Conditional Expected Shortfall

Nonparametric Estimation

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Reviewed Paper

[1] Z. Cai and X. Wang. "Nonparametric estimation of conditional VaR and expected shortfall". In: *Journal of Econometrics* 147.1 (2008), pp. 120-130. ISSN: 0304-4076. DOI: 10.1016/j.jeconom.2008.09.005.

Keywords

Boundary effects, Empirical likelihood, Expected shortfall, Local linear estimation, Nonparametric smoothing, Value-at-risk, Weighted double kernel

Section 1

Risk Measures

Value at Risk

Given time horizon,

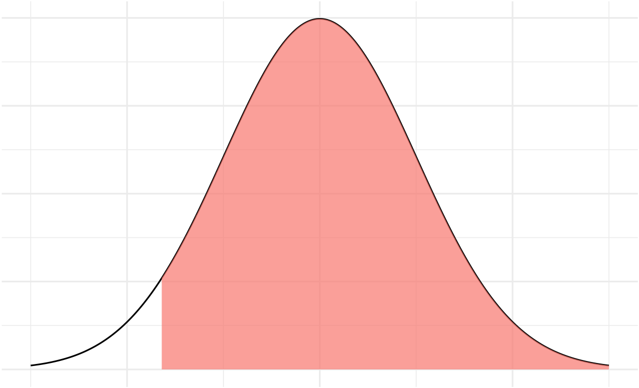


Figure 1: Loss Distribution - Can the financial institution still be in business after a catastrophic event?

Two Viewpoints

Tsay (2010) says that

- Financial institution: Maximal loss of a financial position during a given time period for a given probability
  - Measure of loss under *normal* market conditions
- Regulatory committe: Minimal loss under *extraordinary* market circumstances

Definition

- p: **Right** tail probability
- l: Time horizon
- $L(l)$: loss function of the asset from t to $t+l$
- F_l: CDF of $L(l)$

$$p = P\left[L(l) \geq VaR\right]$$

i.e. VaR can be computed by finding the p-th quantile.

Quantile Loss

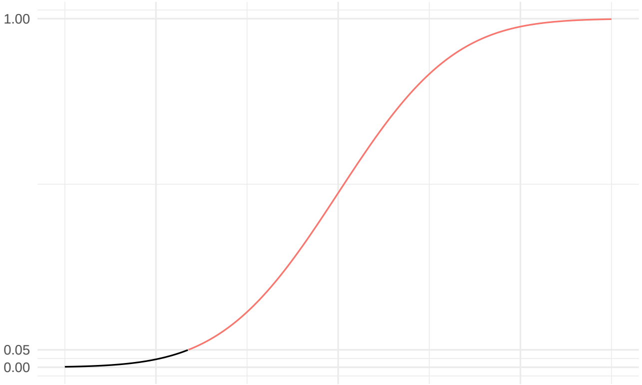


Figure 2: CDF of Loss

$$VaR = \inf\{x: F_l(x) \geq 1 - p\}$$

Loss function and log Returns

Consider dollar $\{P_t\}$.

$$L(l) = P_{t+l} - P_t = R_{t+l} + \ldots + R_{t+1}$$

where $R_t = P_t - P_{t-1}$ is the return series.

- Loss occurs when the return R_t are *negative*
- Log returns $Y_t = \ln R_t$ corresponds *approximately to percentage changes*
- Use *negative log returns*
- VaR by **Upper quantile of the distribution of log return**

VaR using log Return

$$\text{percentage change} \approx \ln \frac{P_{t+1}}{P_t} = Y_{t+1}$$

From t to $t+1$,

$$VaR = P_t \times VaR(Y_{t+1})$$

Subadditivity

- When two portfolios are merged, the risk measure should not be greater than the sum of each.
- VaR *underestimates* the actual loss.
- Thus, Expected shortfall

VaR and Expected Loss

- VaR: Quantile loss of the loss distribution
- ES: Expected value of loss function if the *VaR is exceeded*

$$ES := E\left[L(l) \mid L(l) \geq VaR\right]$$

Conditional information

- $\{X_t\colon t = 1, \ldots n\}$
- Exogenous variable: economic, market variables
- or *past observed returns* e.g. $\{Y_{t-1}\}$

Conditional VaR

- Stationary log-return $\{Y_t : t = 1, \ldots n\}$
- Conditional information $\{X_t : t = 1, \ldots n\}$
- Conditional VaR (CVaR)

$$\nu_p(x) = S^{-1}(p \mid x)$$

where

- $S(y \mid x) := 1 - F(y \mid x)$
- F: conditional CDF of Y_t given $X_t = x$.

Conditional Expected Shortfall

$$\mu_p(x) = E\left[Y_t \mid Y_t \geq \nu_p(x), X_t = x\right]$$

Formulating CES

Let $B \equiv \{\omega \colon Y_t(\omega) \mid X_t = x \geq \nu_p(x)\} \in \mathcal{B}$. Then

$$\begin{aligned}
\mu_p(x) &= E\left[Y_t \mid Y_t \geq \nu_p(x), X_t = x\right] \\
&= \frac{1}{P(B)} \int_B Y_t dP \\
&= \frac{1}{P\left(Y_t \geq \nu_p(x) \mid X_t = x\right)} \int_{\nu_p(x)}^{\infty} y f(y \mid x) dy \\
&= \frac{1}{p} \int_{\nu_p(x)}^{\infty} y f(y \mid x) dy
\end{aligned}$$

Section 2

Nonparametric Estimation

Goal

Risk measures

- CVaR: $\hat{\nu}_p(x)$
- CES: $\hat{\mu}_p(x)$

Workflow of Estimation

Plugging-in Method

$$\hat{\mu}_p(x) = \frac{1}{p}\int_{\hat{\nu}_p(x)}^{\infty} y\hat{f}(y \mid x)dy$$

What to estimate

- Conditional PDF: $\hat{f}(y \mid x)$
- CVaR: $\hat{\nu}_p(x) = \hat{S}^{-1}(p \mid x)$ by inverting the conditional CDF

Section 3

Simulation

AR(1)-GARCH(1, 0)

$$
\begin{cases}
X_t = Y_{t-1} \\
Y_t = 0.01 + 0.62X_t + \sigma_t \epsilon_t \\
\sigma_t^2 = 0.15 + 0.65\sigma_{t-1}^2 \\
\epsilon_t \sim N(0, 1)
\end{cases}
$$

True conditional distribution

Since $\epsilon_t \sim N(0, 1)$,

$$\sigma_t \epsilon_t \sim N(0, \sigma_t^2)$$

$$Y_t \mid X_t \sim N\left(0.01 + 0.62X_t, \sigma_t^2\right)$$

True CES

- For each X_t, `pnorm(x, mean, sd)` gives the conditional cdf value.
- Inverting $S(y \mid x) = 1 - F(y \mid x)$ gives $\nu_p(x)$.

$$\nu_p(x) = S^{-1}(p \mid x)$$

- Plugging-in method gives $\mu_p(x)$.

$$\mu_p(x) = \frac{1}{p} \int_{\nu_p(x)}^{\infty} y f(y \mid x) dy$$

Goal of MC Simulation

- Compute the error between the true $\mu_p(x)$ and $\hat{\mu}_p(x)$
- Is the estimator of Cai and Wang (2008) good?

Process

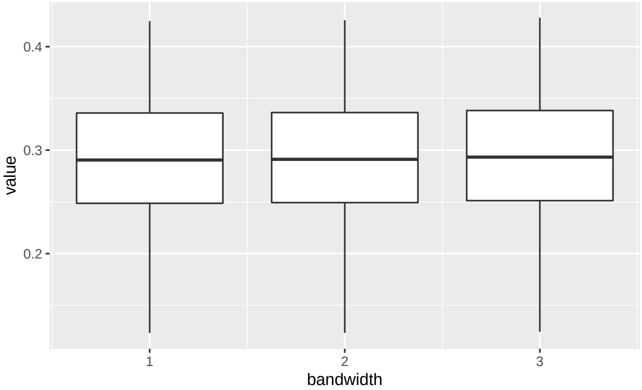
Monte Carlo Samples:

1. For fixed x_t (pre-determined grid points)
2. Generate GARCH(1, 0): (σ_t, ϵ_t)
3. Generate Y_t using AR(1) for each $X_t = Y_{t-1}$
4. AR(1): $Y_t = 0.01 + 0.62 Y_{t-1} + \sigma_t \epsilon_t$

Monte Carlo Samples

```
#>        sigma    garch  mc    xt     yt
#>    1: 0.655 -0.41011  s1 0.005 -0.397
#>    2: 0.655  0.12022  s1 0.010  0.136
#>    3: 0.655 -0.54705  s1 0.015 -0.528
#>    4: 0.655  1.04436  s1 0.020  1.067
#>    5: 0.655  0.21571  s1 0.025  0.241
#>   ---
#> 1996: 0.655 -0.00527 s20 0.480  0.302
#> 1997: 0.655  0.67677 s20 0.485  0.987
#> 1998: 0.655 -0.52315 s20 0.490 -0.209
#> 1999: 0.655  0.65742 s20 0.495  0.974
#> 2000: 0.655 -0.20423 s20 0.500  0.116
```

MC

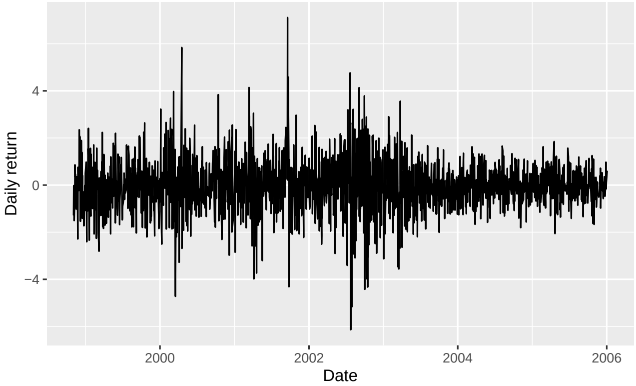


Section 4

Data Analysis

Dow Jones Industrial Index

Cai and Wang (2008) used Dow Jones index with daily return defined by $y_t := -100 \ln \frac{P_t}{P_{t-1}}$



References

Cai, Zongwu, and Xian Wang. 2008. "Nonparametric estimation of conditional VaR and expected shortfall." *Journal of Econometrics* 147 (1): 120–30. https://doi.org/10.1016/j.jeconom.2008.09.005.

Tsay, Ruey S. 2010. *Analysis of Financial Time Series*. John Wiley & Sons.