

# Estimation of the marginal expected shortfall using extreme expectiles

Abdelaati Daouia

*Toulouse School of Economics, University of Toulouse Capitole*

*Based on joint work with :*  
*Stéphane Girard (Inria Grenoble Rhône-Alpes),*  
*Gilles Stupfler (University of Nottingham)*

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# Outline of presentation

- 1 The class of expectiles
- 2 Extremal expectiles
- 3 Estimation of high expectiles
- 4 Expectile-based MES
- 5 Extreme level selection
- 6 Application

# Expectiles vs Quantiles

Let  $Y$  be a random variable and  $\tau$  in  $(0, 1)$ .

- **The  $\tau$ th quantile of  $Y$  [Koenker and Bassett (1978)] :**

$$q_\tau = \arg \min_{\theta} \mathbb{E} \{ |\tau - \mathbb{I}(Y \leq \theta)| \cdot |Y - \theta| \}$$

- **The  $\tau$ th expectile of  $Y$  [Newey and Powel (1987)] :**

$$\xi_\tau = \arg \min_{\theta} \mathbb{E} \{ |\tau - \mathbb{I}(Y \leq \theta)| \cdot |Y - \theta|^2 \}$$

exists as soon as  $\mathbb{E}|Y| < \infty$ .

- **Special case :**

$$\tau = \frac{1}{2} \implies \begin{cases} q_{0.5} & = \text{median}(Y) \\ \xi_{0.5} & = \mathbb{E}(Y) \end{cases}$$

# In terms of interpretability

- $q_\tau$  determines the point below which  $100\tau\%$  of the mass of  $Y$  lies :

$$\mathbb{E} \{ \mathbb{I}(Y \leq q_\tau) \} = \mathbb{P}(Y \leq q_\tau) = \tau$$

- $\xi_\tau$  shares an interpretation similar to  $q_\tau$ , replacing the number of observations by the distance :

$$\frac{\mathbb{E} \{ |Y - \xi_\tau| \cdot \mathbb{I}(Y \leq \xi_\tau) \}}{\mathbb{E} \{ |Y - \xi_\tau| \}} = \tau$$

that is, the average distance from the data below  $\xi_\tau$  to  $\xi_\tau$  itself is  $100\tau\%$ ...

- expectiles = quantiles for a transformation of  $F_Y$  [Jones (1994)]
- expectiles = quantiles in case of a weighted symmetric distribution [Abdous and Remillard (1995)]
- $\xi_\tau = q_{\tau'}$  for different levels  $\tau$  and  $\tau'$  [Yao and Tong (1996)]

## Other merits

Advantages of least asymmetrically weighted squares (LAWS) estimation :

- Computing expedience (though efficient linear programming algorithms are available for quantiles)
- Efficiency of the LAWS estimator :
  - + Expectiles make more efficient use of the available data since they rely on the distance to observations
  - Quantiles only utilize the information on whether an observation is below or above the predictor !
- More valuable tail information :
  - Quantiles only depend on the frequency of tail realizations of  $Y$  and not on their values !
  - + Expectiles depend on both the tail realizations and their probability [Kuan, Yeh and Hsu (2009)]
- Inference on expectiles is much easier than inference on quantiles :  
Calculation of the variance without going via the density of the distribution

# Basic properties

- (i) **Law invariance** : a distribution is uniquely defined by its class of expectiles
- (ii) **Location and scale equivariance** : the  $\tau$ th expectile of the linear transformation  $\tilde{Y} = a + bY$ , where  $a, b \in \mathbb{R}$ , satisfies

$$\xi_{\tilde{Y},\tau} = \begin{cases} a + b\xi_{Y,\tau} & \text{if } b > 0 \\ a + b\xi_{Y,1-\tau} & \text{if } b \leq 0 \end{cases}$$

- (iii) **Coherency** : for any variables  $Y, \tilde{Y} \in L^1$  and for all  $\tau \geq \frac{1}{2}$ ,
- Translation invariance :  $\xi_{Y+a,\tau} = \xi_{Y,\tau} + a$ , for all  $a \in \mathbb{R}$
  - Positive homogeneity :  $\xi_{bY,\tau} = b\xi_{Y,\tau}$ , for all  $b \geq 0$
  - Monotonicity : if  $Y \leq \tilde{Y}$  with probability 1, then  $\xi_{Y,\tau} \leq \xi_{\tilde{Y},\tau}$
  - Subadditivity :  $\xi_{Y+\tilde{Y},\tau} \leq \xi_{Y,\tau} + \xi_{\tilde{Y},\tau}$

# Expectiles as risk measures

Theoretical and numerical results, obtained recently, indicate that expectiles are perfectly reasonable alternatives to quantiles as risk measures :

- Taylor (2008) [[Journal of Financial Econometrics](#)]
- Kuan, Yeh and Hsu (2009) [[Journal of Econometrics](#)]
- Gneiting (2011) [[JASA](#)]
- Bellini (2012) [[Statistics and Probability Letters](#)]
- Bellini, Klar, Müller and Gianina (2014) [[Insurance : Mathematics and Economics](#)]
- Bellini and Di Bernardino (2015) [[The European Journal of Finance](#)]
- Ziegel (2016) [[Mathematical Finance](#)]
- Ehm, Gneiting, Jordan and Krüger (2016) [[JRSS-B](#)] ...

The estimation of expectiles did not, however, receive yet any attention from the perspective of extreme values !

**Aim** : We use tail expectiles to estimate an alternative measures to **Marginal Expected Shortfall** (MES)

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# High expectiles

- Let  $Y$  be the financial position and  $F_Y$  be its cdf with  $\overline{F}_Y = 1 - F_Y$  :
  - non-negative loss variable
  - real-valued variable (the negative of financial returns)

- In statistical finance and actuarial science, Pareto-type distributions describe quite well the tail structure of losses :

$$F_Y(y) = 1 - \ell(y) \cdot y^{-1/\gamma}$$

- $\ell(\lambda y)/\ell(y) \rightarrow 1$  as  $y \rightarrow \infty$  for all  $\lambda > 0$
  - $\gamma \in (0, 1)$  tunes the tail heaviness of  $F_Y$
- Only [Bellini, Klar, Müller and Gianina \(2014\)](#), [Mao, Ng and Hu \(2015\)](#) and [Mao and Yang \(2015\)](#) have described what happens for large  $\xi_\tau$  and how it is linked to extreme  $q_\tau$  :

$$\frac{\overline{F}_Y(\xi_\tau)}{1 - \tau} = \frac{\overline{F}_Y(\xi_\tau)}{\overline{F}_Y(q_\tau)} \sim \gamma^{-1} - 1 \quad \text{as } \tau \rightarrow 1$$

- $\xi_\tau > q_\tau$  when  $\gamma > \frac{1}{2}$ ,
  - $\xi_\tau < q_\tau$  when  $\gamma < \frac{1}{2}$ , for all large  $\tau$

## Second-order regular variation condition

Assume that **the tail quantile function**  $U$  of  $Y$ , defined by

$$U(t) = \inf \left\{ y \in \mathbb{R} \mid \frac{1}{\overline{F}_Y(y)} \geq t \right\}, \quad \forall t > 1,$$

satisfies the second-order condition indexed by  $(\gamma, \rho, A)$ , that is, there exist  $\gamma > 0$ ,  $\rho \leq 0$ , and a function  $A(\cdot)$  converging to 0 at infinity and having constant sign such that :

$\mathcal{C}_2(\gamma, \rho, A)$  for all  $x > 0$ ,

$$\lim_{t \rightarrow \infty} \frac{1}{A(t)} \left[ \frac{U(tx)}{U(t)} - x^\gamma \right] = x^\gamma \frac{x^\rho - 1}{\rho}.$$

Here,  $(x^\rho - 1)/\rho$  is to be understood as  $\log x$  when  $\rho = 0$ .

## Refined asymptotic connection

The precise **bias term** in the asymptotic approximation of  $(\xi_\tau/q_\tau)$  :

### Proposition

Assume that condition  $\mathcal{C}_2(\gamma, \rho, A)$  holds, with  $0 < \gamma < 1$ . If  $F_Y$  is strictly increasing, then

$$\frac{\xi_\tau}{q_\tau} = (\gamma^{-1} - 1)^{-\gamma} (1 + r(\tau))$$

with

$$\begin{aligned} r(\tau) = & \frac{\gamma(\gamma^{-1} - 1)^\gamma \mathbb{E}(Y)}{q_\tau} (1 + o(1)) \\ & + \left( \frac{(\gamma^{-1} - 1)^{-\rho}}{1 - \rho - \gamma} + \frac{(\gamma^{-1} - 1)^{-\rho} - 1}{\rho} + o(1) \right) A((1 - \tau)^{-1}) \end{aligned}$$

as  $\tau \uparrow 1$

Other similar refinements can be found in [Mao et al. \(2015\)](#), [Mao and Yang \(2015\)](#) and [Bellini and Di Bernardino \(2015\)](#)

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# Conceptual results

- **Basic idea :**

- We first estimate the intermediate expectiles of order  $\tau_n \rightarrow 1$  such that  $n(1 - \tau_n) \rightarrow \infty$ ;
- We then extrapolate these estimates to the very extreme level  $\tau'_n$  which approaches 1 at an arbitrarily fast rate in the sense that  $n(1 - \tau'_n) \rightarrow c$ , for some constant  $c$ .

- **Two estimation methods are considered :**

- The first (indirect) is based on the use of the asymptotic connection between expectiles and quantiles ;
- The second relies directly on least asymmetrically weighted squares (LAWS) estimation.

- **Main results :** establish the asymptotic normality of the estimators

- Intermediate expectiles  $\xi_{\tau_n}$  : indirect + direct
- Extreme expectiles  $\xi_{\tau'_n}$  : indirect + direct

## (1) Estimation based on intermediate quantiles :

- Assume that the available data consists of an  $n$ -tuple  $(Y_1, \dots, Y_n)$  of independent copies of  $Y$
- Denote by  $Y_{1,n} \leq \dots \leq Y_{n,n}$  their ascending order statistics
- Consider the intermediate expectile level  $\tau_n \rightarrow 1$  such that  $n(1 - \tau_n) \rightarrow \infty$ , as  $n \rightarrow \infty$
- The asymptotic connection above entails that

$$\frac{\xi_{\tau_n}}{q_{\tau_n}} \sim (\gamma^{-1} - 1)^{-\gamma} \quad \text{as } n \rightarrow \infty$$

- Define, for a suitable estimator  $\hat{\gamma}$  of  $\gamma$ ,

$$\hat{\xi}_{\tau_n} := (\hat{\gamma}^{-1} - 1)^{-\hat{\gamma}} \cdot \hat{q}_{\tau_n}$$

where

$$\hat{q}_{\tau_n} := Y_{n - \lfloor n(1 - \tau_n) \rfloor, n}$$

with  $\lfloor \cdot \rfloor$  being the floor function.

## (2) Asymmetric Least Squares (direct) estimation :

We consider estimating

$$\xi_{\tau_n} = \arg \min_{u \in \mathbb{R}} \mathbb{E} [\eta_{\tau_n}(Y - u)]$$

by

$$\tilde{\xi}_{\tau_n} = \arg \min_{u \in \mathbb{R}} \frac{1}{n} \sum_{i=1}^n \eta_{\tau_n}(Y_i - u)$$

where  $\eta_{\tau}(y) = |\tau - \mathbb{I}\{y \leq 0\}|y^2$  is the expectile check function

# Extreme expectile estimation

- Consider the intermediate expectile level  $\tau_n \rightarrow 1$  such that  $n(1 - \tau_n) \rightarrow \infty$ , as  $n \rightarrow \infty$
- Consider the **extreme** expectile level  $\tau'_n \rightarrow 1$  such that  $n(1 - \tau'_n) \rightarrow c < \infty$ , as  $n \rightarrow \infty$
- The model assumption of Pareto-type tails

$$F_Y(y) = 1 - \ell(y) \cdot y^{-1/\gamma}$$

suggests that

$$\frac{\xi_{\tau'_n}}{\xi_{\tau_n}} \approx \left( \frac{1 - \tau'_n}{1 - \tau_n} \right)^{-\gamma}, \quad n \rightarrow \infty$$

- This approximation motivates the estimators

$$\begin{aligned}\tilde{\xi}_{\tau'_n}^* &:= \left( \frac{1 - \tau'_n}{1 - \tau_n} \right)^{-\hat{\gamma}} \tilde{\xi}_{\tau_n} \\ \hat{\xi}_{\tau'_n}^* &:= \left( \frac{1 - \tau'_n}{1 - \tau_n} \right)^{-\hat{\gamma}} \hat{\xi}_{\tau_n} \equiv (\hat{\gamma}^{-1} - 1)^{-\hat{\gamma}} \hat{q}_{\tau'_n}^*\end{aligned}$$

## Extreme expectile estimation (cont.)

$$\hat{\xi}_{\tau'_n}^* := \left( \frac{1 - \tau'_n}{1 - \tau_n} \right)^{-\hat{\gamma}} \hat{\xi}_{\tau_n} \equiv (\hat{\gamma}^{-1} - 1)^{-\hat{\gamma}} \hat{q}_{\tau'_n}^*$$

### Theorem

Assume that  $F_Y$  is strictly increasing, that condition  $C_2(\gamma, \rho, A)$  holds with  $0 < \gamma < 1$  and  $\rho < 0$ , and that  $\tau_n, \tau'_n \uparrow 1$  with  $n(1 - \tau_n) \rightarrow \infty$  and  $n(1 - \tau'_n) \rightarrow c < \infty$ . Assume further that

$$\sqrt{n(1 - \tau_n)} \left( \hat{\gamma} - \gamma, \frac{\hat{q}_{\tau_n}}{q_{\tau_n}} - 1 \right) \xrightarrow{d} (\Gamma, \Theta).$$

If  $\sqrt{n(1 - \tau_n)} q_{\tau_n}^{-1} \rightarrow \lambda_1 \in \mathbb{R}$ ,  $\sqrt{n(1 - \tau_n)} A((1 - \tau_n)^{-1}) \rightarrow \lambda_2 \in \mathbb{R}$  and  $\sqrt{n(1 - \tau_n)} / \log[(1 - \tau_n)/(1 - \tau'_n)] \rightarrow \infty$ , then

$$\frac{\sqrt{n(1 - \tau_n)}}{\log[(1 - \tau_n)/(1 - \tau'_n)]} \left( \frac{\hat{\xi}_{\tau'_n}^*}{\xi_{\tau'_n}} - 1 \right) \xrightarrow{d} \Gamma$$

# Extreme expectile estimation (cont.)

$$\tilde{\xi}_{\tau'_n}^* := \left( \frac{1 - \tau'_n}{1 - \tau_n} \right)^{-\hat{\gamma}} \tilde{\xi}_{\tau_n}$$

## Theorem

Assume that  $F_Y$  is strictly increasing, there is  $\delta > 0$  such that  $\mathbb{E}|Y_-|^{2+\delta} < \infty$ , condition  $\mathcal{C}_2(\gamma, \rho, A)$  holds with  $0 < \gamma < 1/2$  and  $\rho < 0$ , and that  $\tau_n, \tau'_n \uparrow 1$  with  $n(1 - \tau_n) \rightarrow \infty$  and  $n(1 - \tau'_n) \rightarrow c < \infty$ . If in addition

$$\sqrt{n(1 - \tau_n)}(\hat{\gamma} - \gamma) \xrightarrow{d} \Gamma$$

and  $\sqrt{n(1 - \tau_n)}q_{\tau_n}^{-1} \rightarrow \lambda_1 \in \mathbb{R}$ ,  $\sqrt{n(1 - \tau_n)}A((1 - \tau_n)^{-1}) \rightarrow \lambda_2 \in \mathbb{R}$  and  $\sqrt{n(1 - \tau_n)}/\log[(1 - \tau_n)/(1 - \tau'_n)] \rightarrow \infty$ , then

$$\frac{\sqrt{n(1 - \tau_n)}}{\log[(1 - \tau_n)/(1 - \tau'_n)]} \left( \frac{\tilde{\xi}_{\tau'_n}^*}{\xi_{\tau'_n}} - 1 \right) \xrightarrow{d} \Gamma$$

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# Connection with systemic risk

- With the recent financial crisis and the rising interconnection between financial institutions, interest in the concept of **systemic risk** has grown ;
- **Systemic risk** : the propensity of a financial institution to be undercapitalized when the financial system as a whole is undercapitalized [Acharya *et al.* (2012), Brownlees and Engle (2012), Engle *et al.* (2015)] ;
- Econometric approaches have been proposed to **measure the systemic risk** of financial institutions ;
- An important step in constructing a **systemic risk measure** for a financial institution is to measure the contribution of the institution to a **systemic crisis** ;
- **Systemic crisis** : a major stock market decline that happens once or twice a decade ;
- *The total risk*, measured by the expected capital shortfall in the financial system during a systemic crisis, *can be decomposed* into **firm level contributions** ;
- **Firm level contributions** can be measured by the **Marginal expected shortfall = ?**

# Marginal expected shortfall

- $X$  : the loss return on the equity of a **financial firm**
- $Y$  : the loss return on the equity of **the entire market**
- Marginal expected shortfall :

$$\text{MES} = \mathbb{E}(X|Y > t)$$

where  $t$  is a high threshold reflecting a substantial market decline

- MES at probability level  $(1 - \tau)$  :

$$\text{QMES}(\tau) = \mathbb{E}\{X|Y > q_{Y,\tau}\}$$

- The estimation of  $\text{QMES}(\tau)$ 
  - in [Acharya et al. \(2012\)](#) : relies on daily data from **only** 1 year and assumes a specific **linear** relationship between  $X$  and  $Y$  ;
  - in [Brownlees and Engle \(2012\)](#) and [Engle et al. \(2014\)](#) : a non-parametric kernel estimator was proposed ;

Cannot handle extreme events required for systemic risk measures, *i.e.*,

$$1 - \tau = O(1/n)$$

# Adapted extreme-value tools

Cai, Einmahl, de Haan & Zhou (2015)  $\rightsquigarrow$  Adapted tools for the estimation of

$$\begin{aligned}\text{QMES}(\tau'_n) &= \mathbb{E} \{X|Y > q_{Y,\tau'_n}\} \\ &\approx \left(\frac{1 - \tau'_n}{1 - \tau_n}\right)^{-\gamma_X} \text{QMES}(\tau_n)\end{aligned}$$

without recourse to any parametric structure on  $(X, Y)$  :

$$\widehat{\text{QMES}}^*(\tau'_n) = \left(\frac{1 - \tau'_n}{1 - \tau_n}\right)^{-\widehat{\gamma}_X} \widehat{\text{QMES}}(\tau_n)$$

where

$$\widehat{\text{QMES}}(\tau_n) = \frac{1}{[n(1 - \tau_n)]} \sum_{i=1}^n X_i \mathbb{I}\{X_i > 0, Y_i > \widehat{q}_{Y,\tau_n}\}.$$

**Tail dependence condition  $\mathcal{JC}_2(R, \beta, \kappa)$**  : There exist  $R(\cdot, \cdot)$ ,  $\beta > \gamma_X$  and  $\kappa < 0$  such that

$$\sup_{\substack{x \in (0, \infty) \\ y \in [1/2, 2]}} \left| \frac{t\mathbb{P}(\overline{F}_X(X) \leq x/t, \overline{F}_Y(Y) \leq y/t) - R(x, y)}{\min(x^\beta, 1)} \right| = O(t^\kappa) \text{ as } t \rightarrow \infty$$

# Expectile-based MES

Daouia, Girard & Stupfler (2016) :

$$\begin{aligned}\text{XMES}(\tau'_n) &= \mathbb{E} \{X|Y > \xi_{Y, \tau'_n}\} \\ &\approx \left(\frac{1 - \tau'_n}{1 - \tau_n}\right)^{-\gamma_X} \text{XMES}(\tau_n)\end{aligned}$$

with

$$\text{XMES}(\tau_n) = \mathbb{E} \{X|Y > \xi_{Y, \tau_n}\}$$

**(1) ALS type estimator :**

$$\widetilde{\text{XMES}}^*(\tau'_n) = \left(\frac{1 - \tau'_n}{1 - \tau_n}\right)^{-\widehat{\gamma}_X} \widetilde{\text{XMES}}(\tau_n)$$

where

$$\widetilde{\text{XMES}}(\tau_n) = \frac{\sum_{i=1}^n X_i \mathbb{I}\{X_i > 0, Y_i > \widetilde{\xi}_{Y, \tau_n}\}}{\sum_{i=1}^n \mathbb{I}\{Y_i > \widetilde{\xi}_{Y, \tau_n}\}}.$$

If  $\sqrt{n(1 - \tau_n)} (\widehat{\gamma}_X - \gamma_X) \xrightarrow{d} \Gamma$ , then

$$\frac{\sqrt{n(1 - \tau_n)}}{\log[(1 - \tau_n)/(1 - \tau'_n)]} \left( \frac{\widetilde{\text{XMES}}^*(\tau'_n)}{\text{XMES}(\tau'_n)} - 1 \right) \xrightarrow{d} \Gamma$$

## Expectile-based MES (cont.)

Suppose for all  $(x, y) \in [0, \infty]^2$  such that at least  $x$  or  $y$  is finite, the limit

$$\lim_{t \rightarrow \infty} t\mathbb{P}(\bar{F}_X(X) \leq x/t, \bar{F}_Y(Y) \leq y/t) := R(x, y) \quad \text{exists.}$$

Under this tail dependence condition :

$$\lim_{\tau \uparrow 1} \frac{\text{XMES}(\tau)}{\text{QMES}(\tau)} = (\gamma_Y^{-1} - 1)^{-\gamma_X}$$

**(2) Estimator based on tail QMES :**

$$\widehat{\text{XMES}}^*(\tau'_n) = (\widehat{\gamma}_Y^{-1} - 1)^{-\widehat{\gamma}_X} \widehat{\text{QMES}}^*(\tau'_n).$$

If  $\sqrt{n(1 - \tau_n)} (\widehat{\gamma}_X - \gamma_X) \xrightarrow{d} \Gamma$ , then

$$\frac{\sqrt{n(1 - \tau_n)}}{\log[(1 - \tau_n)/(1 - \tau'_n)]} \left( \frac{\widehat{\text{XMES}}^*(\tau'_n)}{\text{XMES}(\tau'_n)} - 1 \right) \xrightarrow{d} \Gamma$$

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# Expectile level selection

- **Aim** : choice of  $\tau'_n = ?$  in the instruments of risk protection

$$\xi_{\tau'_n}, \quad \text{XMES}(\tau'_n)$$

- **In the case of**

$$q_{\alpha_n}, \quad \text{QMES}(\alpha_n)$$

it is customary to choose

$$\alpha_n \rightarrow 1 \quad \text{with} \quad n(1 - \alpha_n) \rightarrow c < \infty$$

to allow for more 'prudent' risk management  $\rightsquigarrow$  Typical interest in **once-in-a-decade** or **twice-per-decade** events

- **Idea** : select  $\tau'_n$  so that each expectile-based risk measure has the **same intuitive interpretation** as its quantile-based analogue



choose  $\tau'_n = \tau'_n(\alpha_n)$  s.t.  $\xi_{\tau'_n} \equiv q_{\alpha_n}$  for a given relative frequency  $\alpha_n$



$$\tau'_n(\alpha_n) = 1 - \frac{\mathbb{E} \{ |Y - q_{\alpha_n}| \mathbb{I}(Y > q_{\alpha_n}) \}}{\mathbb{E} |Y - q_{\alpha_n}|}$$

## Expectile level selection (cont.)

How to estimate

$$\tau'_n(\alpha_n) = 1 - \frac{\mathbb{E}\{|Y - q_{\alpha_n}| \mathbb{I}(Y > q_{\alpha_n})\}}{\mathbb{E}|Y - q_{\alpha_n}|} \quad ?$$

### Proposition

*Under the model assumption of Pareto-type tails with  $0 < \gamma < 1$ ,*

$$1 - \tau'_n(\alpha_n) \sim (1 - \alpha_n) \frac{\gamma}{1 - \gamma}, \quad n \rightarrow \infty$$

$$\rightsquigarrow \widehat{\tau}'_n(\alpha_n) = 1 - (1 - \alpha_n) \frac{\widehat{\gamma}_n}{1 - \widehat{\gamma}_n}$$

# VaR estimation

With

$$\tau'_n = \widehat{\tau}'_n(\alpha_n) \equiv 1 - (1 - \alpha_n) \frac{\widehat{\gamma}_n}{1 - \widehat{\gamma}_n}$$

both extreme expectile estimators

$$\widetilde{\xi}_{\tau'_n}^* = \left( \frac{1 - \tau'_n}{1 - \tau_n} \right)^{-\widehat{\gamma}_n} \widetilde{\xi}_{\tau_n}$$

$$\widehat{\xi}_{\tau'_n}^* = \left( \frac{1 - \tau'_n}{1 - \tau_n} \right)^{-\widehat{\gamma}_n} \widehat{\xi}_{\tau_n} = (\widehat{\gamma}_n^{-1} - 1)^{-\widehat{\gamma}_n} \widehat{q}_{\tau'_n}^*$$

estimate the same VaR  $\xi_{\tau'_n(\alpha_n)} \equiv q_{\alpha_n}$  as

$$\widehat{q}_{\alpha_n}^* := \left( \frac{1 - \alpha_n}{1 - \tau_n} \right)^{-\widehat{\gamma}} \widehat{q}_{\tau_n}$$

- $\widehat{\xi}_{\tau'_n(\alpha_n)}^* \equiv \widehat{q}_{\alpha_n}^*$
- If  $\sqrt{n(1 - \tau_n)}(\widehat{\gamma}_n - \gamma) \xrightarrow{d} \Gamma$ , then

$$\frac{\sqrt{n(1 - \tau_n)}}{\log[(1 - \tau_n)/(1 - \alpha_n)]} \left( \frac{\widehat{\xi}_{\tau'_n(\alpha_n)}^*}{q_{\alpha_n}} - 1 \right) \xrightarrow{d} \Gamma$$

# MES estimation

With

$$\tau'_n = \widehat{\tau}'_n(\alpha_n) \equiv 1 - (1 - \alpha_n) \frac{\widehat{\gamma}_n}{1 - \widehat{\gamma}_n}$$

both estimators

$$\widetilde{\text{XMES}}^*(\tau'_n) = \left( \frac{1 - \tau'_n}{1 - \tau_n} \right)^{-\widehat{\gamma}_X} \widetilde{\text{XMES}}(\tau_n)$$

$$\widehat{\text{XMES}}^*(\tau'_n) = (\widehat{\gamma}_Y^{-1} - 1)^{-\widehat{\gamma}_X} \widehat{\text{QMES}}^*(\tau'_n)$$

estimate the same MES  $\text{XMES}(\tau'_n(\alpha_n)) \equiv \text{QMES}(\alpha_n)$  as Cai *et al.* (2015)'s estimator

$$\widehat{\text{QMES}}^*(\alpha_n) = \left( \frac{1 - \alpha_n}{1 - \tau_n} \right)^{-\widehat{\gamma}_X} \widehat{\text{QMES}}(\tau_n)$$

- $\widehat{\text{XMES}}^*(\widehat{\tau}'_n(\alpha_n)) \equiv \widehat{\text{QMES}}^*(\alpha_n)$
- If  $\sqrt{n(1 - \tau_n)}(\widehat{\gamma}_X - \gamma_X) \xrightarrow{d} \Gamma$ , then

$$\frac{\sqrt{n(1 - \tau_n)}}{\log[(1 - \tau_n)/(1 - \alpha_n)]} \left( \frac{\widetilde{\text{XMES}}^*(\widehat{\tau}'_n(\alpha_n))}{\widehat{\text{QMES}}(\alpha_n)} - 1 \right) \xrightarrow{d} \Gamma$$

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# MES of three large investment banks

- We consider the same investment banks as in [Brownlees and Engle \(2012\)](#) and [Cai et al. \(2015\)](#) :

[Goldman Sachs](#), [Morgan Stanley](#), [T. Rowe Price](#)

- For the three banks, the dataset consists of the loss returns ( $X_i$ ) on their equity prices at a **daily frequency** from July 3rd, 2000, to June 30th, 2010 (**ten years**)
- We follow the same set-up as in [Cai et al. \(2015\)](#) to extract, for the same time period, daily loss returns ( $Y_i$ ) of a **value-weighted market index** aggregating three markets :
  - New York Stock Exchange
  - American Express stock exchange
  - National Association of Securities Dealers Automated Quotation system
- The interest is on  $\widehat{\text{QMES}}^*(\alpha_n)$  and  $\widehat{\text{XMES}}^*(\widehat{\tau}'_n(\alpha_n))$  that estimate

$$\widehat{\text{QMES}}(\alpha_n) \equiv \widehat{\text{XMES}}(\tau'_n(\alpha_n)) \quad \text{with} \quad \alpha_n = 1 - 1/n$$

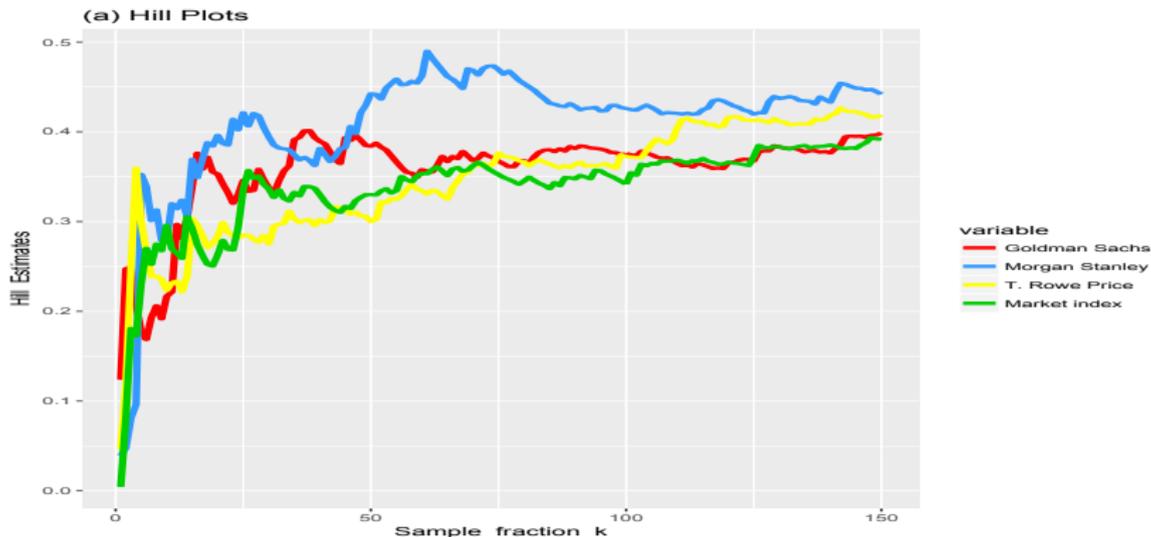
- They represent the average daily loss return for a **once-per-decade market crisis** ( $n = 2513$ )

# Plots of the Hill estimates

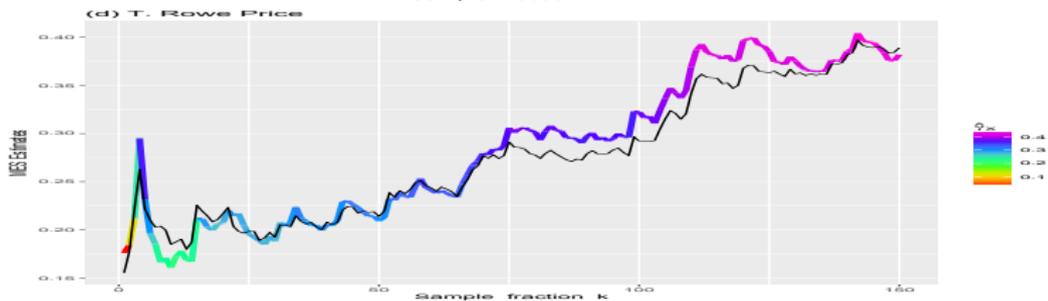
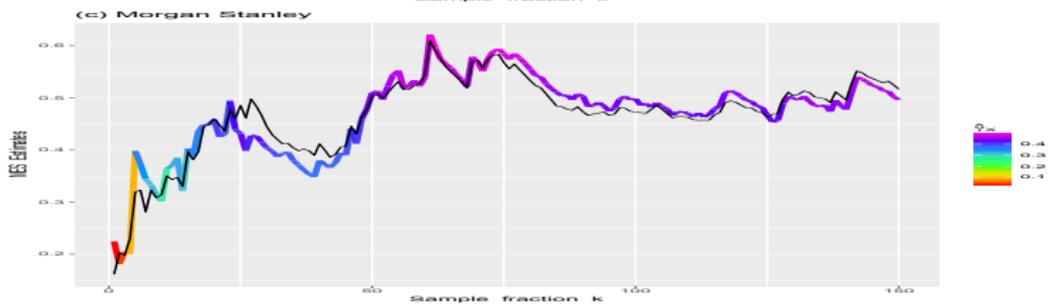
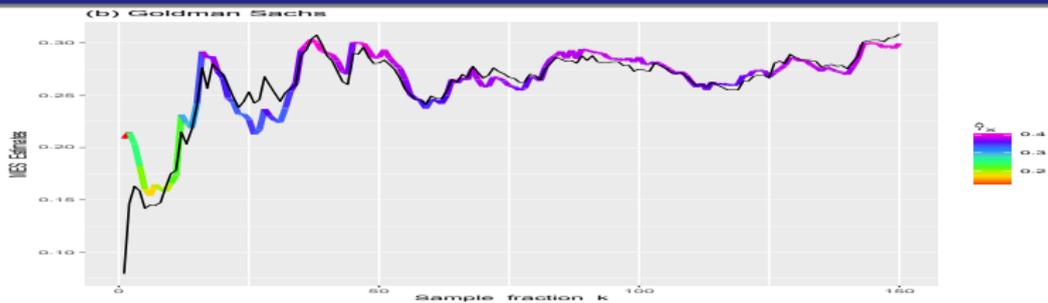
- $\hat{\gamma}_Y$  based on daily loss returns of market index
- $\hat{\gamma}_X$  based on daily loss returns of Goldman Sachs, Morgan Stanley, T. Rowe Price



$$\gamma_X, \gamma_Y < 1/2$$



# $\widehat{QMES}^*$ (black) & $\widehat{XMES}^*$ (rainbow)



## The final MES estimates

<i>Bank</i>	$\widehat{\text{XMES}}^* (\widehat{\tau}_n(\alpha_n))$	$\widehat{\text{QMES}}^* (\alpha_n)$
Goldman Sachs	0.286	0.280
Morgan Stanley	0.485	0.471
T. Rowe Price	0.297	0.279

The final estimates based on averaging the estimates from the first stable regions of the plots :

- The quantile-based **estimates** are less **conservative** than our ALS-based **estimates**, but not by much
- MES levels for **Morgan Stanley** are largely higher than those for **Goldman Sachs** and **T. Rowe Price**