

Measuring Systemic Risks in Insurance - Reinsurance Networks

- Stanford University 2012 -

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Outline

- 1 Modeling Focus, Framework and Question of Interests
 - Focus of the Talk: Insurance Risk
 - The Model: A High-level Overview
 - Insurance: Basics
 - Modeling Framework
 - Questions of Interest
- 2 Counter-party Risk and Settlement Mechanism
 - A Stylized Contractual Model
 - Default Settlement Mechanism
- 3 Qualitative Risk Analysis
 - A Tractable Stylized Risk Factor Model
 - A First Qualitative Analysis
 - The Role of Risk Mitigators
- 4 Enhancing Qualitative Analysis with Efficient Simulation Tools
- 5 Examples and Conclusions

The Impact of Catastrophic Events

- Atlantic City, NJ. About 10 days ago...



Focus of the Model

- Stochastic Risk Networks:

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- **Stochastic Risk Networks:**

- 1) Multidimensional stochastic processes describing evolution of risk exposures

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- 2) Features: counterparty risk, default contagion effects, factor dependence, interconnections, combinatorial nature, etc.

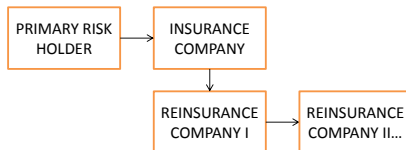
Focus of the Model

- **Stochastic Risk Networks:**

- 1) Multidimensional stochastic processes describing evolution of risk exposures *subject to resource (capital) constraints*
- 2) Features: counterparty risk, default contagion effects, factor dependence, interconnections, combinatorial nature, etc.
- 3) Features → Challenges

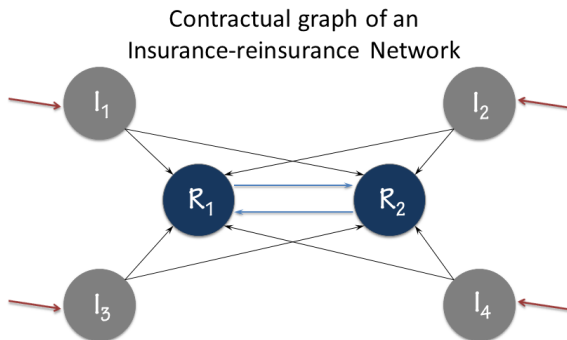
Insurance: Basics

- Insurance flow...



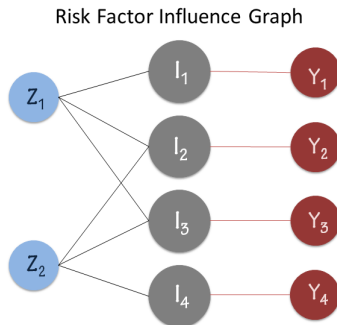
Insurance-Reinsurance Risk Networks: Framework

- Contractual diagram:



Insurance-Reinsurance Risk Networks: Framework (Con'd)

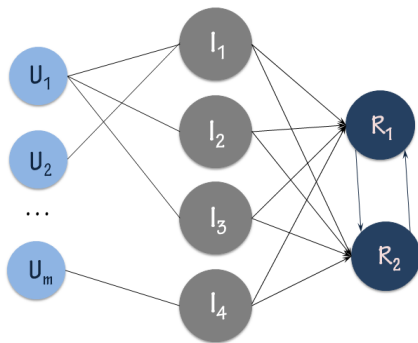
- Risk (Factor) Exposure Map:



Insurance-Reinsurance Risk Networks: Framework (Con'd)

- Combined Factor Exposure & Contractual Directed Graph

Combined Risk Factor & Contractual Graph



Insurance-Reinsurance Risk Analysis: Questions of Interest

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- *How does the presence of reinsurers alter the systemic landscape of the system?*
- *How to enhance the role of reinsurers?*

Insurance-Reinsurance Risk Framework: Goal

Goal

Design models that allow to study these questions systematically both in qualitative and quantitative ways...

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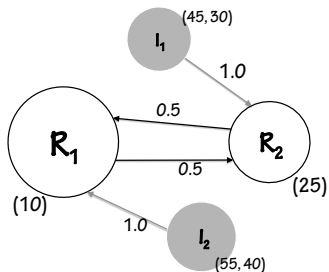
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A Stylized Contractual Model

- **Insurance-reinsurance network:**

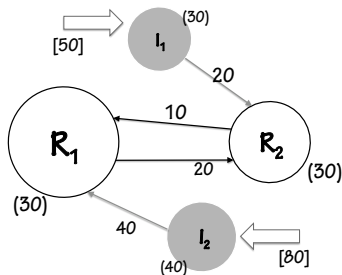
- 1) Insurance companies (set \mathcal{I}) & reinsurance companies (set \mathcal{R}),
 $\mathcal{R} \cap \mathcal{I} = \emptyset$.
- 2) Each insurer $I_i, i \in \mathcal{I}$ enters reinsurance with multiple reinsurers with some given proportions.
- 3) Stop-loss reinsurance contracts and proportional retrocession.
- 4) Spill-over proportions at the time of default denoted by $\rho_{r,i}, \tilde{\rho}_{r,r'}$.

Need for Well-defined Default Contagion Mechanism



Initial configurations:

- (45, 30): (initial reserve, reinsurance deductible)
- (10), (25): initial reserves
- 0.5, 1.0: risk transfer ratio



Before settlements:

- [50], [80]: claim sizes
- (30), (40): effective claim sizes
- 10, 20, 40: transferred amount

Default Mechanism: An Equilibrium Formulation

Formulation

$$\begin{aligned}
 & \min \sum_{i \in \mathcal{I}^+} \pi_i^- + \sum_{r \in \mathcal{R}^+} \psi_r^- \\
 & \text{s.t. } \pi_i^+ - \pi_i^- = e_i + C_i - L_i - \sum_{r \in \mathcal{R}^+} \psi_r^- \cdot \rho_{r,i}, \quad \forall i \in \mathcal{I}^+ \\
 & \psi_r^+ - \psi_r^- = e_r + C_r - L_r - \sum_{r' \in \mathcal{R}^+, r' \neq r} (\psi_{r'}^- \cdot \tilde{\rho}_{r',r} - \kappa \psi_r^- \cdot \tilde{\rho}_{r,r'}), \quad \forall r \in \mathcal{R}^+ \\
 & \pi_i^+, \pi_i^-, \psi_r^+, \psi_r^- \geq 0.
 \end{aligned}$$

Theorem (Blanchet & Shi (2012b))

The LP has a unique optimal solution. The solution is independent of the objective function as long as this one is strictly increasing in π_i^- and ψ_r^- . Moreover, in equilibrium π_i^-, ψ_r^- are losses and π_i^+, ψ_r^+ surpluses (i.e. you can't have both $\pi_i^+ > 0$ and $\pi_i^- > 0$).

Connections to *Eisenberg-Noe (2000)* Formulation

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Our formulation:

- Netting of default
- Solution can be obtained from LOCAL interactions (no need for central planner).

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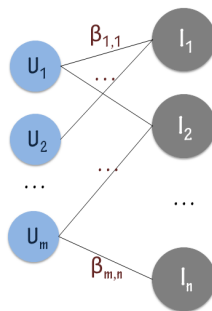
Dependence Structure in Risk Factor Influence Graph

- **Claims:** *Linear model* of m independent *power-law-tail* risk factors

$$P(U_j > b) \approx b^{-\alpha_j}, \quad j = 1, \dots, m,$$

as $b \rightarrow \infty$.

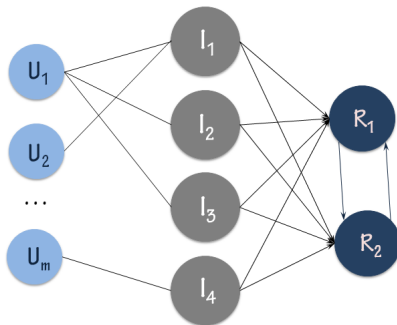
Risk Factor Influence Graph
(weights = coefficients in linear model)



Summary of Dependence: How Risk Factors Influence Companies?

- Write $G_{i,j} = 1$ if there is directed path from j -th factor to company i , otherwise $G_{i,j} = 0$ (e.g. $G_{R_1,m} = 1$, $G_{I_3,m} = 0$)

Combined Risk Factor & Contractual Graph



Some Qualitative Analysis

Theorem (Blanchet & Shi (2012b))

Let \mathcal{A} be a given set of companies, assume that $e_i, e_r = \Theta(b)$ as $b \rightarrow \infty$.

$$P(\text{ruin of set } \mathcal{A}) \approx b^{-\lambda(\mathcal{A})},$$

where λ is the optimal solution to the following (multi-dimensional) Knapsack problem

$$\begin{aligned} \lambda(\mathcal{A}) &= \min \sum_{j=1}^m \alpha_j x_j \\ \text{s.t. } &\sum_{j=1}^m G_{i,j} x_j \geq 1, \quad \forall i \in \mathcal{A} \\ &x_j \in \{0, 1\}. \end{aligned}$$

▶ Jump to numerical results...

Qualitative Risk Analysis: Some Observations

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 - 1 Emphasizes the combinatorial aspect.

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Enhancing the Role of Reinsurance Companies

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Formulation

$$\lambda(\rho, \mathcal{A}) = \min \sum_{j=1}^m \rho \alpha_j x_j + \sum_{j=1}^m \alpha_j y_j$$

$$\text{s.t. } \sum_{j=1}^m G_{l,j} x_j \geq 1, \quad \forall l \in \mathcal{R}(\mathcal{A}) \quad [\text{Default of counterparties of } \mathcal{A}]$$

$$\sum_{j=1}^m G_{i,j} (x_j + y_j) \geq 1, \quad \forall i \in \mathcal{A} \quad [\text{Default of } \mathcal{A}]$$

$$x_j, y_j \in \{0, 1\}.$$

Guidance for Regulatory Policies

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How to Improve Upon Asymptotics via Efficient Monte Carlo

- Let \mathcal{A} be a set of companies & $e_i, e_r = \Theta(b)$, want to compute
$$P(\text{ruin of set } \mathcal{A}) \approx b^{-\lambda}$$

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Goal

Design an *efficient* Monte Carlo estimator $Z_{\mathcal{A}}(b)$ such that

$$\frac{E[Z_{\mathcal{A}}^2(b)]}{P(\text{Ruin of set } \mathcal{A})^2} = O(1)$$

as $b \rightarrow \infty$.

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- In addition, we want cost-per-replication of $Z_{\mathcal{A}}(b)$ to be $O(1)$ as $b \rightarrow \infty$.
- Want conditional expectations given ruin of \mathcal{A} , also with complexity $O(1)$.

Constructing an Efficient Monte Carlo Estimator

- Pick "tractable" set C_b such that

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- Also $\delta > 0$ such that for all $b > 0$

$$\delta P(C_b) \leq P(\text{Ruin of set } \mathcal{A} \text{ by time } M)$$

Constructing an Efficient Monte Carlo Estimator

- Using the structure of the linear program one can explicitly **find** $\gamma > 0$ such that

$$\{\text{Ruin of set } A\} \subset \cup_{(x_1, \dots, x_m)} \{ \cap_{i \in A} \cup_{j: G_{i,j} x_j \geq 1} \{U_j > \gamma b\} \},$$

where (x_1, \dots, x_m) is feasible for the Knapsack problem.

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$$P(\cap_{i \in A} \cup_{j: G_{i,j} x_j \geq 1} \{U_j > \gamma b\})$$

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Algorithm

- *Sample $\mathbf{x} = (x_1, \dots, x_m)$ with (any) probability distribution $w(\mathbf{x}) > 0$*

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- Output estimator

$$Z_{\mathcal{A}} = I\{\text{ruin of } \mathcal{A}\} / \left(\sum_{\mathbf{x}} \frac{w(\mathbf{x}) \times I(\cap_{i \in \mathcal{A}} U_{j:G_{i,j}x_j \geq 1} \{U_j > \gamma b\})}{P(\cap_{i \in \mathcal{A}} U_{j:G_{i,j}x_j \geq 1} \{U_j > \gamma b\})} \right)$$

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Proposition

$$Z_{\mathcal{A}} \leq \frac{\max_{\mathbf{x}} P(\cap_{i \in \mathcal{A}} U_{j:G_{i,j}x_j \geq 1} \{U_j > \gamma b\})}{\min_{\mathbf{x}} w(\mathbf{x})}.$$

In particular, the estimator is strongly efficient.

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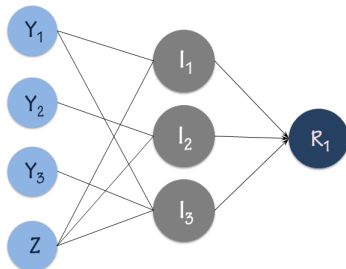
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Numerical Examples

Scenario (power indices)

	1	2	3
α_1	4.9	3.9	2.1
α_2	5.2	2.2	2.8
α_3	6.3	3.3	2.3
α_Z	2.1	6.1	3.4
$\lambda(\rho, \mathcal{A})$	2.1	5.5	4.9

Numerical Example: Combined Risk Factor & Contractual Graph



- Most likely cause of ruin of companies $\mathcal{A} = \{2, 3\}$

▶ Back to Knapsack formulation...

Numerical Examples

- 10^6 Replications
- CSD=Cond. system loss given default of \mathcal{A}

Numerical results for 3 scenarios, $\mathcal{A} = \{2, 3\}$

Scenario # 1. $\hat{p}(s.e./\hat{p}(\%))$ 95% C.I. \widehat{CSD}	$b = 10^7$ 1.03×10^{-8} (2.961%) $(0.97, 1.09) \times 10^{-8}$ 1.857×10^7
Scenario # 2. $\hat{p}(s.e./\hat{p}(\%))$ 95% C.I. \widehat{CSD}	$b = 10^5$ 9.78×10^{-11} (2.90%) $(0.92, 1.03) \times 10^{-10}$ 1.092×10^5
Scenario # 3. $\hat{p}(s.e./\hat{p}(\%))$ 95% C.I. \widehat{CSD}	$b = 10^6$ 6.64×10^{-11} (5.272%) $(5.96, 7.33) \times 10^{-11}$ 8.337×10^5

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- Thank you!

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- **Thank you!**
- Draft version: **Stochastic Risk Networks: Modeling, Analysis and Efficient Monte Carlo** downloadable on SSRN