Robustness issues on regulatory risk measures

Ruodu Wang

http://sas.uwaterloo.ca/~wang

Department of Statistics and Actuarial Science
University of Waterloo

Robust Techniques in Quantitative Finance
Oxford University, UK September 3-7, 2018

Content

Based on some joint work with

Paul Embrechts
(ETH Zurich)

Haiyan Liu
(Michigan State)

Alex Schied
(Waterloo)

Bin Wang
(CAS Beijing)

- Embrechts-Wang-W., Aggregation-robustness and model uncertainty of regulatory risk measures. Finance and Stochastics, 2015
- Embrechts-Liu-W., Quantile-based risk sharing. Operations Research, 2018
- Embrechts-Schied-W., Robustness in the optimization of risk measures. Working paper, 2018

Agenda

Risk Measures

A risk measure $\rho : \mathcal{X} \to \overline{\mathbb{R}} = (-\infty, \infty]$

- Risks are modelled by random losses in a specified period
  - e.g. 10d in Basel III & IV market risk
- $\mathcal{X}$ is a convex cone of rvs in some probability space $(\Omega, \mathcal{F}, \mathbb{P})$

Roles of risk measures

- regulatory capital calculation $\leftarrow$ our main interpretation
- management, optimization and decision making
- performance analysis and capital allocation
- pricing

General Question

Question

What is a "good" risk measure for regulatory capital calculation?

- Regulator's and firm manager's perspectives can be different or even conflicting
  - well-being of the society versus interest of the shareholders
  - systemic risk in an economy versus risk of a single firm

Value-at-Risk and Expected Shortfall

Value-at-Risk (VaR) at level $p \in (0,1)$

$\mathrm{VaR}_p : L^0 \to \mathbb{R}$,

$$\mathrm{VaR}_p(X) = F_X^{-1}(p) = \inf\{x \in \mathbb{R} : \mathbb{P}(X \le x) \ge p\}.$$

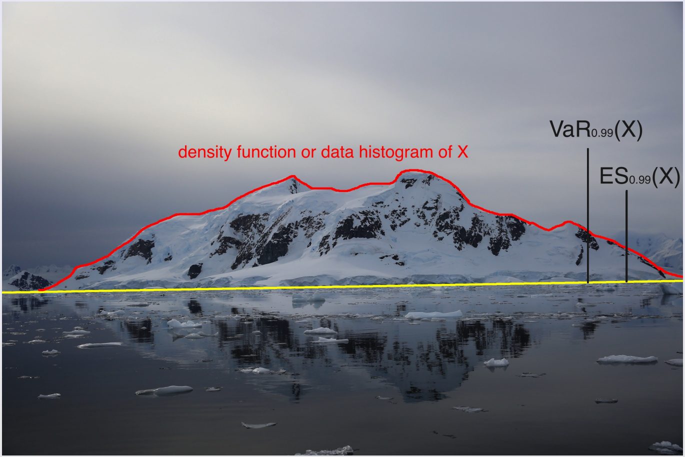
Expected Shortfall (ES/TVaR/CVaR/AVaR) at level $p \in (0,1)$

$\mathrm{ES}_p : L^0 \to \overline{\mathbb{R}}$,

$$\mathrm{ES}_p(X) = \frac{1}{1-p}\int_p^1 \mathrm{VaR}_q(X)\mathrm{d}q \underset{(F_X \text{ cont.})}{=} \mathbb{E}\left[X | X > \mathrm{VaR}_p(X)\right].$$

F_X above is the distribution function of X.

Value-at-Risk and Expected Shortfall



Value-at-Risk and Expected Shortfall

The ongoing co-existence of VaR and ES:

- Basel IV - both
- Solvency II - VaR
- Swiss Solvency Test - ES

Academic Inputs

- ES is generally advocated by academia for desirable properties in the past two decades; in particular,
  - subadditivity or coherence (Artzner-Delbaen-Eber-Heath'99)
  - convex optimization properties (Rockafellar-Uryasev'00)
- Some other examples of impact from academic research
  - Gneiting'11: backtesting ES is unclear, whereas backtesting VaR is straightforward
  - Cont-Deguest-Scandolo'10: ES is not robust, whereas VaR is

VaR versus ES

BCBS Consultative Document, May 2012, Page 41, *Question 8*:

"*What are the likely constraints with moving from VaR to ES, including any challenges in delivering robust backtesting, and how might these be best overcome?*"

VaR versus ES

Features/Risk measure	VaR	Tail-VaR
Frequency captured?	Yes	Yes
Severity captured?	No	Yes
Sub-additive?	Not always	Always
Diversification captured?	Issues	Yes
Back-testing?	Straight-forward	Issues
Estimation?	Feasible	Issues with data limitation
Model uncertainty?	Sensitive to aggregation	Sensitive to tail modelling
Robustness I (with respect to "Lévy metric[33]")?	Almost, only minor issues	No
Robustness II (with respect to "Wasserstein metric[34]")?	Yes	Yes

Table copied from IAIS Consultation Document Dec 2014, page 42

Progress

Model Uncertainty

VaR and ES are law-based (thus statistical risk functionals):
$\rho(X) = \rho(Y)$ if $X \stackrel{\mathrm{d}}{=}_{\mathbb{P}} Y$ (equal in distribution under $\mathbb{P}$)

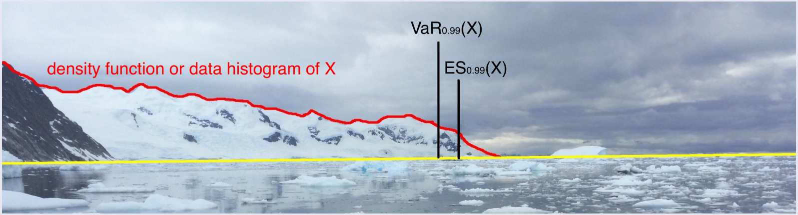
- The calculation requires knowledge of the distribution of a risk
- This may never be the exact case: model uncertainty
  - statistical error
  - computational error
  - modeling error
  - conceptual error
- Models are at most "approximately correct" $\Rightarrow$ robustness!

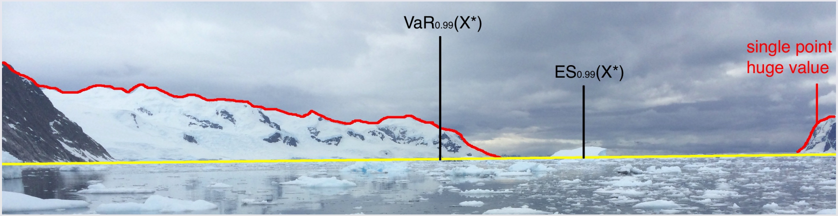
Robust Statistics

Statistical robustness addresses the question of "what if the data is compromised with small error?" (e.g. outlier)

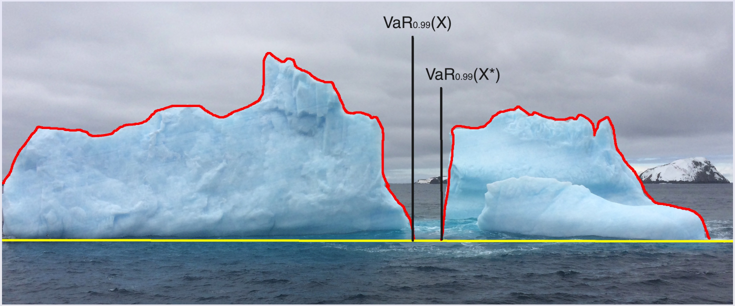
- Originally robustness is defined on estimators (estimation procedures)
- Would the estimation be ruined if the underlying model is compromised?
  - e.g. an outlier is added to the sample

VaR and ES Robustness





VaR and ES Robustness



- Non-robustness of VaR_p only happens if the quantile has a gap at p
- Is this situation relevant for risk management practice?
  - one must be very unlucky to hit precisely where it has a gap ...

Robust Statistics

Classic qualitative robustness:

- Hampel'71: the robustness of a consistent estimator of T is equivalent to the continuity of T with respect to underlying distributions (both with respect to the same metric)
- When we talk about the robustness of a statistical functional, (Huber-Hampel's) robustness typically refers to continuity with respect to some metric.
- (Pseudo-)metrics: $\pi^q = L^q$ ($q \geq 1$), $\pi^\infty = L^\infty$, $\pi^W =$ Lévy, ...

General reference: Huber-Ronchetti'07

Robustness of Risk Measures

Consider the continuity of $\rho : \mathcal{X} \to \mathbb{R}$.

- A strong sense of continuity is w.r.t. weak convergence.
  - $X_n \to X$ in distribution $\Rightarrow \rho(X_n) \to \rho(X)$.
- Quite restrictive
- Practitioners like weak convergence (e.g. estimation, simulation)

Robustness of Risk Measures

- With respect to weak convergence $p \in (0,1)$:
  - VaR_p is continuous at distributions whose quantile is continuous at p. VaR_p is argued as being almost robust.
  - ES_p is not continuous for any $\mathcal{X} \supset L^\infty$
- ES_p is continuous w.r.t. some other (stronger) metric, e.g. π^q (or the Wasserstein-L^q metric)

Range-Value-at-Risk (RVaR)

A two-parameter family of risk measures, for $\alpha, \beta > 0$, $\alpha + \beta < 1$,

$$\mathrm{RVaR}_{\alpha,\beta}(X) = \frac{1}{\beta}\int_{\alpha}^{\alpha+\beta} \mathrm{VaR}_{\gamma}(X)\mathrm{d}\gamma, \quad X \in \mathcal{X}.$$

- RVaR bridges the gap between VaR and ES (limiting cases).
- RVaR is continuous w.r.t. weak convergence
- RVaR is not convex or coherent; it is finite on L^0
- Practically:

$$\mathrm{RVaR}_{\alpha,\beta}(X) \underset{(F_X \text{ cont.})}{=} \mathbb{E}[X|\mathrm{VaR}_{\alpha}(X) < X \le \mathrm{VaR}_{\alpha+\beta}(X)].$$

First proposed by Cont-Deguest-Scandolo'10; name in W.-Bignozzi-Tsanakas'15

Classic Robustness

The general perception of robustness, from worst to best:

$$\mathrm{ES} \prec \mathrm{VaR} \prec \mathrm{RVaR}$$

Distortion Risk Measures

A distortion risk measure is defined as, for $X \in \mathcal{X}$,

$$\rho(X) = \int_0^\infty h(\mathbb{P}(X > x))\mathrm{d}x + \int_{-\infty}(h(\mathbb{P}(X > x)) - 1)\mathrm{d}x,$$

where h is an increasing function on $[0, 1]$ with $h(0) = 0$ and $h(1) = 1$. h is called a distortion function. If h is continuous,

$$\rho(X) = \int_0^1 \mathrm{VaR}_p(X)\mathrm{d}g(p), \; X \in \mathcal{X},$$

where $g(t) = 1 - h(1 - t)$, $t \in [0, 1]$.

- ES and VaR are special cases of distortion risk measures

Yaari'87's dual utility

Distortion Risk Measures

Some summary.

- A distortion risk measure is continuous (wrt π^W) on L^∞ $\Leftrightarrow$ its distortion function has a derivative which vanishes at neighbourhoods of 0 and 1 (classic property of L-statistics).
- From weak to strong:
  - Continuity w.r.t. π^∞: all monetary risk measures
  - Continuity w.r.t. π^q, $q \geq 1$: finite convex risk measures on L^q, e.g. ES_p
  - Continuity w.r.t. weak/a.s./P convergence: e.g. $\mathrm{RVaR}_{\alpha,\beta}$, VaR_p (almost); no convex risk measure satisfies this

Some results: Bäuerle-Müller'06, Cont-Deguest-Scandolo'10, Kou-Peng-Heyde'13; general references: Rüschendorf'13, Föllmer-Schied'16

Robustness of Risk Measures

Is robustness w.r.t. weak convergence necessarily a good thing?

- Toy example.
  - Let $X_n = n^2 \mathrm{I}_{\{U \le 1/n\}}$ for some U[0,1] random variable U (e.g. a credit default risk). Clearly $X_n \to 0$ a.s. but X_n is getting more "dangerous" in many senses. If ρ preserves weak convergence, then

$$\rho(X_n) \to \rho(0) \quad (= 0 \quad \text{typically}).$$

  - $\mathrm{VaR}_{0.999}(X_{10000}) = 0$
  - $\mathrm{ES}_{0.999}(X_{10000}) = 10^7$
- May be reasonable for internal management; not so much for regulation.

One-in-ten-thousand Event

On the other hand,

- the 1/10,000-event-type risks are very difficult to capture statistically (accuracy is impossible)

UK House of Lords/House of Commons, June 12, 2013, Output of a "stress test" exercise, from HBOS:

"*We actually got an external advisor [to assess how frequently a particular event might happen] and they came out with one in 100,000 years and we said "no", and I think we submitted one in 10,000 years. But that was a year and a half before it happened. It doesn't mean to say it was wrong: it was just unfortunate that the 10,000th year was so near.*"

Progress

Uncertainty in Risk Aggregation

General setup

- To calculate $\rho(S)$ where $S = \Lambda(X_1, \dots, X_n)$ for risk factors $X_1, \dots, X_n \in \mathcal{X}$ and aggregation function $\Lambda : \mathbb{R}^n \to \mathbb{R}$
- Two levels of model uncertainty:
  - the marginal distributions F_i of X_i, $i = 1, \dots, n$
  - the dependence structure (copula) of $(X_1, \dots, X_n)$
- Both $\mathrm{VaR}_p(S)$ and $\mathrm{ES}_p(S)$ depend on both levels
  - The second level of uncertainty is arguably more challenging due to data, computation and modeling limitations
  - In the Basel IV market risk formulas, the value of $\mathrm{ES}_p(S)$ requires a calculation under the worst-case dependence

---

Some references on risk aggregation under dependence uncertainty: Embrechts-Puccetti-Rüschendorf'13, Bernard-Jiang-W.'14, Cai-Liu-W.'18

Uncertainty in Risk Aggregation

- Uncertainty at the second level (with first level fixed):
  - Robustness: is $\rho \circ \Lambda$ continuous with respect to the modeling in dependence (π^W)? $\Rightarrow$ robustness in risk aggregation
  - Uncertainty spread: how large is the spread of $\rho \circ \Lambda$ if we do not know about the dependence?
- We focus on the natural aggregation function $\Lambda(x_1 + \cdots + x_n) = \sum_{i=1}^n x_i$.
- $\mathcal{X} = L^1, L^\infty, \ldots$

Robustness in Risk Aggregation

Some results. In the problem of risk aggregation,

- A distortion risk measure is robust on L^∞ $\Leftrightarrow$ its distortion function is continuous on $[0, 1]$.
- ES_p is robust on L^1;
- VaR_p is not robust on L^∞ (but almost)
- $\mathrm{RVaR}_{\alpha,\beta}$ is robust on L^0
- The uncertainty spread of VaR_p is generally bigger than that of ES_q for $q \le p$
  - In Basel III & IV market risk calculation, $\mathrm{VaR}_{0.99}$ is replaced by $\mathrm{ES}_{0.975}$

Embrechts-Wang-W.'15

Robustness in Risk Aggregation

On robustness in risk aggregation:

$$\mathrm{VaR} \prec \mathrm{ES} \prec \mathrm{RVaR}$$

Remark.

- The robustness of ES_p is due to uniform integrability in risk aggregation.

Krätschmer-Schied-Zähle'17

Robustness in Risk Sharing

Simplistic setup

- n agents sharing a total risk (or asset) $X \in \mathcal{X}$ (set of rvs)
- $\rho_1, \ldots, \rho_n$: underlying risk measures (objectives to minimize)
  - The risk measures are chosen as VaR, ES and RVaR.
- Optimality: aggregate risk $\Leftrightarrow$ collaborative $\Leftarrow$ competitive
- Robustness: small model misspecification does not lead to very different aggregate risk value

Robustness in Risk Sharing

Some results.

- There exists a π^1-robust optimal allocation of X $\Leftrightarrow$ no VaR is involved
- If X is bounded, then there exists a π^∞-robust optimal allocation of X $\Leftrightarrow$ no VaR is involved
- There exists a π^W-robust optimal allocation of X $\Leftrightarrow$ no VaR is involved and at least one RVaR.

On robustness in risk sharing:

$$\mathrm{VaR} \lll \mathrm{ES} \prec \mathrm{RVaR}$$

Results in Embrechts-Liu-W.'18

Progress

The Optimization Problem

General setup

- $\mathcal{G}_n = \{$measurable functions from $\mathbb{R}^n$ to $\mathbb{R}\}$
- $X \in (L^0)^n$ is an economic vector, representing all random sources
- $\mathcal{G} \subset \mathcal{G}_n$ is an admissible set (decision set)
- $g(X)$ for $g \in \mathcal{G}$ represents a risky position of an investor
- ρ is an objective functional mapping $\{g(X) : g \in \mathcal{G}\}$ to $\overline{\mathbb{R}}$

"The optimization problem":

to minimize $\rho(g(X))$ over $g \in \mathcal{G}$

(e.g. think about a classic hedging/optimal investment problem)

The Optimization Problem

Denote

$$\rho(X;\mathcal{G}) = \inf\{\rho(g(X)) : g \in \mathcal{G}\},$$

and (possibly empty)

$$\mathcal{G}^*(X,\rho) = \{g \in \mathcal{G} : \rho(g(X)) = \rho(X;\mathcal{G})\},$$

We call

- $g^* \in \mathcal{G}^*(X,\rho)$ an optimizing function
- $g^*(X)$ an optimized position

Uncertainty in Optimization

- The optimization problem is often subject to severe model uncertainty resulting from the assumptions made for X.
- Let $\mathcal{Z}$ be a set of possible economic vectors including X; $\mathcal{Z}$ may be interpreted as the set of alternative models.
  - E.g. a parametric family of models (parameter uncertainty)
- The real economic vector $Z \in \mathcal{Z}$ is likely different from the perceived economic vector X.
  - X: best-of-knowledge model
  - Z: real model (unknowable)

Uncertainty in Optimization

- We choose $g \in \mathcal{G}^*(X, \rho)$ to optimize our objective ρ (best-of-knowledge decision).
  - real position $g(Z)$
  - perceived position $g(X)$
- If the modeling is good, Z and X are close to each other according to some metric π
- $\rho(g(Z))$ should be close to $\rho(g(X))$ to make sense of the optimizing function g
- We desire some continuity of the mapping $Z \mapsto \rho(g(Z))$ at $Z = X$

Robustness in Optimization

- We call $(\mathcal{G}, \mathcal{Z}, \pi_{\mathcal{Z}})$ an uncertainty triplet if $\mathcal{G} \subset \mathcal{G}_n$ and $(\mathcal{Z}, \pi_{\mathcal{Z}})$ is a pseudo-metric space of n-random vectors.
- ρ is compatible if it maps $\mathcal{G}(\mathcal{Z})$ to $\overline{\mathbb{R}}$, and $\rho(g(Y)) = \rho(g(Z))$ for all $g \in \mathcal{G}$ and $Y, Z \in \mathcal{Z}$ with $\pi_{\mathcal{Z}}(Y, Z) = 0$.

Definition 1

A compatible objective functional ρ is robust at $X \in \mathcal{Z}$ relative to the uncertainty triplet $(\mathcal{G}, \mathcal{Z}, \pi_{\mathcal{Z}})$ if there exists $g \in \mathcal{G}^*(X, \rho)$ such that the function $Z \mapsto \rho(g(Z))$ is $\pi_{\mathcal{Z}}$-continuous at $Z = X$.

Robustness in Optimization

Remarks.

- Robustness is a joint property of the tuple $(\rho, X, \mathcal{G}, \mathcal{Z}, \pi_{\mathcal{Z}})$
- Only a $\pi_{\mathcal{Z}}$-neighbourhood of X in $\mathcal{Z}$ matters
- If ρ is robust at X relative to $(\mathcal{G}, \mathcal{Z}, \pi_{\mathcal{Z}})$, then ρ is also
  - robust at X relative to $(\mathcal{G}, \mathcal{Y}, \pi_{\mathcal{Z}})$ if $X \in \mathcal{Y} \subset \mathcal{Z}$;
  - robust at X relative to $(\mathcal{G}, \mathcal{Z}, \hat{\pi}_{\mathcal{Z}})$ if $\hat{\pi}_{\mathcal{Z}}$ is stronger than $\pi_{\mathcal{Z}}$
- If $\mathcal{G}^*(X, \rho) = \varnothing$, then ρ is not robust at X
-
  - One can use topologies instead of metrics
  - One can use uncertainty on $\mathbb{P}$ instead of on X
  - Conceptually different from the field of robust optimization or optimizing robust preferences

Representative Optimization Problems

Representative optimization problems.

- $n = 1$ and X is a random loss
- The pricing density $\gamma = \gamma(X)$ is a measurable function of X
  - $\gamma > 0$, $\mathbb{E}[\gamma] = 1$ and $\mathbb{E}[\gamma X] < \infty$
- The budget constraint is $\mathbb{E}[\gamma g(X)] \geq x_0$
- Problems: to minimize $\rho(g(X))$ over $g \in \mathcal{G}$ for some $\mathcal{G} \subset \mathcal{G}_n$ in three settings $\mathcal{G} = \mathcal{G}_{\mathrm{cm}}, \mathcal{G}_{\mathrm{ns}}, \mathcal{G}_{\mathrm{bd}}$

Representative Optimization Problems

(a) Complete market:

$$\mathcal{G}_{\rm cm} = \{g \in \mathcal{G}_1 : \mathbb{E}[\gamma g(X)] \ge x_0\}.$$

(b) No short-selling or over-hedging constraint:

$$\mathcal{G}_{\rm ns} = \{g \in \mathcal{G}_1 : \mathbb{E}[\gamma g(X)] \ge x_0,\ 0 \le g(X) \le X\}.$$

Assume $0 \le x_0 < \mathbb{E}[\gamma X]$ to avoid triviality.

(c) Bounded constraint: for some $m > 0$,

$$\mathcal{G}_{\rm bd} = \{g \in \mathcal{G}_1 : \mathbb{E}[\gamma g(X)] \ge x_0,\ 0 \le g(X) \le m\}.$$

Assume $0 \le x_0 < m$ to avoid triviality.

Representative Optimization Problems

Remark.

- Problem (c) is not a special case of Problem (b) as X in (b) is both the constraint and the source of randomness

For (a)-(c), assume

- $X \geq 0$ and the distribution function of X is continuous and strictly increasing on $(\text{ess-inf} X, \text{ess-sup} X)$.
- $X \in \mathcal{Z}$, and $(\mathcal{Z}, \pi_{\mathcal{Z}})$ is one of the classic choices (L^q, π^q) for $q \in [1, \infty]$ and (L^0, π^W).

Problem (c) for some distortion risk measures is studied by He-Zhou'11

Robustness in the Optimization of VaR

Let

$$q = \mathrm{VaR}_p(X; \mathcal{G}_{\mathrm{ns}}) = \inf \left\{ \mathrm{VaR}_p(g(X)) : g \in \mathcal{G}_{\mathrm{ns}} \right\},$$

$$q' = \mathrm{VaR}_p(X; \mathcal{G}_{\mathrm{bd}}) = \inf \left\{ \mathrm{VaR}_p(g(X)) : g \in \mathcal{G}_{\mathrm{bd}} \right\}.$$

Assumption 1

$q > 0$ *and* $\mathbb{P}(\gamma(X - q) \leq \mathrm{VaR}_p(\gamma(X - q))) = p.$

Assumption 2

$q' > 0$ *and* $\mathbb{P}(\gamma \leq \mathrm{VaR}_p(\gamma)) = p.$

- $q, q' > 0$ means the optimization does not result in zero risk
- Assumptions 1-2 are very weak

Robustness in the Optimization of VaR

Theorem 2

For $p \in (0,1)$ and $X \in \mathcal{Z}$,

(i) VaR_p *is not robust relative to* $(\mathcal{G}_{\mathrm{cm}}, \mathcal{Z}, \pi_{\mathcal{Z}})$;

(ii) *under Assumption 1,* VaR_p *is not robust at* X *relative to* $(\mathcal{G}_{\mathrm{ns}}, \mathcal{Z}, \pi_{\mathcal{Z}})$;

(iii) *under Assumption 2,* VaR_p *is not robust at* X *relative to* $(\mathcal{G}_{\mathrm{bd}}, \mathcal{Z}, \pi_{\mathcal{Z}})$.

- Robustness of VaR in optimization is very bad

Robustness in the Optimization of ES

Assumption 3

$\text{ess-sup}\gamma \leq \frac{1}{1-p}$.

- Assumption 3 may be interpreted as a no-arbitrage condition for a market with ES participants

Assumption 4

Either γ is a constant, or γ is a continuous function and $\gamma(X)$ is continuously distributed.

- Assumption 4 is commonly satisfied

Robustness in the Optimization of ES

Theorem 3

For $p \in (0,1)$ and $X \in \mathcal{Z}$,

(i) *under Assumption 3, ES_p is robust at X relative to $(\mathcal{G}_{\mathrm{cm}}, \mathcal{Z}, \pi_{\mathcal{Z}})$;*

(ii) *under Assumption 4, ES_p is robust at X relative to $(\mathcal{G}_{\mathrm{ns}}, \mathcal{Z}, \pi_{\mathcal{Z}})$, where $(\mathcal{Z}, \pi_{\mathcal{Z}}) = (L^q, \pi^q)$ for $q \in [1, \infty]$;*

(iii) *under Assumption 4, ES_p is robust at X relative to $(\mathcal{G}_{\mathrm{bd}}, \mathcal{Z}, \pi_{\mathcal{Z}})$, where $(\mathcal{Z}, \pi_{\mathcal{Z}}) = (L^q, \pi^q)$ for $q \in [1, \infty]$.*

- Robustness of ES in optimization is quite good

Robustness in Optimization for VaR and ES

On robustness in optimization:

$$\mathrm{VaR} \lll \mathrm{ES} \quad (\mathrm{RVaR}/\mathrm{ES} \text{ not easy to compare})$$

Observations.

- The discontinuity in $Z \mapsto g^*(Z)$ comes from the fact that optimizing VaR is "too greedy": always ignores tail risk, and hoping the probability of the tail risk is correctly modelled.
- None of the two values

$$\mathrm{VaR}_p(g^*(X)) \text{ and } \mathrm{VaR}_p(g^*(Z))$$

is a rational measure of the "optimized" risk.

Robustness in Optimization for VaR and ES

Is risk positions of type g^* realistic?

"Starting in 2006, the CDO group at UBS noticed that their risk-management systems treated AAA securities as essentially riskless even though they yielded a premium (the proverbial free lunch). So they decided to hold onto them rather than sell them. "

- From Feb 06 to Sep 07, UBS increased investment in AAA-rated CDOs by more than 10 times; many large banks did the same.
  - Take a risk of big loss with small probability, $X_i = X\mathrm{I}_{A_i}$
  - Treat it as free money - profit
  - Model uncertainty?

---

quoted from Acharya-Cooley-Richardson-Walter'10

Other Questions

Other questions

- other risk measures
- other optimization problems
- utility maximization problems
- risk measures as constraints instead of objectives
- robust preferences

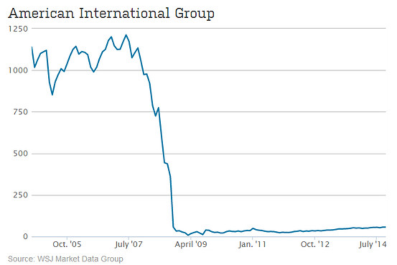
Progress

Conclusion

Some conclusions on robustness

- Classic notion
  - $\text{ES} \prec \text{VaR} \prec \text{RVaR}$
  - However this robustness may not be desirable
- Novel perspectives
  - $\text{VaR} \prec \text{ES} \prec \text{RVaR}$ in risk aggregation
  - $\text{VaR} \lll \text{ES} \prec \text{RVaR}$ in risk sharing
  - $\text{VaR} \lll \text{ES}$ in optimization
  - The rationality of optimizing VaR under model uncertainty is questionable

AIG



CEO of AIG Financial Products, August 2007:

"*It is hard for us, without being flippant, to even see a scenario within any kind of realm of reason that would see us losing one dollar in any of those transactions.*"

- AIGFP sold protection on super-senior tranches of CDOs
- $180 billion bailout from the federal government in September 2008

Thank You

Industry Perspectives

From the **International Association of Insurance Supervisors**:

- Document (version June 2015)
  Compiled Responses to ICS Consultation 17 Dec 2014 - 16 Feb 2015

In summary

- Responses from insurance organizations and companies in the world.
- 49 responses are public
- 34 commented on Q42: VaR versus ES (TVaR)

Industry Perspectives

- 5 responses are supportive about ES:
  - Canadian Institute of Actuaries, CA
  - Liberty Mutual Insurance Group, US
  - National Association of Insurance Commissioners, US
  - Nematrian Limited, UK
  - Swiss Reinsurance Company, CH
- Some are indecisive; most favour VaR.

Regulator and firms may have different views

Discussion

Major reasons to favour VaR from the insurance industry (IAIS report June 2015)

- Implementation of ES is expensive (staff, software, capital)
- ES does not exist for certain heavy-tailed risks
- ES is more costly on distributional information, data and simulation
- ES has trouble with a change of currency