

Asymptotic comparison at optimal levels of reduced-bias extreme value index estimators*

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Abstract

In this paper we are interested in the asymptotic comparison, at optimal levels, of a set of semi-parametric reduced-bias extreme value index estimators, valid for a wide class of heavy-tailed models, underlying the available data. Again, as in the classical case, there is not any estimator that can always dominate the alternatives, but interesting clear-cut patterns are found. Consequently, and in practice, a suitable choice of a set of extreme value index estimators will jointly enable us to better estimate the extreme value index γ , the primary parameter of extreme or even rare events.

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1 The estimators under study and scope of the paper

Let us consider a sample of size n of independent, identically distributed (i.i.d.) random variables (r.v.'s), X_1, X_2, \dots, X_n , with a common distribution function (d.f.) F . Let us denote by $X_{1:n} \leq X_{2:n} \leq \dots \leq X_{n:n}$ the associated ascending order statistics (o.s.) and let us assume that there exist sequences of real constants $\{a_n > 0\}$ and $\{b_n \in \mathbb{R}\}$ such that the maximum, linearly

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normalized, i.e., $(X_{n:n} - b_n)/a_n$, converges in distribution towards a non-degenerate r.v. Then the limit distribution is necessarily of the type of the general *extreme value* (EV) d.f., given by

$$EV_\gamma(x) = \begin{cases} \exp(-(1 + \gamma x)^{-1/\gamma}), 1 + \gamma x > 0 & \text{if } \gamma \neq 0 \\ \exp(-\exp(-x)), x \in \mathbb{R} & \text{if } \gamma = 0. \end{cases} \quad (1.1)$$

The d.f. F is said to belong to the max-domain of attraction of EV_γ , and we write $F \in \mathcal{D}_{\mathcal{M}}(EV_\gamma)$. The parameter γ is the *extreme value index* (EVI), the primary parameter of extreme events. This index measures the heaviness of the right *tail function* $\bar{F} := 1 - F$, and the heavier the right tail, the larger γ is. In this paper we shall work with heavy-tailed models, i.e., Pareto-type underlying d.f.'s, with a strict positive EVI. These heavy-tailed models are quite common in the most diversified areas of application, like computer science, telecommunications, insurance, finance, bibliometrics and biostatistics, among others. Also very popular in insurance and finance are all right tails of the type, $\bar{F}(x) = 1 - F(x) = \exp\{-H(x)\}$, $H \in RV_{1/\theta}$, $\theta > 1$, with RV_α denoting the class of regularly varying functions at infinity, with an index of regular variation equal to α (see Bingham *et al.*, 1987). In a context of *extreme value theory* we have then a null EVI, i.e., $\gamma = 0$, in (1.1), but we are working with those tails in the domain of attraction for maxima of $EV_0(\cdot)$, which exhibit a penultimate behaviour (see Fisher and Tippett, 1928, Gomes, 1984, and Diebolt and Guillou, 2005, among others), looking more similar to Pareto tails than to exponential tails. These distributions belong to the class of sub-exponential models, another possible class of heavy-tailed models.

For heavy-tailed models in $\mathcal{D}_{\mathcal{M}}^+(EV_\gamma)_{\gamma>0}$, the classical EVI-estimators are the Hill estimators (Hill, 1975), which are the average of the scaled log-spacings as well as of the log-excesses, given by

$$U_i := i \left\{ \ln \frac{X_{n-i+1:n}}{X_{n-i:n}} \right\} \quad \text{and} \quad V_{ik} := \ln \frac{X_{n-i+1:n}}{X_{n-k:n}}, \quad 1 \leq i \leq k < n, \quad (1.2)$$

respectively. We have

$$H_n(k) \equiv H(k) = \frac{1}{k} \sum_{i=1}^k U_i = \frac{1}{k} \sum_{i=1}^k V_{ik}, \quad 1 \leq k < n. \quad (1.3)$$

But the EVI-estimators in (1.3) have often a strong asymptotic bias for moderate up to large values of k . Consequently, the adequate accommodation of the bias of Hill's estimators

has been extensively addressed in recent years by several authors. We mention the pioneering papers by Peng (1998), Beirlant *et al.* (1999), Feuerverger and Hall (1999) and Gomes *et al.* (2000). In all these papers, authors are led to second-order reduced-bias EVI-estimators, with asymptotic variances always larger or equal to $(\gamma (1 - \rho)/\rho)^2$, the minimal asymptotic variance of an “asymptotically unbiased” estimator in Drees’ class of functionals (Drees, 1998), where $\rho < 0$ is a shape second-order parameter ruling the rate of convergence of the normalized sequence of maximum values towards the limiting law EV_γ , in (1.1). Recently, Caeiro *et al.* (2005) and Gomes *et al.* (2007a;2008) considered, in different ways, the problem of corrected-bias EVI-estimation, being able to reduce the bias without increasing the asymptotic variance, which was shown to be kept at the value γ^2 , the asymptotic variance of Hill’s estimator, the maximum likelihood estimator of γ for an underlying Pareto d.f., $F_P(x) = 1 - (x/C)^{-1/\gamma}$, $x \geq C$. Those estimators, called *minimum-variance reduced-bias* (MVRB) EVI-estimators, are all based on an adequate external estimation of a pair of second-order parameters, $(\beta, \rho) \in (\mathbb{R}, \mathbb{R}^-)$, done through estimators denoted now $(\hat{\beta}, \hat{\rho})$. Gomes *et al.* (2008) considered the first estimator of this type, an EVI-estimator based on a linear combination of the log-excesses V_{ik} , in (1.2), given by

$$\overline{WH}_{\hat{\beta}, \hat{\rho}}(k) := \frac{1}{k} \sum_{i=1}^k e^{-\hat{\beta} (n/k)^{\hat{\rho}} \psi_{ik}(\hat{\rho})} V_{ik}, \quad \psi_{ik}(\rho) = \psi_{ik} = -\frac{(i/k)^{-\rho} - 1}{\rho \ln(i/k)}, \quad (1.4)$$

WH standing here for *weighted Hill* estimator. Caeiro *et al.* (2005) considered two estimators of this same type, here denoted,

$$CH_{\hat{\beta}, \hat{\rho}}(k) := H(k) \left(1 - \frac{\hat{\beta}}{1 - \hat{\rho}} \left(\frac{n}{k}\right)^{\hat{\rho}}\right) \quad \text{and} \quad \overline{CH}_{\hat{\beta}, \hat{\rho}}(k) := H(k) \exp\left(-\frac{\hat{\beta}}{1 - \hat{\rho}} \left(\frac{n}{k}\right)^{\hat{\rho}}\right). \quad (1.5)$$

A third class was introduced in Gomes *et al.* (2007a), and it has the functional form

$$ML_{\hat{\beta}, \hat{\rho}}(k) := H(k) - \hat{\beta} \left(\frac{n}{k}\right)^{\hat{\rho}} \left(\frac{1}{k} \sum_{i=1}^k \left(\frac{i}{k}\right)^{-\hat{\rho}} U_i\right), \quad (1.6)$$

with U_i given in (1.2). These authors considered also the estimator

$$\overline{ML}_{\hat{\beta}, \hat{\rho}}(k) := \frac{1}{k} \sum_{i=1}^k \exp(-\hat{\beta}(n/i)^{\hat{\rho}}) U_i, \quad (1.7)$$

the estimator directly derived from the likelihood equation for γ with β and ρ fixed and based upon the exponential approximation $U_i \approx \gamma \exp(\beta(n/i)^\rho) E_i$, $1 \leq i \leq k$, with $\{E_i\}_{i \geq 1}$ denoting a sequence of independent, standard exponential r.v.’s, being claimed a better performance of the

ML estimator, comparatively to the \overline{ML} estimator, for a large class of models. This is the reason why we shall also work with a first order approximation for the estimator $\overline{WH}_{\hat{\beta}, \hat{\rho}}(k)$, in (1.4), the bias-corrected Hill estimator

$$WH_{\hat{\beta}, \hat{\rho}}(k) := H(k) - \hat{\beta} \left(\frac{n}{k}\right)^{\hat{\rho}} \left(\frac{1}{k} \sum_{i=1}^k \psi_{ik} V_{ik}\right), \quad (1.8)$$

with ψ_{ik} given in (1.4). For the estimation of ρ it has been advised the use of the simplest class of estimators in Fraga Alves *et al.* (2003), denoted now $\hat{\rho}(k)$, which are computed at $k_1 = n^{1-\epsilon}$, for any small value ϵ , like $\epsilon = 0.01$. In the notation of this paper, $\hat{\rho} = \hat{\rho}(k_1)$. The estimation of β has been performed through the use of a statistic dependent on a consistent estimator of ρ , denoted $\hat{\beta}(k; \hat{\rho})$, introduced in Gomes and Martins (2002), and also computed at the same k_1 , i.e., $\hat{\beta} = \hat{\beta}(k_1; \hat{\rho})$.

Apart from any of the above mentioned MVRB statistics, denoted generally $UH_{\hat{\beta}, \hat{\rho}}(k)$, with UH standing for *unbiased Hill*, we shall also consider the statistics

$$UH_{\hat{\rho}}^*(k) := UH_{\hat{\beta}(k; \hat{\rho}), \hat{\rho}}(k), \quad (1.9)$$

with an asymptotic variance that is no longer γ^2 but $\gamma^2(1 - \rho)^2/\rho^2 > \gamma^2$ for every ρ . As mentioned before, in the $UH_{\hat{\beta}, \hat{\rho}}(k)$ and $UH_{\hat{\rho}}^*(k)$ classes, $(\hat{\beta}, \hat{\rho})$ or $\hat{\rho}$, respectively, need to be adequate consistent estimators of the second-order parameters, if we want to keep the same properties of $UH_{\beta, \rho}(k)$ or $UH_{\rho}^*(k)$, the associated r.v.'s. For details on such a type of estimation see, for instance, Caeiro and Gomes (2008), Caeiro *et al.* (2009) and Gomes *et al.* (2009), among others.

In this paper, we compare asymptotically, at optimal levels, the above mentioned MVRB statistics, denoted generically $UH(k)$, and the reduced-bias statistics $UH^*(k)$ (assuming thus that β and ρ are known or adequately estimated). In Section 2, we provide a brief review of the most common first, second and third-order frameworks for heavy-tailed models. In Section 3, we derive, for a large class of models in $\mathcal{D}_{\mathcal{M}}^+$, the asymptotic properties of $UH(k)$ and $UH^*(k)$, and finally, in Section 4, we provide a full asymptotic comparison, at optimal levels, of $UH(k)$ and $UH^*(k)$ for $UH = CH, ML$ and WH .

2 A brief review of first, second and third-order conditions for heavy tails

In the most common frameworks in the area of *statistics of extremes*, a model F is said to be *heavy-tailed* whenever the tail function \bar{F} is a *regularly varying function* with a negative index of regular variation equal to $\{-1/\gamma\}$, $\gamma > 0$, or equivalently, the reciprocal quantile function $U(t) = F^{\leftarrow}(1 - 1/t)$, $t \geq 1$, with $F^{\leftarrow}(x) = \inf\{y : F(y) \geq x\}$, is of regular variation with index γ , i.e., for all $x > 0$,

$$\lim_{t \rightarrow \infty} \frac{\bar{F}(tx)}{\bar{F}(t)} = x^{-1/\gamma} \iff \lim_{t \rightarrow \infty} \frac{U(tx)}{U(t)} = x^\gamma \iff F \in \mathcal{D}_{\mathcal{M}}^+. \quad (2.1)$$

The *second-order parameter*, $\rho (\leq 0)$, rules the rate of convergence in the first-order condition (2.1), and is the non-positive parameter appearing in the limiting relation

$$\lim_{t \rightarrow \infty} \frac{\ln U(tx) - \ln U(t) - \gamma \ln x}{A(t)} = \frac{x^\rho - 1}{\rho}, \quad (2.2)$$

which is assumed to hold for every $x > 0$, and where $|A|$ must then be of regular variation with index ρ (Geluk and de Haan, 1987).

In order to obtain information on the order of the asymptotic bias of second-order reduced-bias EVI-estimators, it is necessary to further assume a third-order condition, ruling the rate of convergence in (2.2), and which guarantees that, for all $x > 0$,

$$\lim_{t \rightarrow \infty} \frac{\frac{\ln U(tx) - \ln U(t) - \gamma \ln x}{A(t)} - \frac{x^\rho - 1}{\rho}}{B(t)} = \frac{x^{\rho + \rho'} - 1}{\rho + \rho'}, \quad (2.3)$$

where $|B(t)|$ must then be of regular variation with index ρ' . There appears then this extra non-positive third-order parameter $\rho' \leq 0$. Such a condition has already been used in Gomes *et al.* (2002) and Fraga Alves *et al.* (2003), for the full derivation of the asymptotic behaviour of ρ -estimators, in Gomes *et al.* (2004), for the study of a reduced-bias EVI-estimator and more recently in Caeiro *et al.* (2009), for a comparison of some of the MVRB estimators in this paper.

In this paper, similarly to what has been done in Gomes *et al.* (2007a), we consider a Pareto-type class of models, with a tail function

$$1 - F(x) = Cx^{-1/\gamma} (1 + D_1 x^{\rho/\gamma} + D_2 x^{2\rho/\gamma} + o(x^{2\rho/\gamma})), \quad (2.4)$$

as $x \rightarrow \infty$, with $C > 0$, $D_1, D_2 \neq 0$, $\rho < 0$. Note that to assume (2.4) is equivalent to say that (2.3) holds with $\rho = \rho' < 0$ and that we may there choose

$$A(t) = \alpha t^\rho =: \gamma \beta t^\rho, \quad B(t) = \beta' t^\rho = \frac{\beta' A(t)}{\beta \gamma}, \quad \beta, \beta' \neq 0, \quad (2.5)$$

with β and β' “scale” second and third-order parameters, respectively.

Remark 2.1. *Several common heavy-tailed models belong to the class in (2.4). Among them we mention:*

- the Fréchet model, with d.f. $F(x) = \exp(-x^{-1/\gamma})$, $x \geq 0$, $\gamma > 0$, for which $\rho' = \rho = -1$, $\beta = 0.5$ and $\beta' = 5/6$;
- the Generalized Pareto (GP) model, with d.f. $F(x) = 1 - (1 + \gamma x)^{-1/\gamma}$, $x \geq 0$, $\gamma > 0$, for which $\rho' = \rho = -\gamma$ and $\beta = \beta' = 1$;
- the Burr model, with d.f. $F(x) = 1 - (1 + x^{-\rho/\gamma})^{1/\rho}$, $x \geq 0$, $\gamma > 0$, $\rho' = \rho < 0$ and, as for the GP model, $\beta = \beta' = 1$;
- the Student’s t_ν -model with ν degrees of freedom, with a probability density function (p.d.f.)

$$f_{t_\nu}(t) = \Gamma((\nu + 1)/2) [1 + t^2/\nu]^{-(\nu+1)/2} / (\sqrt{\pi\nu} \Gamma(\nu/2)), \quad t \in \mathbb{R} \quad (\nu > 0),$$

for which $\gamma = 1/\nu$ and $\rho' = \rho = -2/\nu$. Regarding the values of (β, β') , we provide Table 1. For an explicit expression of β and β' as a function of ν , see [Caeiro and Gomes \(2008\)](#).

Table 1: Values of β and β' for a Student d.f with ν degrees of freedom.

ν	1	2	3	4	5	6	7	8
β	6.580	3.000	2.249	1.925	1.742	1.625	1.542	1.480
β'	4.606	2.334	1.848	1.636	1.516	1.439	1.385	1.344
$\xi := \beta'/\beta$	0.700	0.778	0.821	0.850	0.870	0.886	0.898	0.907

In order to have consistency of any of the EVI-estimators mentioned in Section 1, in all $\mathcal{D}_{\mathcal{M}}^+$, we need to work with intermediate values of k , i.e., a sequence of integers $k = k_n$, $1 \leq k < n$, such that

$$k = k_n \rightarrow \infty \quad \text{and} \quad k_n = o(n), \quad \text{as } n \rightarrow \infty. \quad (2.6)$$

Under the second order framework, in (2.2), the asymptotic distributional representation

$$H_n(k) \stackrel{d}{=} \gamma + \frac{\gamma}{\sqrt{k}} Z_k + \frac{1}{1-\rho} A(n/k)(1 + o_p(1))$$

holds (de Haan and Peng, 1998), where, with $\{E_i\}$ a sequence of i.i.d. standard exponential r.v.'s,

$$Z_k = \sqrt{k} \left(\sum_{i=1}^k E_i/k - 1 \right) \quad (2.7)$$

is an asymptotically standard normal r.v. Under adequate conditions on k , we get, for any of the above mentioned MVRB statistics, in (1.4), (1.5), (1.6), (1.7) and (1.8), denoted generally $UH_{\hat{\beta}, \hat{\rho}}(k)$, the validity of the asymptotic distributional representation

$$UH_{\hat{\beta}, \hat{\rho}}(k) \stackrel{d}{=} \gamma + \frac{\gamma}{\sqrt{k}} Z_k + o_p(A(n/k)).$$

Under similar conditions, and for any of the reduced-bias statistics in (1.9), we get

$$UH_{\hat{\rho}}^*(k) \stackrel{d}{=} \gamma + \frac{\gamma(1-\rho)}{\rho\sqrt{k}} Z_k + o_p^*(A(n/k)).$$

Detailed information on the remainder terms $o_p(A(n/k))$ and $o_p^*(A(n/k))$ will be given next, in Section 3.

3 The asymptotic behaviour of UH and UH^*

We now state the following result, a particular case, with some additions related with the \overline{UH} statistics, of Theorem 3.1 and Theorem 3.2 in Caeiro *et al.* (2009).

Theorem 3.1. *Under the third-order framework in (2.4), with $A(t)$ given in (2.5), Z_k given in (2.7), and for intermediate k , i.e., if (2.6) holds, we can write*

$$UH_{\beta, \rho}(k) \stackrel{d}{=} \gamma + \frac{\gamma Z_k}{\sqrt{k}} + \left(b_{UH} A^2(n/k) + O_p\left(\frac{A(n/k)}{\sqrt{k}}\right) \right) (1 + o_p(1)),$$

and

$$UH_{\rho}^*(k) \stackrel{d}{=} \gamma + \frac{\gamma(1-\rho) Z_k}{|\rho|\sqrt{k}} + \left(b_{UH}^* A^2(n/k) + O_p\left(\frac{A(n/k)}{\sqrt{k}}\right) \right) (1 + o_p(1)),$$

where, with $\xi = \beta'/\beta$,

$$b_{cH} = \frac{1}{\gamma} \left(\frac{\xi}{1-2\rho} - \frac{1}{(1-\rho)^2} \right), \quad b_{cH} = \frac{1}{\gamma} \left(\frac{\xi}{1-2\rho} - \frac{1}{2(1-\rho)^2} \right),$$

$$\begin{aligned}
b_{ML} &= \frac{\xi - 1}{\gamma(1 - 2\rho)}, & b_{\overline{ML}} &= \frac{2\xi - 1}{2\gamma(1 - 2\rho)}, \\
b_{CH}^* &= -\frac{1}{\gamma(1 - 3\rho)} \left(\frac{\xi(1 - \rho)}{1 - 2\rho} - \frac{2\rho^2 - \rho + 1}{(1 - \rho)^2} \right), & b_{\overline{CH}}^* &= -\frac{1}{\gamma(1 - 3\rho)} \left(\frac{\xi(1 - \rho)}{1 - 2\rho} - \frac{4\rho^2 - 5\rho + 3}{2(1 - \rho)^2} \right), \\
b_{ML}^* &= -\frac{(1 - \rho)(\xi - 1)}{\gamma(1 - 2\rho)(1 - 3\rho)}, & b_{\overline{ML}}^* &= -\frac{2\xi(1 - \rho) - (3 - 5\rho)}{2\gamma(1 - 2\rho)(1 - 3\rho)},
\end{aligned}$$

and with

$$\begin{aligned}
a_2(\rho) &= -(\ln(1 - 2\rho) - 2\ln(1 - \rho)) / \rho^2, \\
b_{WH} &= \frac{1}{\gamma} \left(\frac{\xi}{1 - 2\rho} - a_2(\rho) \right), & b_{\overline{WH}} &= \frac{1}{\gamma} \left(\frac{\xi}{1 - 2\rho} - \frac{a_2(\rho)}{2} \right), \\
b_{WH}^* &= -\frac{1}{\gamma(1 - 3\rho)} \left(\frac{\xi(1 - \rho)}{1 - 2\rho} - 2 + (1 - 3\rho)a_2(\rho) \right), \\
b_{\overline{WH}}^* &= -\frac{1}{\gamma(1 - 3\rho)} \left(\frac{\xi(1 - \rho)}{1 - 2\rho} - \frac{4 - (1 - 3\rho)a_2(\rho)}{2} \right).
\end{aligned}$$

Consequently, even if $\sqrt{k} A(n/k) \rightarrow \infty$, with $\sqrt{k} A^2(n/k) \rightarrow \lambda_A$, finite,

$$\sqrt{k} (UH_{\beta,\rho}(k) - \gamma) \xrightarrow[n \rightarrow \infty]{d} \text{Normal}(\lambda_A b_{UH}, \sigma_{UH}^2 = \gamma^2) \quad (3.1)$$

and

$$\sqrt{k} (UH_{\rho}^*(k) - \gamma) \xrightarrow[n \rightarrow \infty]{d} \text{Normal}(\lambda_A b_{UH}^*, \sigma_{UH^*}^2 = \frac{\gamma^2(1 - \rho)^2}{\rho^2}). \quad (3.2)$$

If $\sqrt{k} A^2(n/k) \rightarrow \infty$, both $(UH_{\beta,\rho}(k) - \gamma)$ and $(UH_{\rho}^*(k) - \gamma)$ are $O_p(A^2(n/k))$.

Moreover, if we consistently estimate the vector (β, ρ) of second-order parameters through $(\hat{\beta}, \hat{\rho})$, with $\hat{\rho} - \rho = o_p(\ln(n/k)) / (\sqrt{k}A(n/k))$, (3.1) and (3.2) still hold, with $UH_{\beta,\rho}(k)$ and $UH_{\rho}^*(k)$ replaced by $UH_{\hat{\beta},\hat{\rho}}(k)$ and $UH_{\hat{\rho}}^*(k)$, respectively.

Proof. The results for \overline{UH} follow straightforwardly from the results for UH , derived in Caeiro *et al.* (2009). Indeed, as $n \rightarrow \infty$, we have

$$\overline{WH}_{\beta,\rho} - WH_{\beta,\rho} \stackrel{p}{\sim} a_2(\rho)A^2(n/k)/(2\gamma),$$

$$\overline{CH}_{\beta,\rho} - CH_{\beta,\rho} \stackrel{p}{\sim} A^2(n/k)/(2\gamma(1 - \rho)^2)$$

and

$$\overline{ML}_{\beta,\rho} - ML_{\beta,\rho} \stackrel{p}{\sim} A^2(n/k)/(2\gamma(1 - 2\rho)).$$

■

Remark 3.1. For the adequate estimation of (β, ρ) see Gomes and Pestana (2007) and Caeiro et al. (2009), among others.

Remark 3.2. Note that $b_{ML} = b_{ML^*} = 0$ whenever $\xi = 1$ ($\beta' = \beta$). This happens for important models like the Burr and the GP, and it is a point in favour of the ML-statistic, as already mentioned in Gomes et al. (2007a).

Remark 3.3. Note also that, as already mentioned in Caeiro et al. (2009), since $\lambda_A \geq 0$ and $1/(2a_2(\rho)) > (1 - \rho)^2 > 1/a_2(\rho) > 1 - 2\rho$ for any $\rho < 0$, $b_{\overline{WH}} \geq b_{CH} \geq b_{WH} \geq b_{ML}$. All depends then on the sign of the bias, but we expect the sample paths of \overline{WH} to be always above the sample paths of CH, which should be in turn above the sample paths of WH, these ones above the ones of ML. The ML-statistics are then preferable to the other ones whenever the bias are all positive. If the bias are all negative, \overline{WH} is expected to outperform the other statistics.

4 Asymptotic comparison of the estimators at optimal levels

Following the comparison done in Gomes et al. (2007a) for the MVRB estimators ML and ML^* , we shall next proceed to the comparison of the estimators under study at their optimal levels. This is again done in a way similar to the one used in de Haan and Peng (1998), Gomes and Martins (2001), Gomes et al. (2005, 2007b), Gomes and Neves (2007) and Gomes and Henriques-Rodrigues (2009) for the classical EVI-estimators. Let us assume that $\hat{\gamma}_n^\bullet(k)$ denotes any arbitrary reduced-bias semi-parametric estimator of the extreme value index γ , for which we have

$$\hat{\gamma}_n^\bullet(k) = \gamma + \frac{\sigma_\bullet}{\sqrt{k}} Z_k^\bullet + b_\bullet A^2(n/k) + o_p(A(n/k)) \quad (4.1)$$

for any intermediate sequence of integers $k = k_n$, and where Z_k^\bullet is an asymptotically standard normal r.v. Then, $\sqrt{k}(\hat{\gamma}_n^\bullet(k) - \gamma) \xrightarrow{d} N(\lambda_A b_\bullet, \sigma_\bullet^2)$ provided that k is such that $\sqrt{k} A^2(n/k) \rightarrow \lambda_A$, finite, as $n \rightarrow \infty$. We then write $Bias_\infty(\hat{\gamma}_n^\bullet(k)) := b_\bullet A^2(n/k)$ and $Var_\infty(\hat{\gamma}_n^\bullet(k)) := \sigma_\bullet^2/k$. The so-called Asymptotic Mean Square Error (AMSE) is then given by

$$AMSE(\hat{\gamma}_n^\bullet(k)) := \frac{\sigma_\bullet^2}{k} + b_\bullet^2 A^4(n/k).$$

Regular variation theory (Bingham et al., 1997), enables us to show that, whenever $b_\bullet \neq 0$, there exists a function $\varphi(n) = \varphi(n, \gamma, \rho)$, such that

$$\lim_{n \rightarrow \infty} \varphi(n) AMSE(\hat{\gamma}_{n0}^\bullet) = (\sigma_\bullet^2)^{-\frac{4\rho}{1-4\rho}} (b_\bullet^2)^{\frac{1}{1-4\rho}} =: LMSE(\hat{\gamma}_{n0}^\bullet),$$

where $\hat{\gamma}_{n0}^\bullet := \hat{\gamma}_{n, k_0^\bullet(n)}^\bullet$ and $k_0^\bullet(n) := \arg \inf_k AMSE(\hat{\gamma}_n^\bullet(k))$.

It is then sensible to consider the following:

Definition 4.1. Given two biased estimators $\hat{\gamma}_n^{(1)}(k)$ and $\hat{\gamma}_n^{(2)}(k)$, for which a distributional representation of the type of the one in (4.1) holds, with constants (σ_1, b_1) and (σ_2, b_2) , $b_1, b_2 \neq 0$, respectively, both computed at their optimal levels, the Asymptotic Root Efficiency (AREFF) of $\hat{\gamma}_{n0}^{(1)}$ relatively to $\hat{\gamma}_{n0}^{(2)}$ is

$$AREFF_{1|2} \equiv AREFF_{\hat{\gamma}_{n0}^{(1)}|\hat{\gamma}_{n0}^{(2)}} := \sqrt{LMSE[\hat{\gamma}_{n0}^{(2)}]/LMSE[\hat{\gamma}_{n0}^{(1)}]} = \left(\left(\frac{\sigma_2}{\sigma_1} \right)^{-4\rho} \left| \frac{b_2}{b_1} \right| \right)^{\frac{1}{1-4\rho}}. \quad (4.2)$$

Remark 4.1. Note that the AREFF indicator, in (4.2), has been conceived so that the highest the AREFF indicator is, the better is the first estimator.

We first present in Figures 1, 2 and 3, the measure $AREFF_{UH|\overline{UH}}$ for $UH = CH, ML, WH$, respectively.

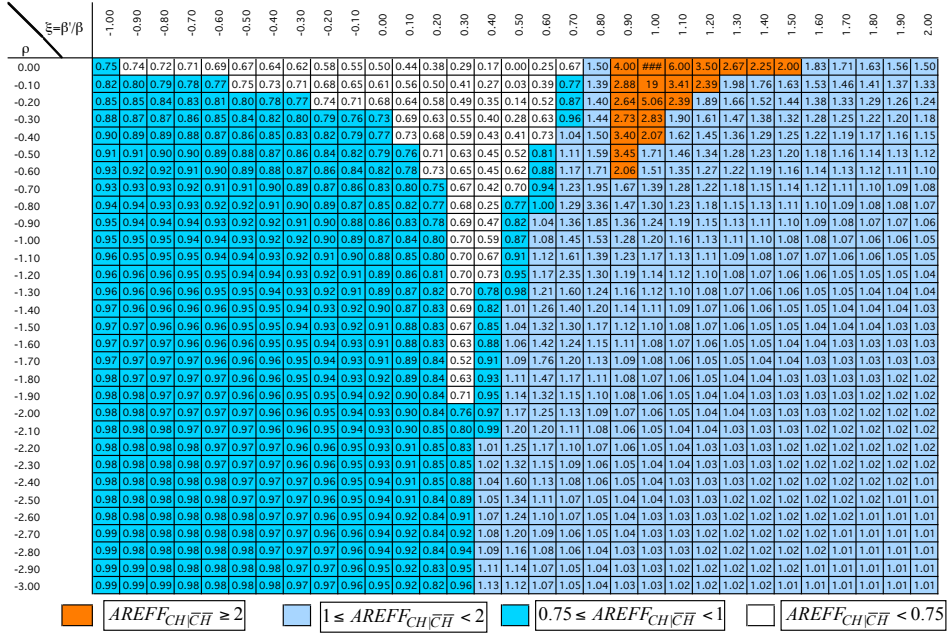


Figure 1: $AREFF_{CH|\overline{CH}}$, in the (ξ, ρ) -plane.

From these figures it is possible to see that, as expected, there is not a big difference between the relative behaviour between UH and \overline{UH} for $UH = CH, ML$ and CH , but their simultaneous use will for sure enable us to better estimate γ , the primary parameter of extreme events.

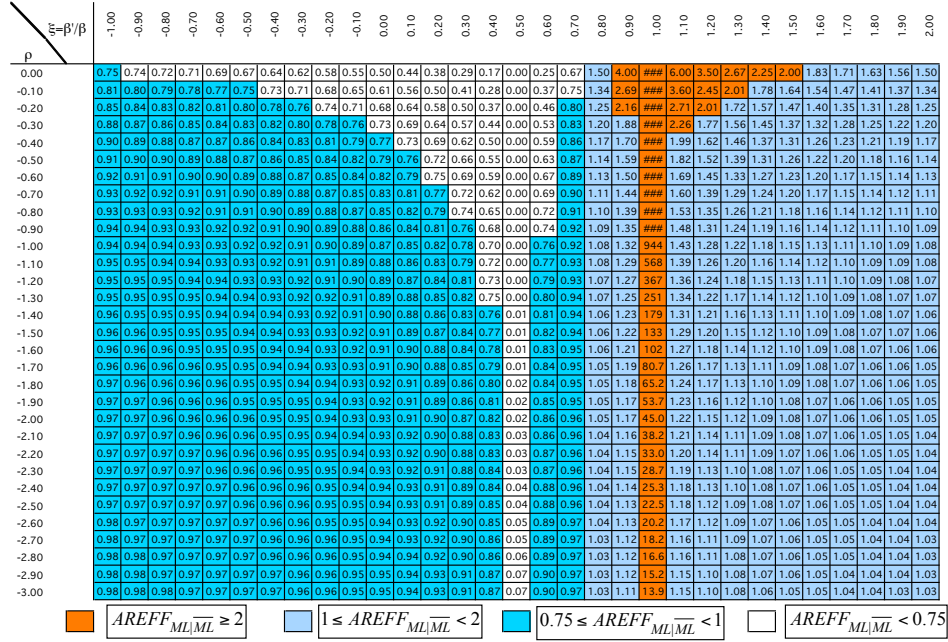
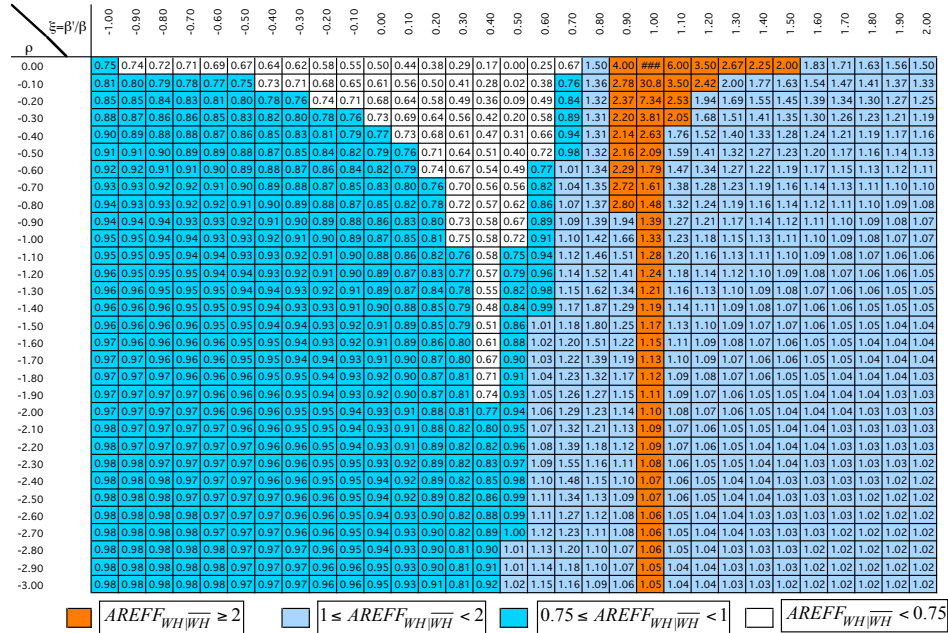


Figure 2: $AREFF_{ML|\overline{ML}}$, in the (ξ, ρ) -plane.



As already proved in Proposition 2.1 of Gomes *et al.* (2007a), ML beats ML^* asymptotically at optimal levels for all $\beta \neq \beta'$ and $\rho < 0$. Asymptotically and at optimal levels, WH also beats WH^* over almost all (ξ, ρ) -plane. A similar comment applies to the equivalent behaviour of CH relatively to CH^* , as can be seen from Figure 4, illustrative of the comparative behaviour of the statistics UH and UH^* .

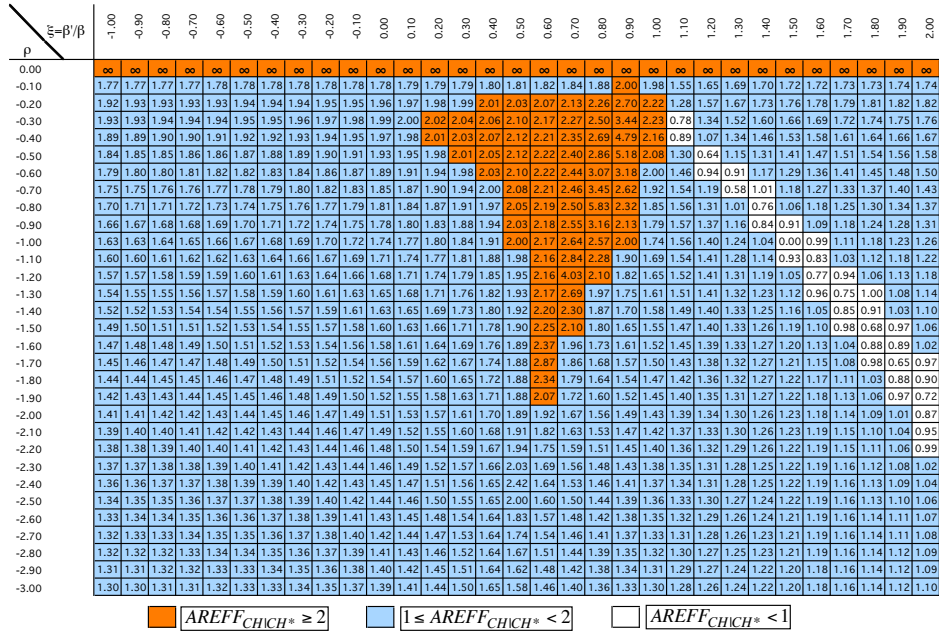


Figure 4: $AREFF_{CH/CH^*}$, in the (ξ, ρ) -plane.

Despite of the fact that we have $|b_{UH}^*| \leq |b_{UH}|$ for a large region of the (γ, ρ) -plane, as $\sigma_{UH} = \gamma < \sigma_{UH}^* = \gamma(1 - \rho)/|\rho|$ for all ρ , the UH -statistics are able to outperform the UH^* -statistics at optimal levels, unless we are in a region of the (ξ, ρ) -plane around the line $b_{UH}^* = 0$. A similar comment applies to the relative behaviour of \overline{UH} and \overline{UH}^* , as well as to the comparative behaviour of \overline{UH} and UH^* . This is indeed a point in favour of the UH statistics. The lines in (ξ, ρ) -plane associated to null bias of the different statistics are presented in Figure 5.

The general behaviour of UH , \overline{UH} , UH^* and \overline{UH}^* , again for $UH = CH, ML, WH$, is shown in Figures 6, 7 and 8, respectively, where we register the estimator with the highest efficiency among the ones considered, i.e., the one with maximum $AREFF$, or equivalently, minimum $LMSE$.

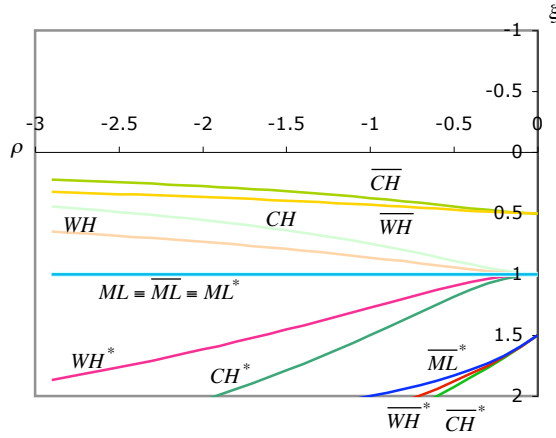


Figure 5: Lines where $b_{UH} = 0$ and $b_{UH}^* = 0$, $UH = CH$, ML and WH .

$\frac{\xi}{\rho} = \beta/\beta$	-1.00	-0.90	-0.80	-0.70	-0.60	-0.50	-0.40	-0.30	-0.20	-0.10	0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.90	2.00											
0.00	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb									
-0.10	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb								
-0.20	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb							
-0.30	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb						
-0.40	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb					
-0.50	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb				
-0.60	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb			
-0.70	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb			
-0.80	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb		
-0.90	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb		
-1.00	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	
-1.10	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	
-1.20	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	
-1.30	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	
-1.40	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	
-1.50	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	
-1.60	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-1.70	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-1.80	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-1.90	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-2.00	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-2.10	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-2.20	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-2.30	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-2.40	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-2.50	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-2.60	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-2.70	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-2.80	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-2.90	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb
-3.00	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb	CHb

Figure 6: Estimator with minimum LMSE among CH , \overline{CH} (CHb), CH^* and \overline{CH}^* (CHb*).

Finally, in Figure 9 we picture together all the CH and ML statistics and in Figure 10 we put together all the CH , the ML and the WH statistics.

As mentioned before, none of the estimators can always dominate the alternatives, but on the basis of initial estimates of (ξ, ρ) , the following figures can help us to choose the most adequate estimator. Estimators of ρ have already been dealt with by several authors. Apart from the above

5 Some additional comparisons

The $AREFF_{WH|WH^*}$ indicator is presented in Figure 11.

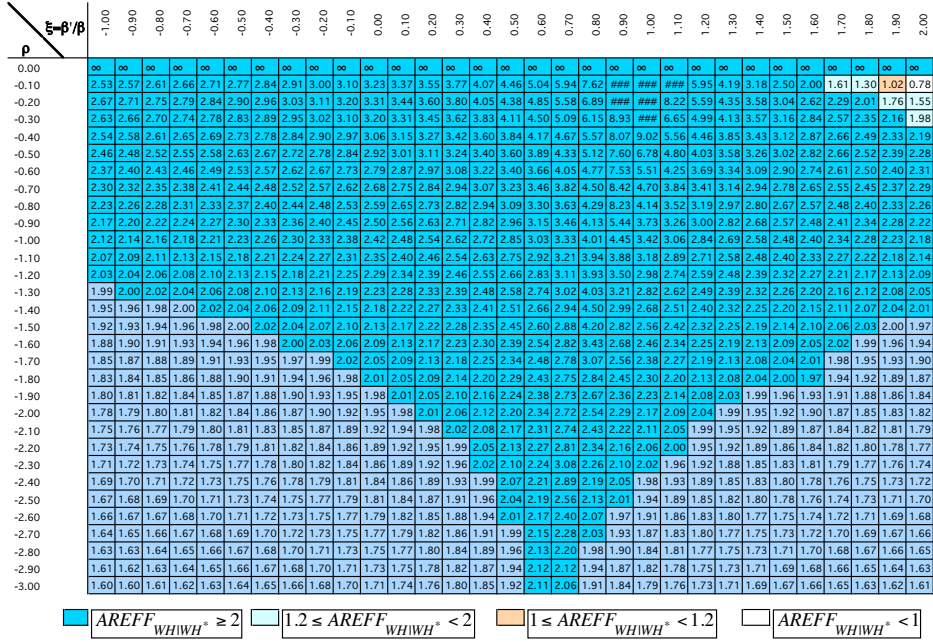


Figure 11: $AREFF_{WH|WH^*}$, in the (ξ, ρ) -plane.

We next present the relative behaviour of \overline{UH} and $\overline{UH^*}$ for $UH = CH, ML$ and WH , in Figures 12, 13 and 14, respectively.

Finally, in Figures 15, 16 and 17, we provide the comparative behaviour of \overline{UH} and UH^* , again for $UH = CH, ML$ and WH , respectively.

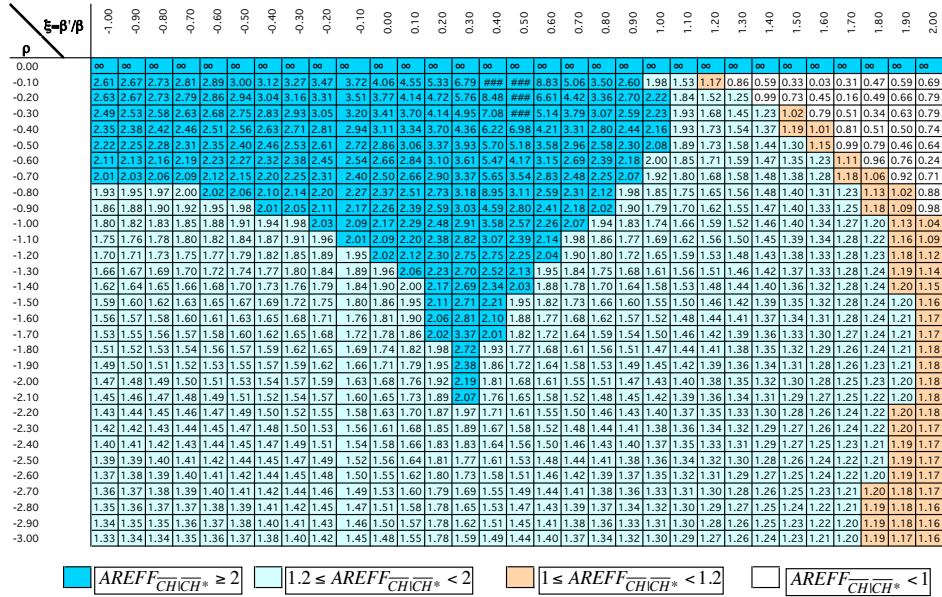
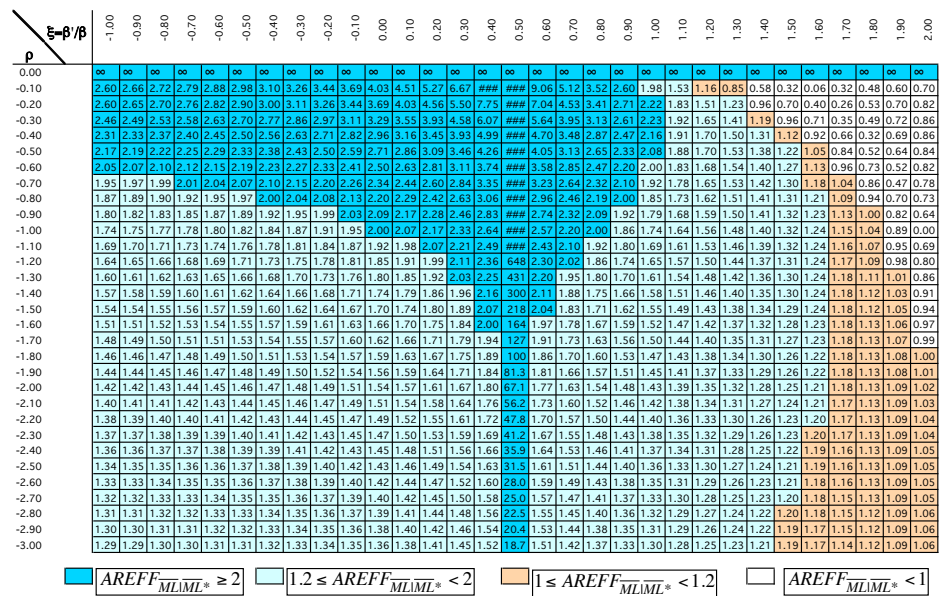


Figure 12: $AREFF_{CH|CH^*}$, in the (ξ, ρ) -plane.



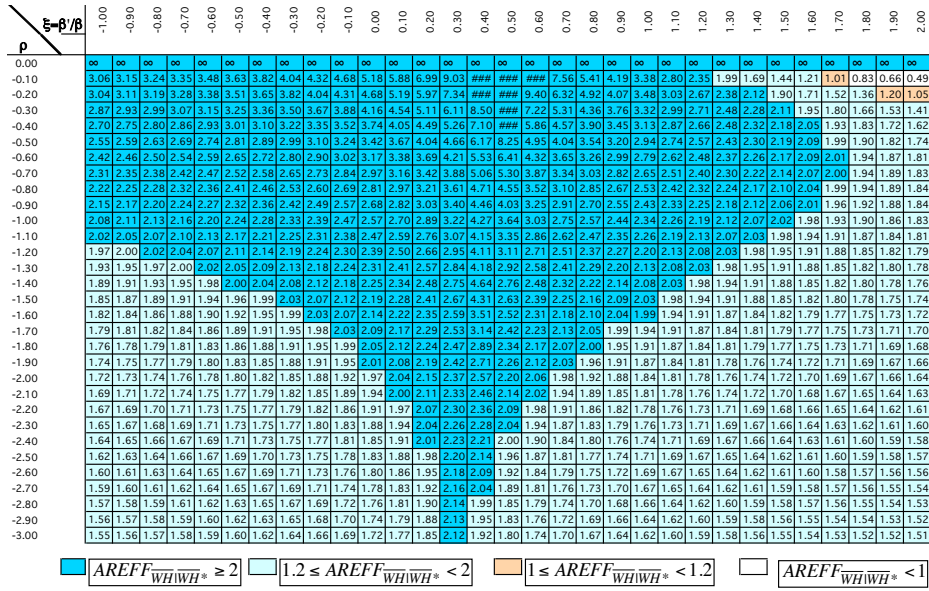
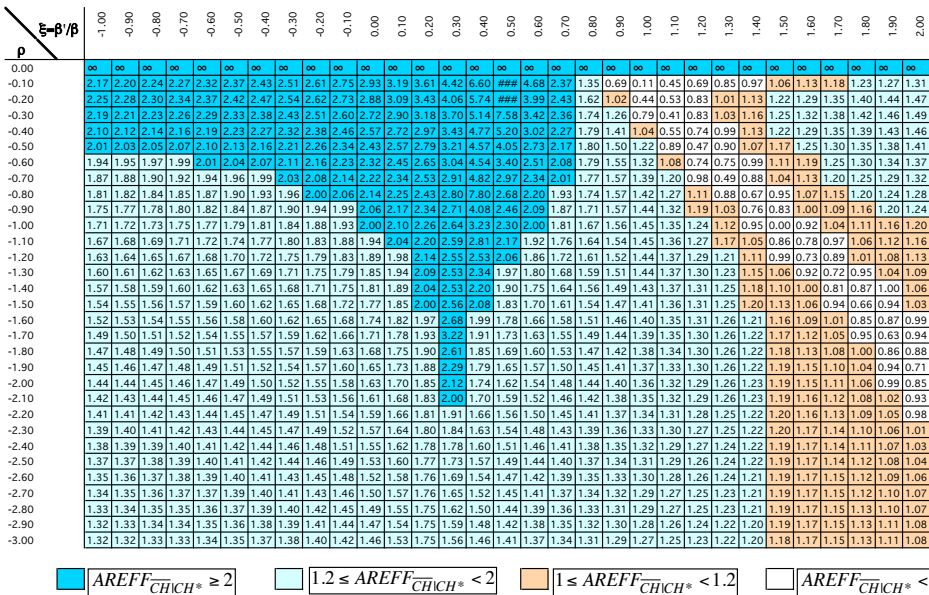
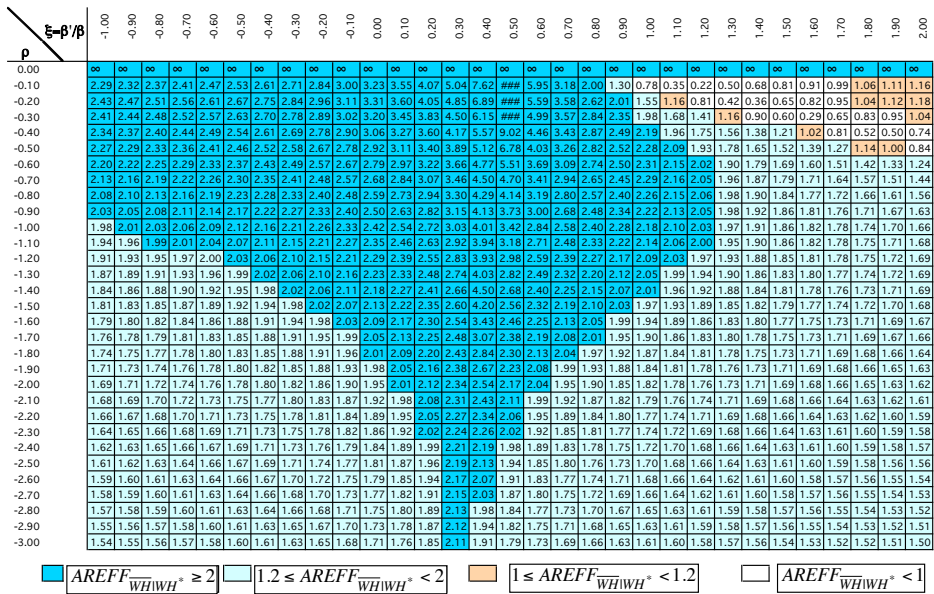
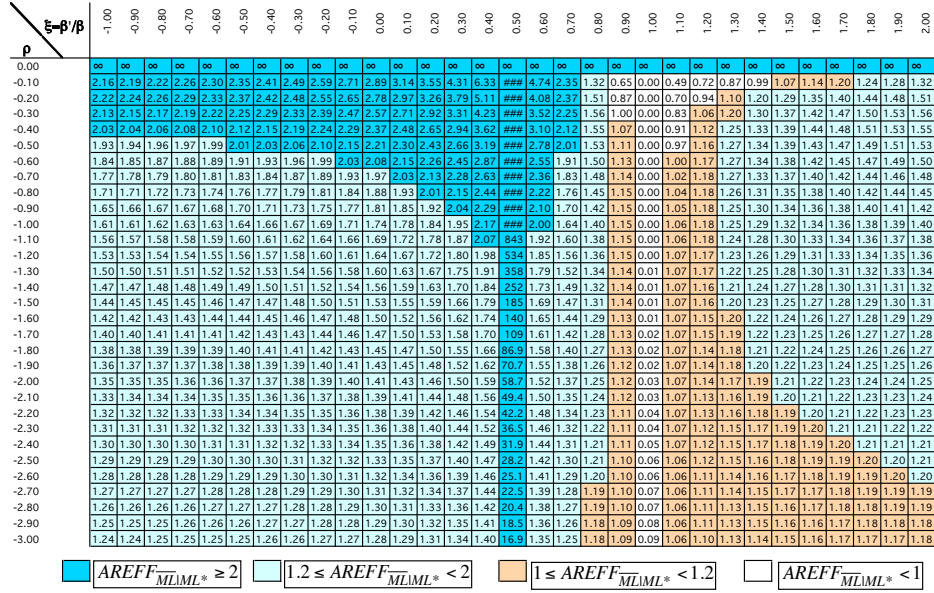


Figure 14: $AREFF_{WH|WH^*}$, in the (ξ, ρ) -plane.





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