A Data Science Approach to Systemic Risk

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joint work with

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1. Introduction
2. Data Science meets Systemic Risk
3. Results: Impact of Collateralization
4. Appendix

Outline

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The Previous Financial Crisis

- The 07/08 crisis challanged the fundamental assumption that banks cannot fail.
- The failure of a bank causes massive economic damages - and potentially more bank failures.
- This "systemic risk" is seen as particularly prevalent in the interbank derivatives market.
- The problem of reducing "systemic risk" is addressed by regulators worldwide and discussed by experts, who disagree in their judgement.
- No final conclusion has been reached.

Gap between the Micro- and Macro-economics

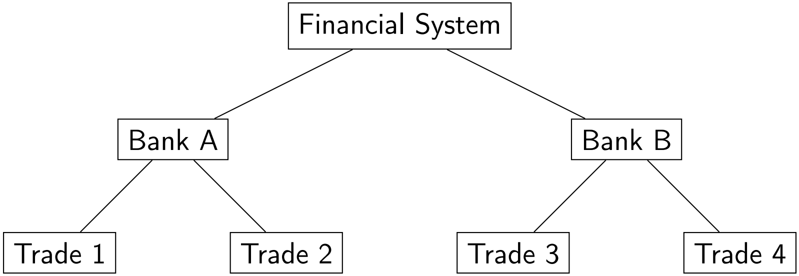
Micro

- studies a single bank in all its complexities
- ignores systemic effects
- has well-defined types of risk (market risk, credit risk, liquidity risk, model risk, operational risk...) and of risk metrics (VaR, EEPE, LCR, Basel-II-Traffic light test..)
- risk metrics are globally aligned and its use is enforced by regulators
- done primarily in dealer banks

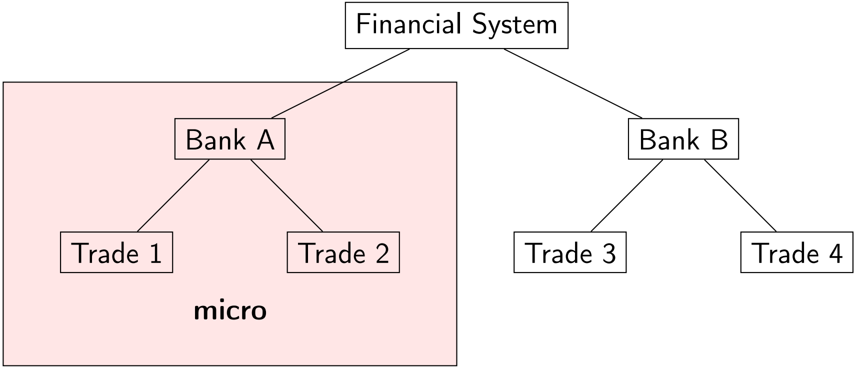
Macro

- largely ignores the complexities of single banks
- studies mainly systemic effects
- the US *Office for Financial Research* published "Survey of Systemic Risk Metrics" analysing 31 different metrics of "systemic risk"
- there is not really a consensus on what "systemic risk" precisely is and in what metric it should be measured
- done primarily in central banks and universities

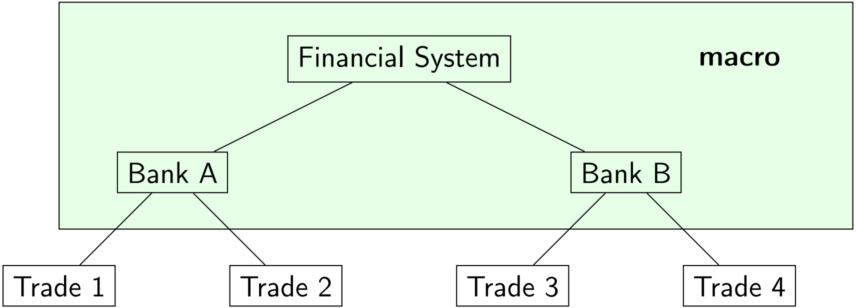
Micro- vs. Macro-economics



Micro- vs. Macro-economics

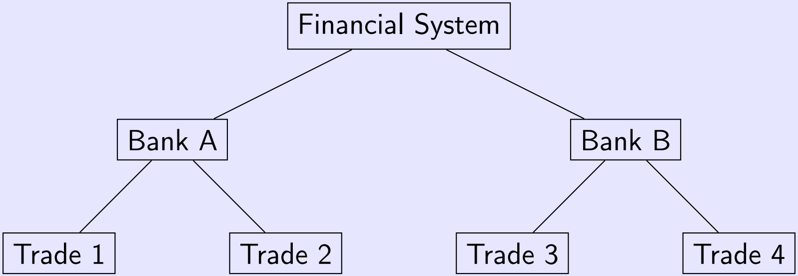


Micro- vs. Macro-economics



Micro- vs. Macro-economics

data science



A Data Science Approach

Strategy

Understand the macro via an aggregation of all the micro

Problem: All current trade data of all banks is confidential.

$\Longrightarrow$ **use simulation**

Aims

Evaluate	Has the regulation implemented since the last crisis reduced systemic risk?
Predict	How to predict the impact of financial regulation before it is implemented?
Optimize	How to find the best possible financial regulation?

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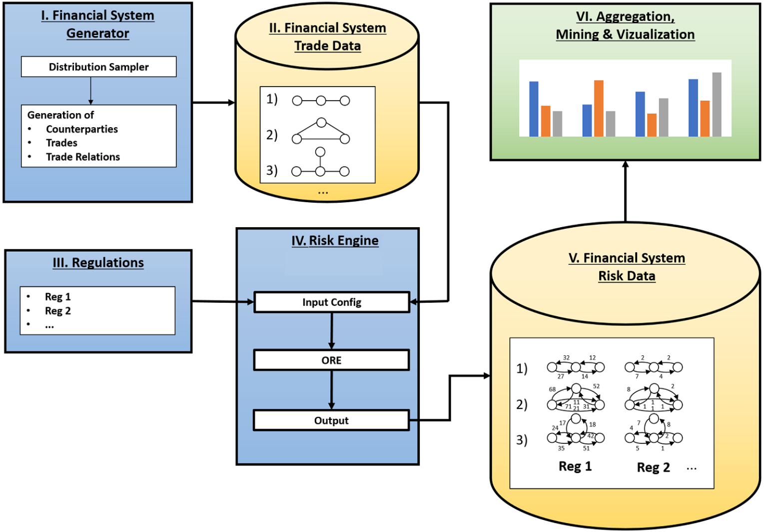
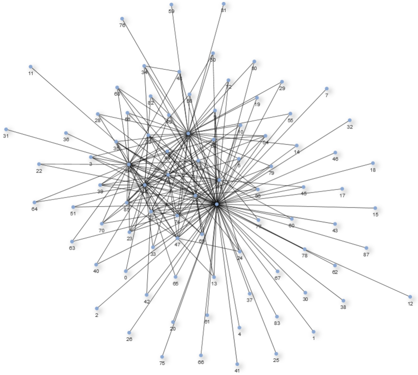
System Architecture



Technology Stack

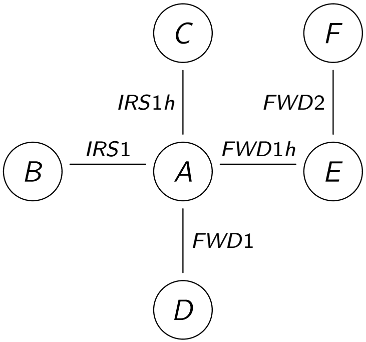
- Python: lxml, numpy, networkx, pyvizjs, bqplot, matplotlib seaborn, panadas,json, jupyter
- C++: boost, QuantLib, Open Source Risk Engine

I.) Random Graph Generation



- The nodedegree in a trade relation graph is empirically known to be Pareto distributed.
- Generating Pareto distributed random sequences of numbers is easy (`numpy.random.Pareto`).
- Finding graphs that realize a given sequence of node degrees is hard and finding algorithms that compute this is even harder and still subject to active mathematical research.
- We just use the `configuration_erase` factory from `networkx` for now.

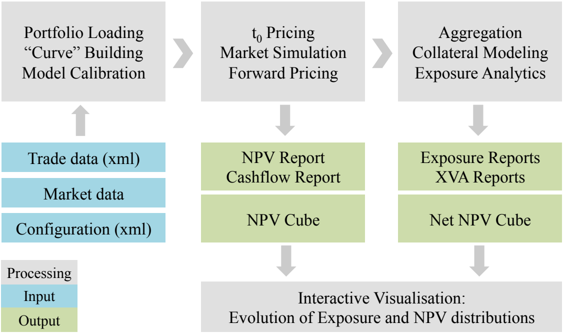
II.) A Graph Model of Financial Systems



We model a financial system FS $= (B, T, \tau)$ as an undirected *trade relation graph*.

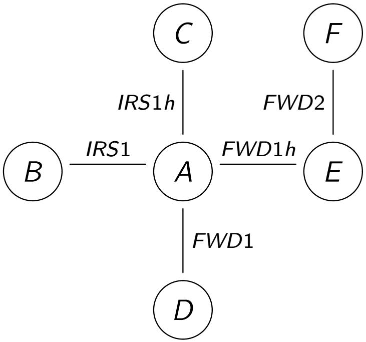
- The nodes B represent the banks.
- The links T represent the trade relations between them.
- All data about the trades is attached to the links via a trade data function $\tau : T \to Y$ (for instance by mapping each trade relation to a list of trade IDs).

IV.) Open Source Risk Engine (ORE)



- Computes the risk in a derivatives portfolio from the perspective of a single bank using MonteCarlo simulation and risk factor modeling.
- Has been used in consulting projects by Quaternion Risk Management in various tier 1 banks and released initially in 2016.
- Extensive technology stack in `C++`, based on QuantLib ($\sim$400k lines of code).

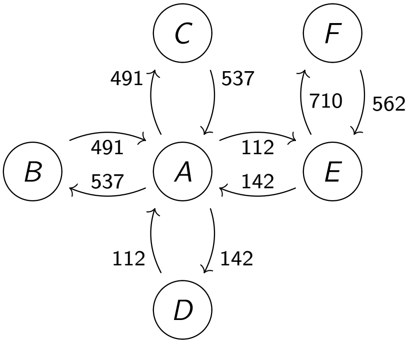
V.) Risk Graph



The *risk graph* $\mathrm{RG} = (B, A, w)$ of a trade relation graph $\mathrm{FS} = (B, T, \tau)$ is a directed graph.

- The nodes B represent the same banks.
- Each undirected trade relation in T is replaced by two arrows in A between the same nodes in opposite directions.
- $w : A \to \mathbb{R}^k$ is a (possibly multivariate) weight function representing the risk induced from the tail to the head of an arrow.

V.) Risk Graph



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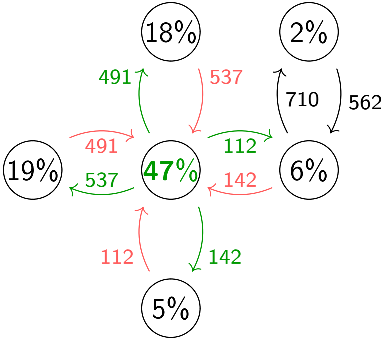
VI.) Aggregation



Using a weighted out-/in-degree the information in a *risk graph* RG $= (B, A, w)$ can be aggregated from the arrows $a \in A$ to the nodes $b \in B$

$$w^{+/-}(b) := \sum_{\substack{a \in A \\ a \text{ starts / ends at v}}} w(a)$$

and expressed as a percentage of the total of the weight $w(\mathrm{RG}) := \sum_{a \in A} w(a)$ via

$$\rho^{+/-}(b) := \frac{w^{+/-}(b)}{w(\mathrm{RG})}.$$

Any of the quantities $w(\mathrm{RG})$, $\max_{b \in B} w^{+}(b)$, $\max_{b \in B} \rho^{+}(b)$ is a metric of systemic risk.

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Collateralization of Derivative Trades

Regulations

- REG_1 Uncollateralized Trading
- REG_2 Variation Margin (VM) collateralized with Thresholds and Minimum Transfer Amounts
- REG_3 Full Variation Margin collateralization
- REG_4 Full collateralization with Variation Margin (VM) and Initial Margin (IM)

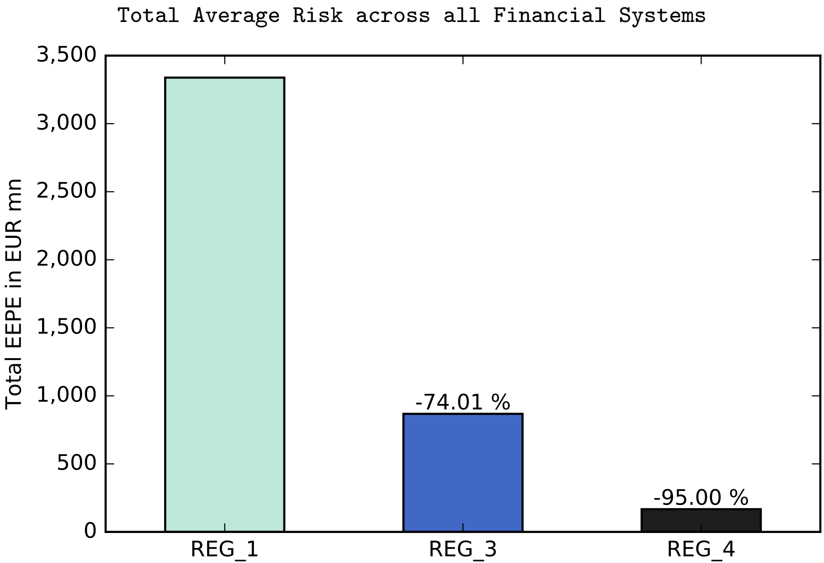
Impact Levels

1. Regulation
2. Financial System
3. Bank
4. Portfolio
5. Trade

Simulation Parameters

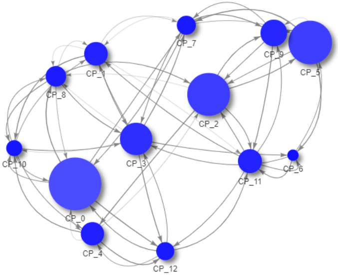
Risk Metric: EEPE (credit risk)
Trade Types: IR/FX Derivatives Number of financial systems: 10
Number of banks in each system: ≤ 50
Number of trades: 2360

1.) Total Impact of Regulation

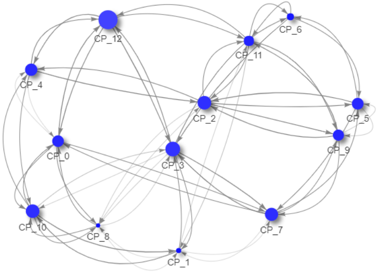


2.) Impact on a Financial System

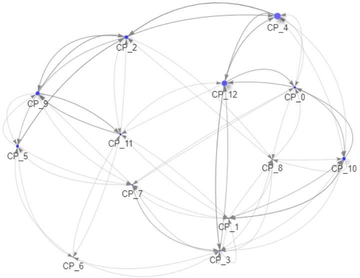
`REG_1 (uncoll.)`



`REG_3 (VM coll.)`



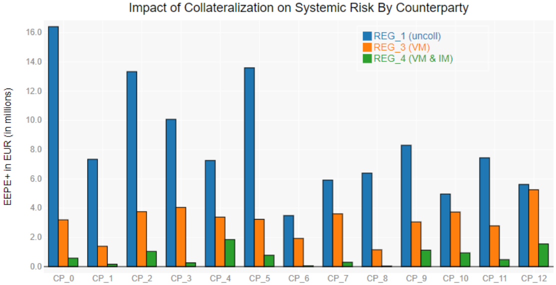
`REG_4 (VM & IM coll.)`



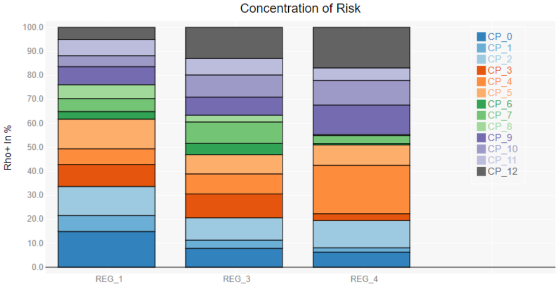
Size of nodes indicates w^+, i.e. absolute risk induced into the financial system.

3.) Impact on Bank Level in a Financial System

Absolute Risk in Example System

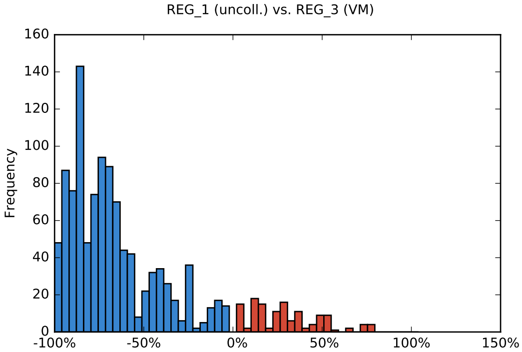


Relative Risk in Example System

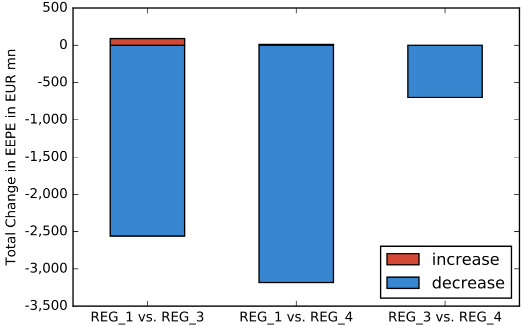


4.) Data Mining Impacts on Portfolio Level

Histogram of Relative Impacts on Portfolios



Absolute Impact on all Portfolios



Conclusion

Results

- Collateralization reduces systemic credit risk significantly (measured in EEPE, i.e. the cost of resolving a failed system).
- Collateralization does not materially change the concentration of credit risk in a financial system.
- In corner cases (deeply out of the money portfolios), VM collateralization can increase credit risk.
- The overall approach is sound.

Future Research

- Large scale simulation
- Dependence on distributions of the trades
- Joint analysis of market, credit, liquidity, operational and model risk
- Initial Margin and Funding Costs
- Derivatives Market vs. Money Market
- Study of central clearing regulation
- Agent based creation of trade relation graphs

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  https://ssrn.com/abstract=3132008

Thanks

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Thank you!

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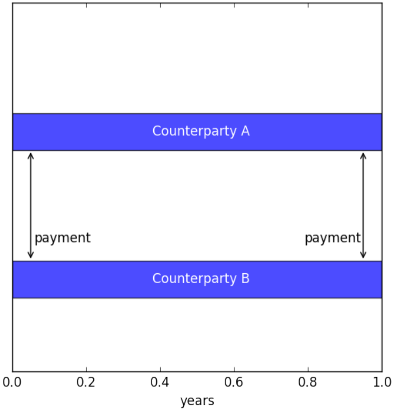
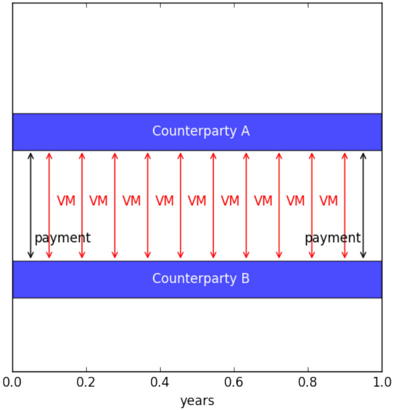
Reg_1: Uncollateralized



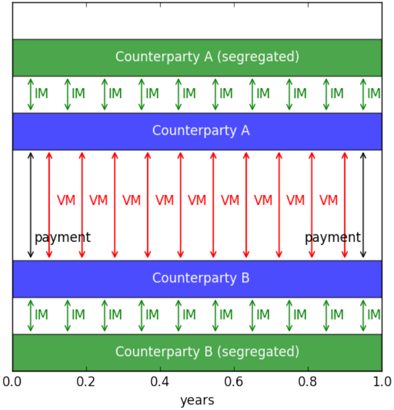
- The value of a derivatives contract stems from payments in the future that are not yet settled.
- Example: An FX Forward is a derivative that pay out $N(FX_T - K)$ at $T > 0$, i.e. it pays out the difference between an exchange rate FX_T (say GBP/USD) prevailing at T (say $T = 1Y$ from now) and a fixed strike rate (say $K = 1.30$) times a notional say $N = 10$ mn).
- A bank that holds a derivative contract that is highly valuable is exposed to the default of its counterparty.
- In case the counterpary default, the derivative is worth nothing and the surviving counterparty incurs a hefty loss.

Reg_3: Variation Margin (VM) Collateralized



- To mititage the credit risk in a derivatives contract, the counterpartys can agree to exchange variation margin (VM).
- In that case, if the derivative has positive value for bank A, then bank B has to pay this amount to bank A (say in cash) as collateral.
- This is updated every day, so if the value of the derivative changes back in B's favour, then A has to pay collateral to B.

Reg_4: Variaiton Margin (VM) and Initial Margin (IM) Collateralized



- Even a fully VM collateralized trade exposes the counterparies to some credit risk: In case of a default the surviving counterparty needs time to close out the position and enter into a new contract with a third party.
- Because the default of a bank causes significant market turmoil, this will take some time, called Margin Period of Risk (MPOR), during which the markets move against the surviving counterparty.
- To mitigate this gap risk, counterparties can agree to post Initial Margin to each other on top of the Variation margin. Despite its name, this also gets re-adjusted potentially daily.