

A DATA SCIENCE APPROACH TO PREDICT THE IMPACT OF COLLATERALIZATION ON SYSTEMIC RISK

How to evaluate, predict and optimize financial regulation?

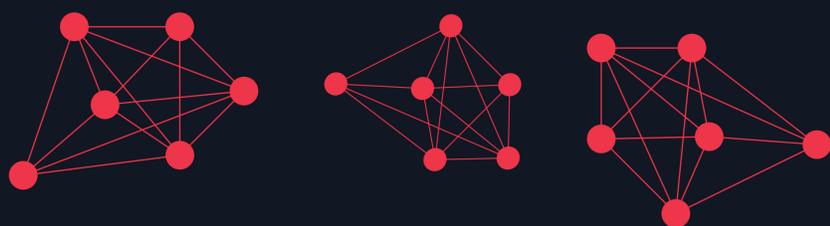


Expert Judgement vs Data Science

Key Challenges:

- Lack of Data (Trade Data is proprietary).
- Large time lag between decision about regulation and implementation.
- Gap in disciplines: Micro- vs. Macroprudential regulation.
- Inconsistent metrics and unclear definitions.

1. Representation and Generation of Financial Systems



Trade Relation Graphs

Key Concepts:

- Represent trade relations in a financial system as an **undirected** graph. Each node represents a bank and the links represent trading activity.
- Use cutting edge simulation technology to randomly generate a set of financial systems.
- Calibrate the simulation on (publicly) available data.

2. Simulation using the Open Source Risk Engine



uncollateralized
VM collateralized
IM & VM collateralized
(US Swap margin rule)



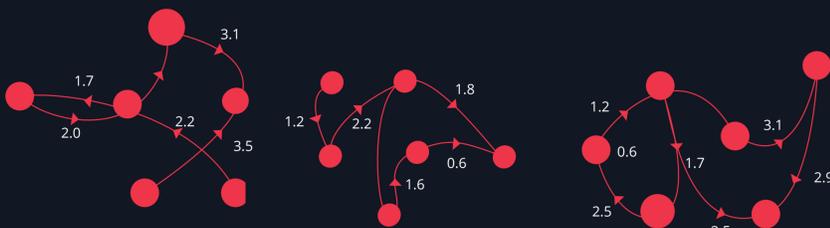
OPEN
SOURCE RISK

Financial Regulations

Key Concepts:

- The Open Source Risk Engine (ORE) uses advanced stochastic and Monte Carlo simulation to predict the future value of trades and netting sets.
- It uses about 400k lines of C++ and is built on top of boost and QuantLib.

3. Computing Systemic Risk in a Graph Model



Risk Graphs

Key Concepts:

- Represent the risks in a financial system as a weighted **directed** graph. The nodes represent the banks, the arrows represent risk that is induced and the weights are a metric of that risk, for instance EEPE, PFE or CVA.
- The risk metrics on the arrows can be aggregated to the nodes, which tells us how much risk each bank induces into the system.
- Finally, the metrics can be aggregated to a graph level, which gives us a consistent metric of systemic risk.

4. Visualization, Aggregation & Drill-Down



Total Impact of different Regulations



Drill-down on individual banks



Data Mining on the Netting Sets