 1, the penalized log-likelihood  $\ell(\beta, \gamma)$  has a local maximum  $\hat{\beta}$  in the interior of a sphere around  $\beta_0$ .

Lemma 3 yields the first part of Theorem 1. Now we move to the second part of Theorem 1. The asymptotic normality of the PMLE  $\hat{\beta}$  is derived from a second-order Taylor expansion of the score equation (1) around the true parameter  $\beta_0$ . The Taylor expansion of (1) yields

$$\mathbf{m}(\beta_0) - \mathbf{P}(\gamma)\beta_0 + \{\boldsymbol{\phi}(\beta_0) - \mathbf{P}(\gamma)\}(\hat{\beta} - \beta_0) + \mathbf{r} = \mathbf{0}_{p(1+q\bar{d})},$$

where

$$\mathbf{r} = \frac{1}{2}(\hat{\beta} - \beta_0)^\top \frac{\partial^2 \mathbf{m}(\beta)}{\partial \beta \partial \beta^\top} \Big|_{\beta=\beta^*} (\hat{\beta} - \beta_0), \quad (3)$$

and  $\beta^*$  is such that  $\|\beta^* - \beta_0\| \leq \|\hat{\beta} - \beta_0\|$ . Dividing (3) by  $n_r^{1/2}$ , we obtain

$$\frac{1}{n_r} \{\boldsymbol{\phi}(\beta_0) - \mathbf{P}(\gamma) + \bar{\mathbf{r}}\} n_r^{1/2} (\hat{\beta} - \beta_0) = n_r^{-1/2} \{\mathbf{P}(\gamma)\beta_0 - \mathbf{m}(\beta_0)\}, \quad (4)$$

where

$$\bar{\mathbf{r}} = \frac{1}{2}(\hat{\beta} - \beta_0)^\top \frac{\partial^2 \mathbf{m}(\beta)}{\partial \beta \partial \beta^\top} \Big|_{\beta=\beta^*}.$$

The consistency of  $\hat{\beta}$  and the assumption on the third order derivative of  $\log\{h(\mathbf{w}; \beta)\}$  in (A2) implies that  $\bar{\mathbf{r}} \xrightarrow{p} 0$ . Assumption (A1) implies that the terms involving  $\mathbf{P}(\gamma)$  vanish in probability. Since  $n_r^{-1/2} \mathbf{m}(\beta_0) \xrightarrow{d} N(0, \mathbf{i}(\beta_0))$  and  $n_r^{-1} \boldsymbol{\phi}(\beta_0) \xrightarrow{p} -\mathbf{i}(\beta_0)$  (see above), Slutsky's theorem implies that  $n_r^{1/2} (\hat{\beta} - \beta_0) \xrightarrow{d} N(0, \mathbf{i}(\beta_0)^{-1})$  and proves hence the second part of Theorem 1.

## 2 | EXTREME TEMPERATURE ANALYSIS

This section supplements Section 5.2 in the paper.

### Dependence of extreme high winter temperatures

The Dirichlet model of Table 2 is fitted to the pseudo-sample of extreme high temperatures where the angular observations corresponding to a radial component exceeding its 90%, 93%, and 97% quantiles, are considered. Figure

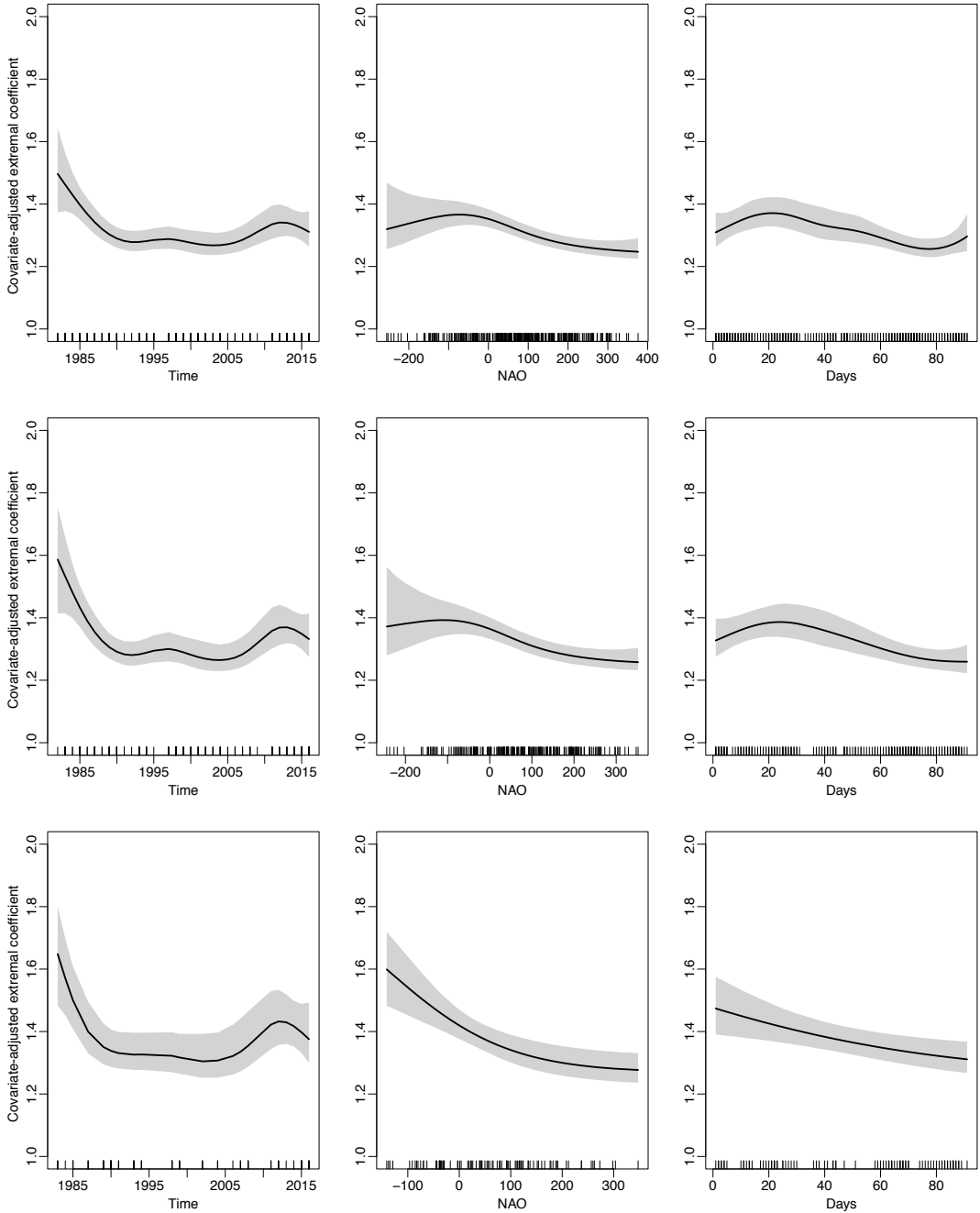
1 displays the fitted smooth effects of time, NAO, and day in season on the extremal coefficient, along with their associated 95% confidence intervals.

## Dependence of extreme low winter temperatures

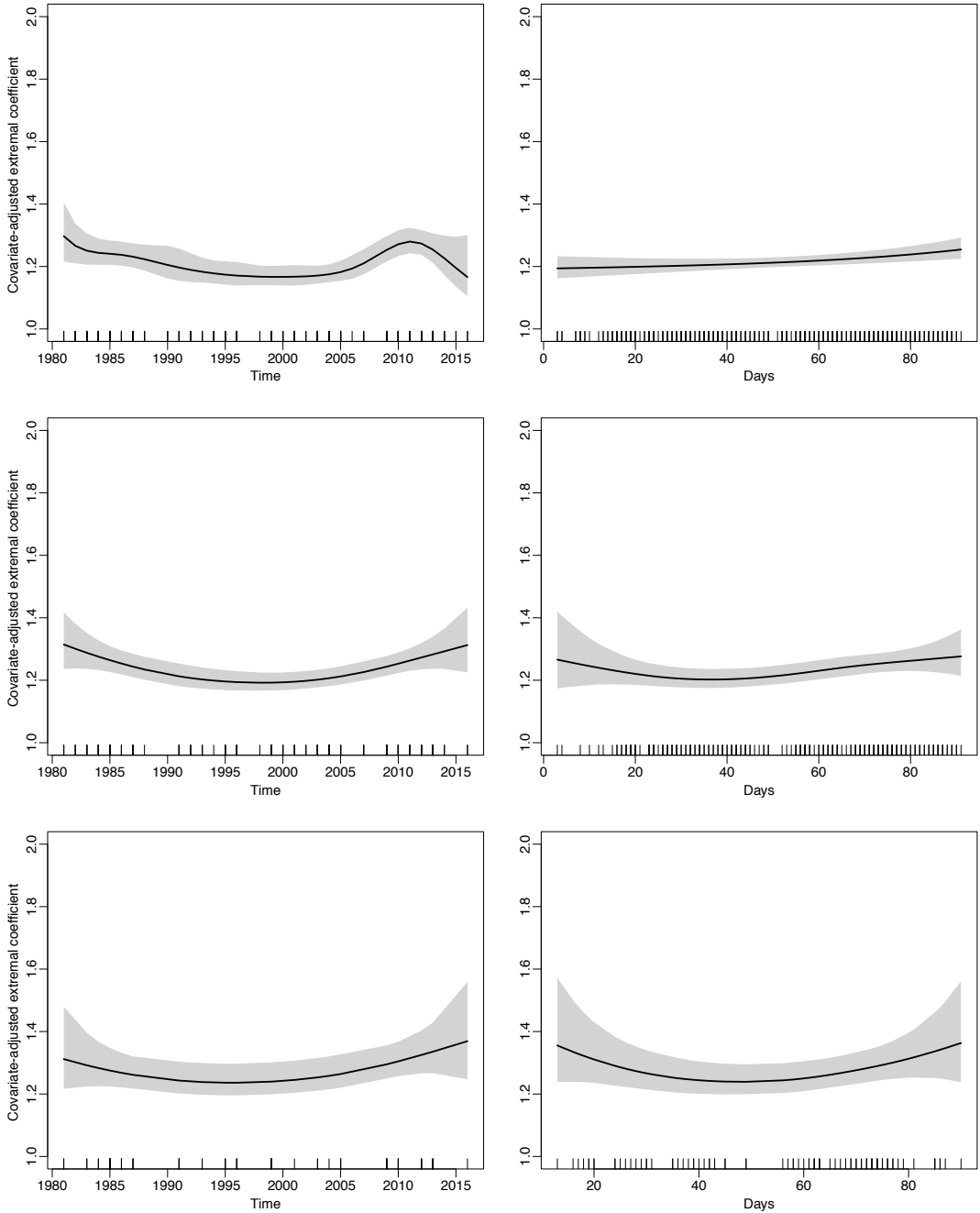
The Dirichlet model of Table 3 is fitted to the pseudo-sample of extreme low temperatures where the angular observations corresponding to a radial component exceeding its 90%, 93%, and 97% quantiles, are considered. Figure 2 displays the fitted smooth effects of time and day in season on the extremal coefficient, along with their associated 95% confidence intervals.

## References

Newey, W. K. and McFadden, D. (1994) Large sample estimation and hypothesis testing. In *Handbook of econometrics* (eds. R. F. Engle and D. McFadden), 2111–2245.



**FIGURE 1** Fitted smooth effects for the extremal coefficient under the Dirichlet model of Table 2 along with their associated 95% (pointwise) asymptotic confidence bands. Different radial thresholds are considered: the 90% quantile (top), the 93% quantile (middle), and the 97% quantile (bottom).



**FIGURE 2** Fitted smooth effects for the extremal coefficient under the Dirichlet model of Table 3 along with their associated 95% (pointwise) asymptotic confidence bands. Different radial thresholds are considered: the 90% quantile (top), the 93% quantile (middle), and the 97% quantile (bottom).