BANK OF ENGLAND

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On the Origins of Systemic Risk

A New Microstructural Approach

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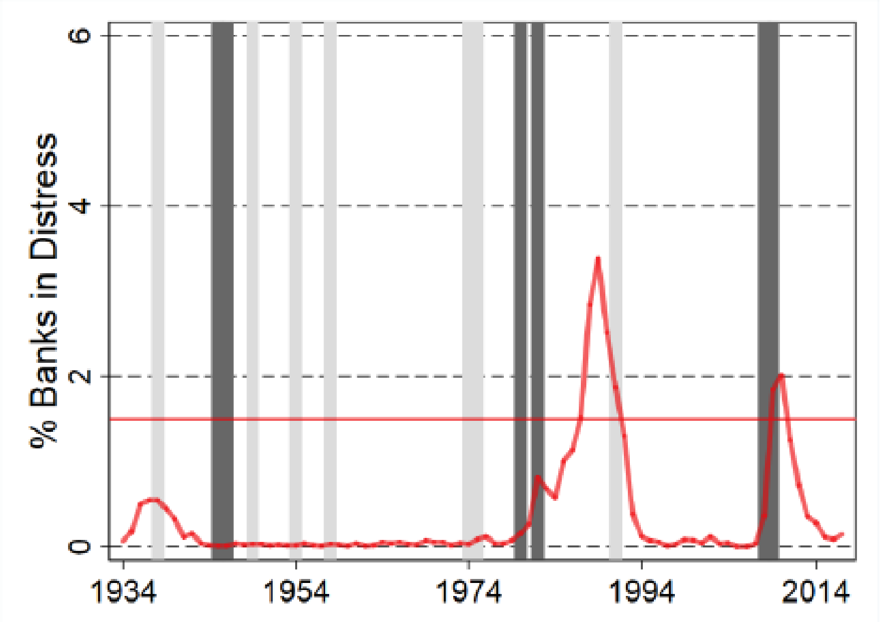
1. Motivation

Motivation

1. **Series of Number of Bank Defaults** ⟶ Binary System

   ➢ Very high correlation among banks default probabilities

   ➢ Very high auto-correlation over time



2. **Definition of Systemic Event in Banking**

   ➢ Time period (quarter or year) where a large number of banks goes simultaneously into distress or default ~ 1.5%

3. **Definition of Systemic Risk**

   ➢ Probability that a systemic event takes place in a year ~ 3.3% (3 events over the last 90 years)

4. **Why Can Systemic Events Happen?** ⟶ Banks' Assets Correlation

   - What are the relevant sources of these events?
   - What is their probability to happen in the future?
   - How can we prevent them?

2. Literature Review

Literature Review

1. Market-based Data

- VAR Models: Alter and Bayer (2013); Diebold and Yilmaz (2009/11) Demirer et al. (2017) and Bassu et al. (2017)
- Price-based Systemic Risk rankings: Demirer et al. (2017) – **VaR**; Adrian and Brunnermeier (2014) – **CoVaR**; Acharya et al. (2010) - **MES**; Acharya et al. (2012) – **SRISK**.
- Price correlations (no actual linkages), reduced sample of banks, no policy exercise.

2. Bank-Balance Sheet Data -> Microstructure of the System

- **Seminal Work:** Allen and Gale (2000), Eisenberg and Noe (2001);
- **Simulated Networks or limited coverage:** Nier et al. (2007), Lu and Zhou (2010), Halaj and Kok (2013), Alter et al.(2014); (AT, DE, IT Interbank Market).
- **Risk Topology:** Battiston et al. (2012), Craig and von Peter (2015), Glasserman and Young (2016);
- **Multilayer:** Kok and Montagna (2013), Bargigli et al. (2015);
- **Liquidity Shock, Fire Sales:** Brunnermeier and Petersen (2009), Gai et al. (2011); Caballero and Simsek (2013); Caccioli et al. (2014); Cont and Schanning (2017).
- **Exogenous Shock:** level of systemic risk conditionally to an exogenous shock hitting the system .

Contribution to the Literature

1. Quantifiable Definition of Systemic Risk
   - Probability of Systemic Event taking place in the next time period (quarter or year)
2. Analytical Model to Decompose Systemic Risk
   - Systemic Risk is a function of: 1) Banks' probabilities of default $\pi_{i,t}$; 2) The dependency structure across such probabilities;
3. Microstructural Model able to Reproduce Endogenously Systemic Crises
   - Stochastic Component: Banks' exposures towards the real economy (NFCs, FCs, and HHs)
   - Deterministic Component: Financial Contagion and Amplification Mechanisms

3. Most Comprehensive Granular Banking Dataset Worldwide
   - Granular Exposures: long-term, short-term and security exposures (Nodes: 13.000; Tot Assets: 22 Tr., Q12015-Q1019)

4. Policy Laboratory
   - Calibration of Capital and Liquidity Requirements

2. Analytical Model

Endogenous Probabilistic Assessment of Systemic Risk

❑ Standard Approach - Exogenous shock:

- Monitor the behaviours of a system in stressed conditions;
- However, it fails to describe the phenomenon of systemic risk in relation to the economic system;
- The distribution of the initial shock is unknown;

❑ Endogenous Systemic Risk:

1. The stochasticity comes from the real economy, i.e. by modelling the loss distribution of banks' exposures towards NFCs, HHs, and FCs (via entity-specific PDs, exposure-specific LGDs and Estimated Correlation Matrix of PDs);
2. While, interbank contagion is a deterministic process acting as a highly non-linear map of the risks coming from the real economy to the realization of systemic events.
3. Allows for probabilistic assessment of systemic events by mean of simulations (and analytical formulas) offering a more complete understandings of the causes and consequences of tail events.
4. Modelling Banks' Asset Correlation (Directly and Indirectly)

Modelling Indirect Banks’ Assets Correlation

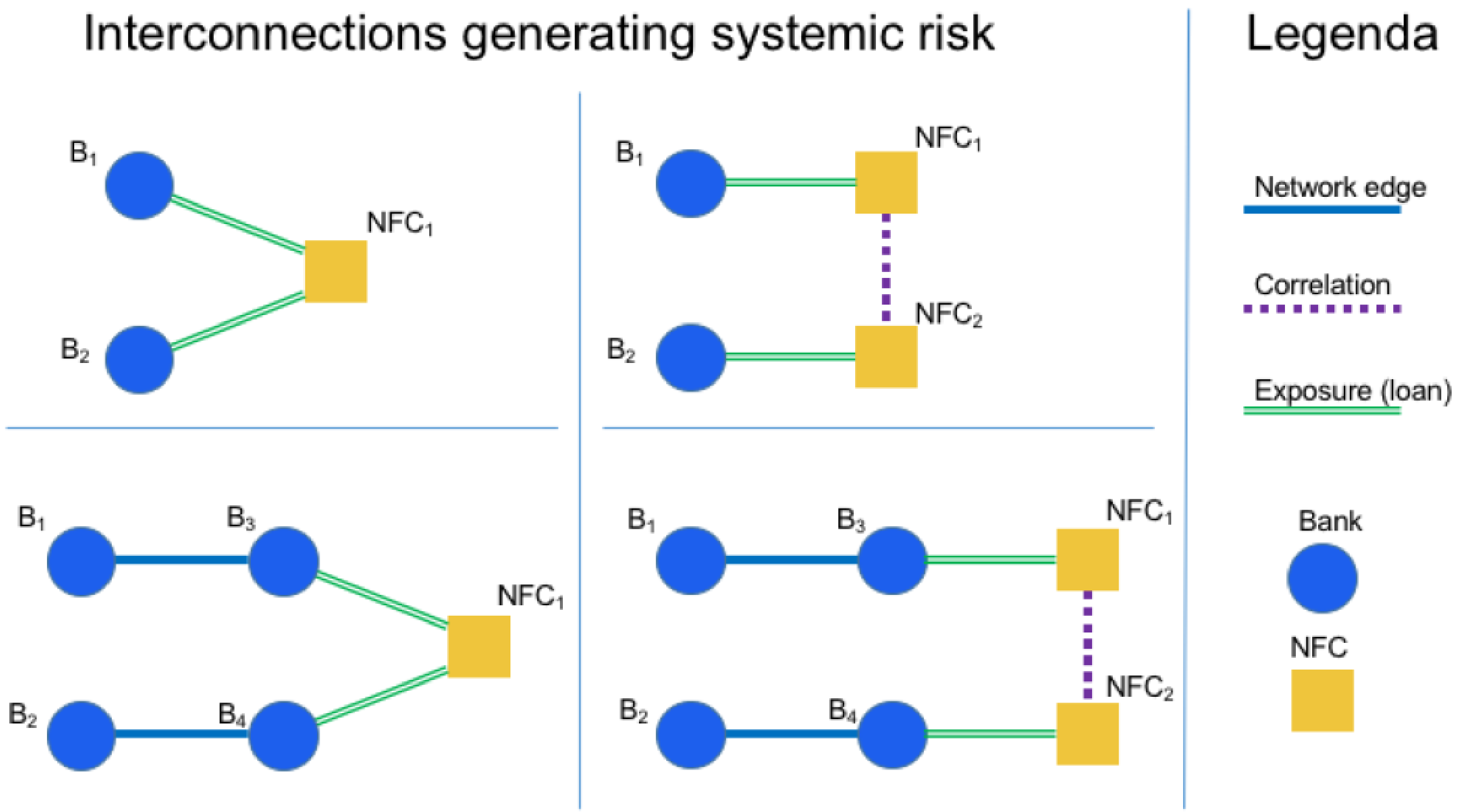


Figure 1. The picture shows graphically the interaction among different determinants that can generate correlation across banks assets in a system with overlapped and correlated exposures, and a network contagion channel.

Analytical Model - Theoretical Approach

- The assets of each bank are modeled as stochastic processes, correlated geometrical Brownian motions that represent the shocks from the real economy as follows:

$$e_{i,t} = \xi_{i,t} + f_i(\mathrm{M}, \xi_{1,t}, \dots, \xi_{i,t}, \dots, \xi_{N,t})$$

- $\xi_{i,t}$ the log return of the process for the real economy with a Gaussian distribution
- f_i is a generic function of the return of all the other assets and the network structure
- M represents the network structure of the banking system

- Assuming the network effects are linear as described by the matrix F, where the element j,i denotes the coefficient for the effect of node j on node i:

- Role of assets' correlations in determining systemic risk
- The interaction among network effects and economic risk

$$\boxed{e_{i,t} = \xi_{i,t} + \sum_{j=1}^{n} F_{ji} e_{j,t},}$$

Analytical Model – Correlation among Banks' Asset Returns

- By solving for e_t , assuming that the matrix $(\mathrm{I}-F)$ is invertible, we obtain:

$$\boxed{e_{i,t} = \sum_{j=1}^{n} S_{ji}\xi_{j,t},}$$

  - S_{ji} maps risks for bank (i) taken from bank (j) due to both direct shocks and network effects.

- The covariances of each couple (e_i, e_j) can be represented as:

$$\mathbb{C}(e_i, e_j) = \mathbb{C}\left(\left(\xi_i + \sum_{k=1}^{N} s_{ki}^{(0)}\xi_k\right), \left(\xi_j + \sum_{k=1}^{N} s_{kj}^{(0)}\xi_k\right)\right)$$

$$\mathbb{C}(\xi_i, \xi_j)+$$

$$\sum_{k=1}^{N} s_{ki}^{(0)} s_{kj}^{(0)} \mathbb{V}(\xi_k) + s_{ii}^{(0)}\mathbb{V}(\xi_i) + s_{jj}^{(0)}\mathbb{V}(\xi_j)+$$

$$\sum_{k=1}^{N}\sum_{l=1,l\neq k}^{N} s_{ki}^{(0)} s_{lj}^{(0)} \mathbb{C}(\xi_k, \xi_l) + \sum_{k=1,k\neq i}^{N} s_{ki}^{(0)}\mathbb{C}(\xi_k, \xi_i) + \sum_{k=1,k\neq j}^{N} s_{ki}^{(0)}\mathbb{C}(\xi_k, \xi_j)$$

- Three components:

1) real-economy shocks;

2) network effects;

3) the interaction term of (1) with (2);

Theoretical Approach - Risk Decomposition

- By standardizing the covariances, we obtain the decomposition of banks' assets correlations:

$$\rho_{ij}^{E} = \mathbb{C}(\xi_i, \xi_j)/\sqrt{\mathbb{V}(e_i)\mathbb{V}(e_j)},$$

$$\rho_{ij}^{N} = \left(\sum_{k=1}^{N} s_{ki}^{(0)} s_{kj}^{(0)} \mathbb{V}(\xi_k) + s_{ii}^{(0)} \mathbb{V}(\xi_i) + s_{jj}^{(0)} \mathbb{V}(\xi_j)\right) / \sqrt{\mathbb{V}(e_i)\mathbb{V}(e_j)},$$

$$\rho_{ij}^{I} = \left(\sum_{k=1}^{N} \sum_{l=1, l\neq k}^{N} s_{ki}^{(0)} s_{lj}^{(0)} \mathbb{C}(\xi_k, \xi_l) + \sum_{k=1, k\neq i}^{N} s_{ki}^{(0)} \mathbb{C}(\xi_k, \xi_i) + \sum_{k=1, k\neq j}^{N} s_{ki}^{(0)} \mathbb{C}(\xi_k, \xi_j)\right) / \sqrt{\mathbb{V}(e_i)\mathbb{V}(e_j)},$$

$$\boxed{\rho_{ij}^{TOT} = \rho_{ij}^{E} + \rho_{ij}^{N} + \rho_{ij}^{I}.}$$

- Simple Analytical model with only two determinants of systemic risk, that is, the correlated shocks from the real economy and the linear network effects.

3. Dataset

Network Composition

Table 1. Summary Statistics for 2018-Q4. Values are reported in trillion euro for columns (3) to (6), while columns (8) and (9) report amounts in euro billion. Granular exposures refer to the exposure amount mapped with exposure-specic information, securities refer to the exposure amount mapped with ISIN information, while aggregate exposures refer to the exposure amount mapped on aggregate sector-country counterparty basis. LGD reports the share of total exposure amount used to impute credit risk losses. AVG edge refers to the average exposure amount per edge, while AVG node reports the average exposure amount per counterparty.

Sector	Edges	Nodes	Gran.	Sec.	Agg.	Tot.	LGD	Avg. edge	Avg. node
CI	8580	1175	3.0	0.6	-	3.6	14%	0.4	3.1
NFC	14497	5866	1.9	0.7	0.9	3.5	22%	0.2	0.6
FC	7762	4324	1.3	0.9	3.6	5.9	10%	0.8	1.4
GOV	4823	1257	2.9	2.0	-	4.8	24%	1.0	3.8
HH	820	297	0.04	-	5.3	5.3	17%	6.5	17.8
Total	36482	12919	9.1	4.3	9.8	23.2	18%	0.6	1.8

The Global Network of Euro Area Banks’ Exposures

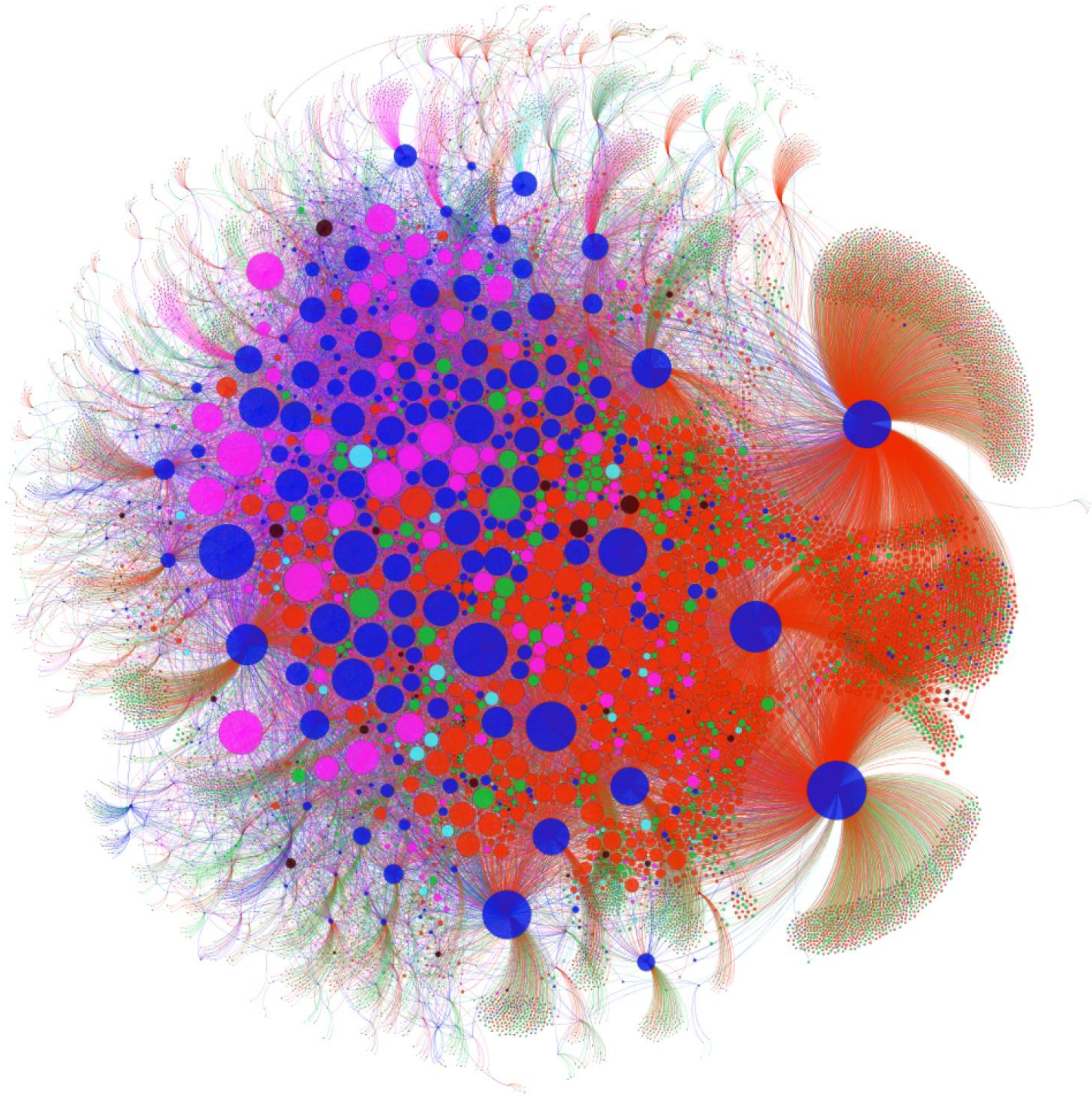
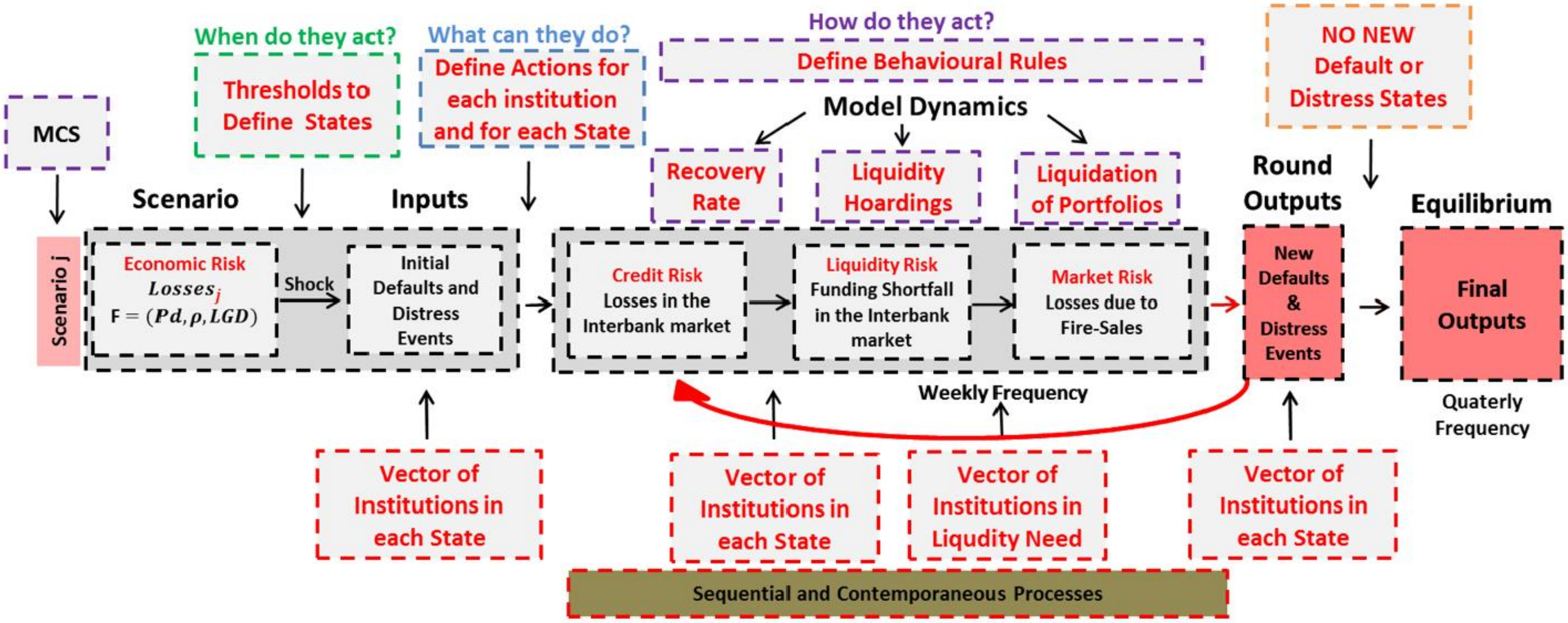


Figure 2. Network of the granular and aggregate exposures captured by our data. The total amount of exposures for 2018-Q4 is Euro 23.2 trillion. The network is built by assigning the eigenvector centrality metrics to the size of the nodes, while the colour of the edges to the node reporting the exposure on the asset side. Blue nodes represent the banking sector, red nodes non-financial corporates, purple nodes the government sector, green nodes the financial corporate sector, and finally the light blue nodes the householdsector.

4. Stochastic Microstructural Multilayer Model

Stochastic Microstructural Multilayer Model



Scenario Uncertainty and Financial Amplification Mechanisms

1. Stochastic process determining the initial vector of banks in default or distress
   - Vector of defaults of economic entities (one for each scenario) derived via entity-specific PDs (Moodys) and a correlation matrix by country and sector of these PDs estimated using NFCs and FCs' CDS spreads correlation;
   - Vector of banks' losses computed using exposure-specific LGD and the vector of defaults derived at point (1);
   - Vector of banks' default and distress events by checking whether real economic losses have breached banks' minimum capital requirements or capital buffers requirements, respectively;
2. Deterministic map of contagion and risk amplification in the banking sector by modelling:
   - Transmission of credit risk losses through long-term exposures
   - Transmission of liquidity risk through short-term exposures
   - Transmission of Market risk through sales of securities
3. Final vector of banks' default and distress events for each scenario
   - Probabilistic assessment of systemic risk: How many events can be classified as systemic?

Systemic Risk Definition

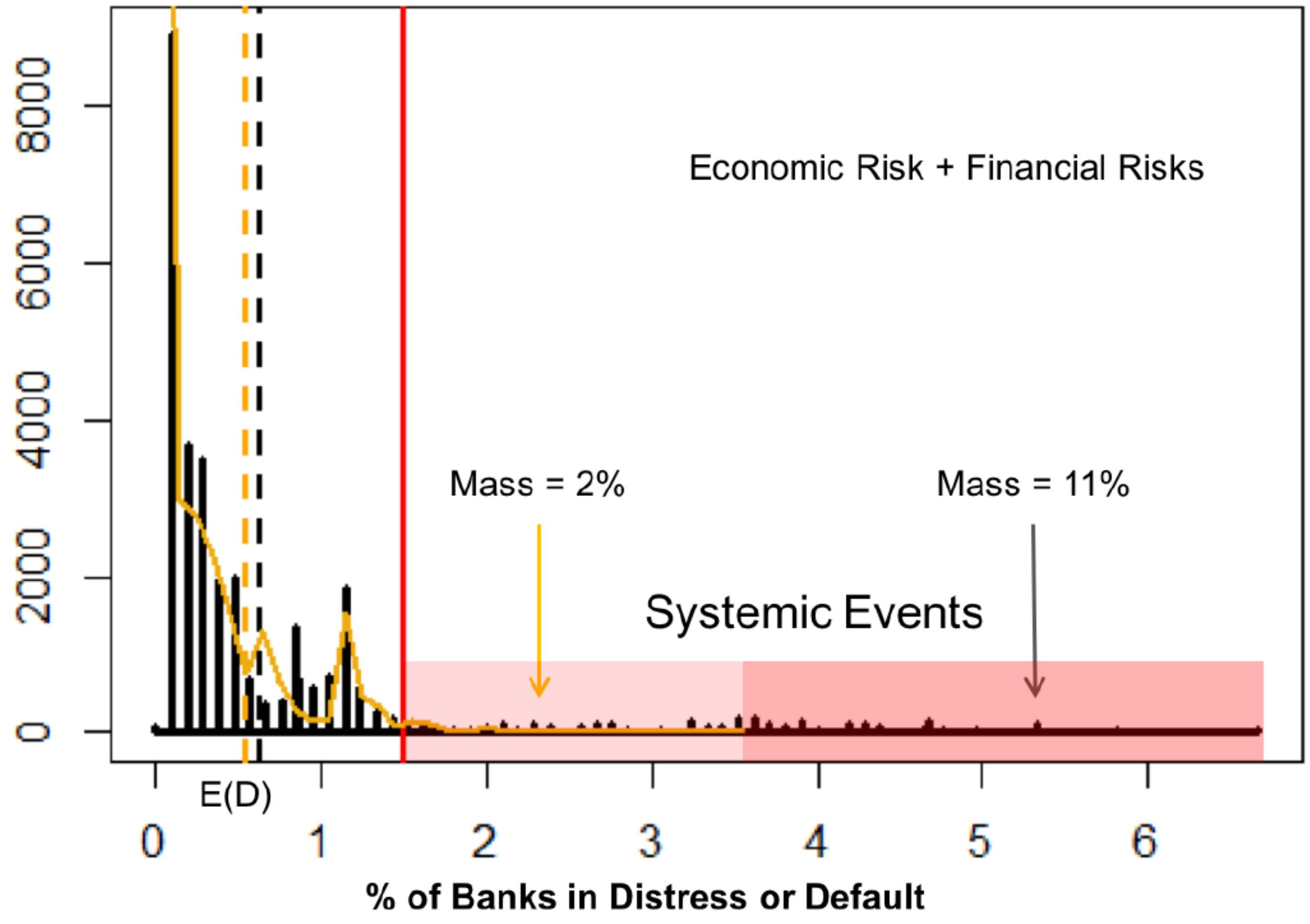
❑ Probability that a systemic event will take place in the next year, derived as the total number of systemic events over the number of simulations.

- N: Number of Banks in the System
- $\pi_{i,t}$: probability a bank i defaults in the period t
- D_t: total number of banks' default at time t
- $\bar{D}$: Systemic Event Threshold (1.5% of N)

$$\boldsymbol{SR} = Pr\left(\frac{D_t}{N} > \bar{D} \middle| \boldsymbol{I}_{t-\Delta t}\right).$$

5. Results

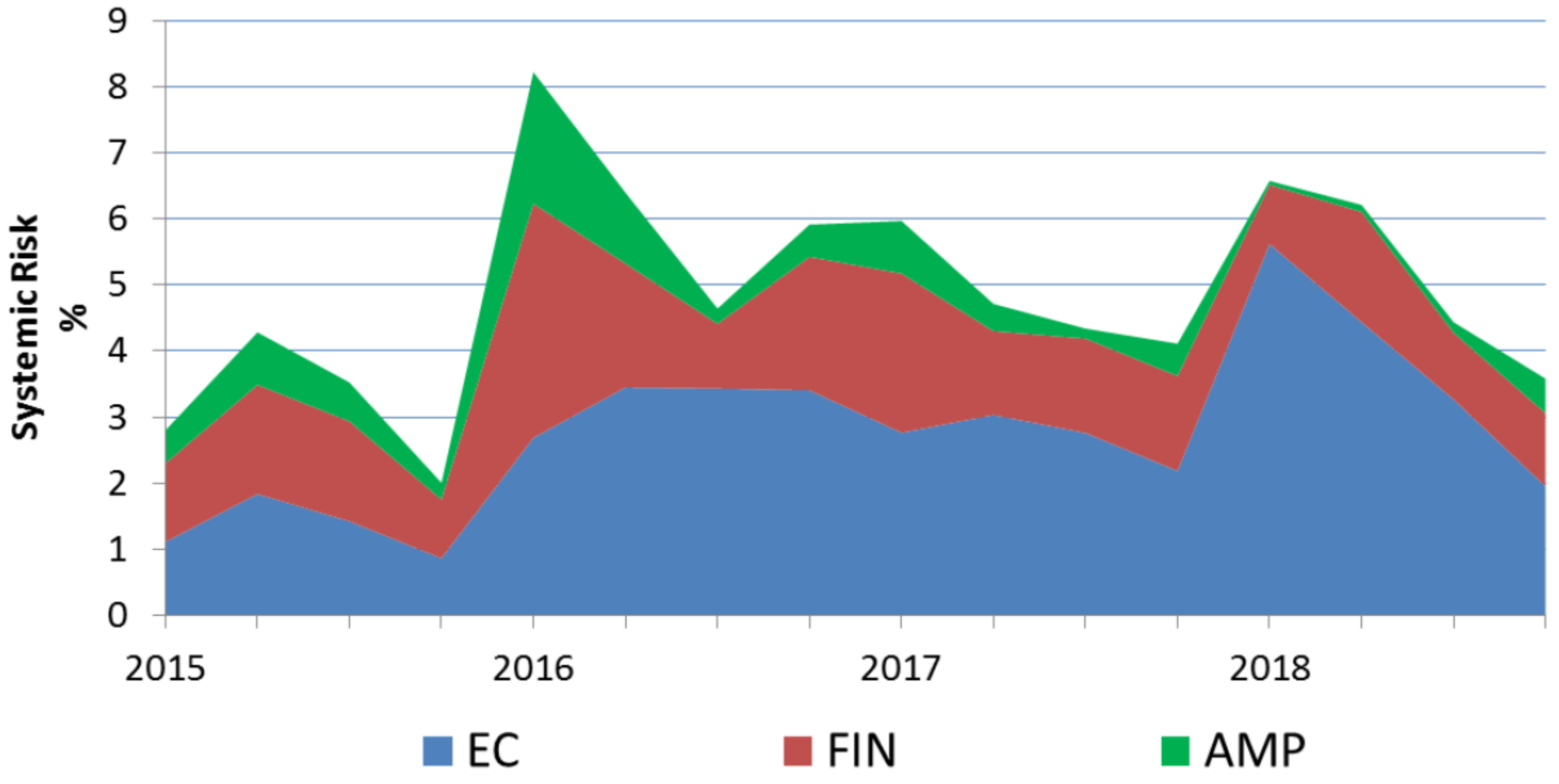
Results (1) – Fatter Tail Distribution due to Financial Contagion



Insight (1):

- Systemic crises can be generated by economic shocks only;
- Financial amplification mechanisms impact much more the tail of the distribution than the mean;
- The number of defaults in the tail as % of total defaults across all simulations (CoVar) is amplified by a factor of 5 by financial amplification mechanisms.

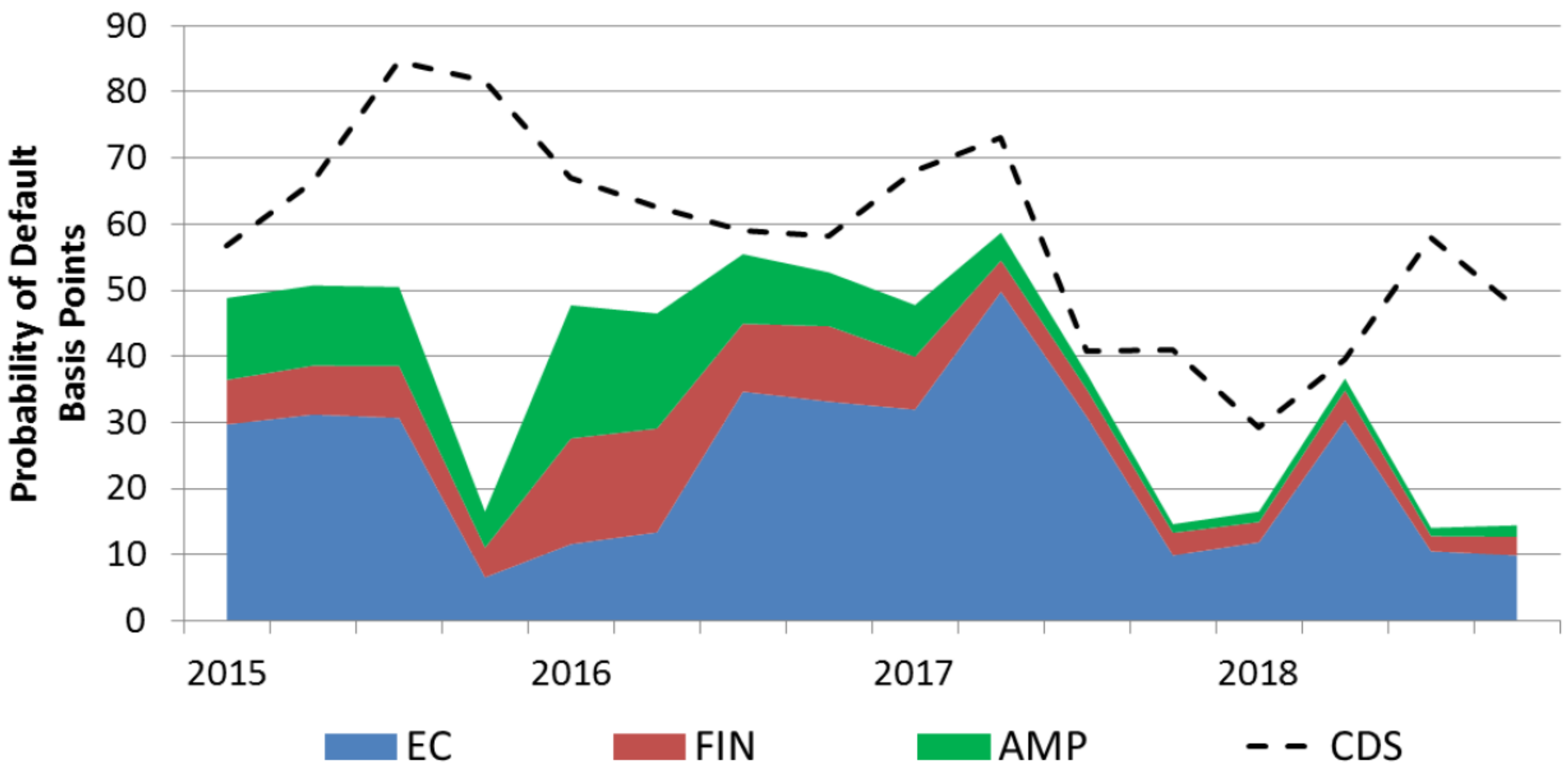
Results (2) – Systemic Risk and its Decomposition



Insight (2)

- Systemic events are strongly affected by financial amplification mechanisms (FIN) and by their interactions (AMP);
- Even with low probabilities of default and during an expansionary cycle, systemic risk seems to be non-negligible;

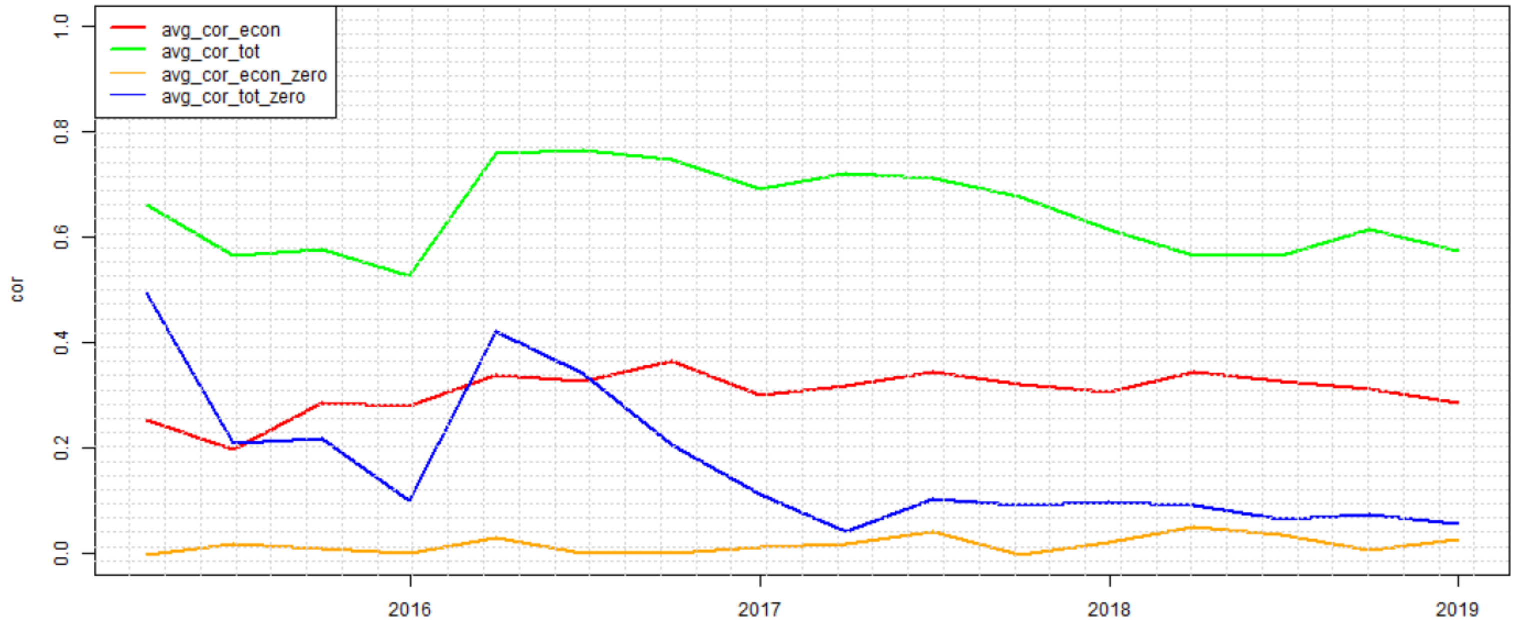
Results (3) – Average Probability of Bank Default



Insight (3)

- Economic losses are the main determinant of banks' default probabilities;
- Average bank PD estimate resembles in trend and level the market estimate of average bank PD proxied by the average bank 5-year senior CDS spread;
- financial conditions matter most in the tail of the distributions as in Adrian et al. 2017;

Results (4) – Correlation among Bank Defaults



Insight (4)

- Correlation among bank's PDs is roughly 40% determined by correlation among real economy shocks, and 60% by financial factors and their interactions with the economic shocks.

Average default correlation for the 15 largest banks in the system. Total refer to the simulation scenario with economic shocks from the real economy and interbank contagion dynamics, while econ. shocks to the scenario without contagion. zero refer to an alternative set of simulation in which the default correlation among non-financial corporation is set to zero. Simulation are repeated for each quarter on the basis of 50,000 runs.

5. Conclusive Remarks

Prudential Policy Applications

- **By mean of counterfactual policy exercises we can study the state of the financial system (banking system) in relation with the economic system.**

- Hence, we can identify the origins of systemic risk:
  1. Potential hot-spots in the real economy triggering the realization of systemic events (at firm/sectoral/geographical level);
  2. Excessive risk-taking in the banking sector via credit, liquidity and market risks;
  3. Fragile or central nodes in the chain of financial relations;
- Allow us to assess the effectiveness of micro and macro prudential regulation in reducing each bank's PD and the overall level of Systemic Risk (considering banks' PDs correlation structure);
- We can monitor the build-up in the real economy or in the financial sector of firms' specific risk.

Conclusion

❑ Stochastic Microstructural Multilayer Stress Testing framework

1. Decompose systemic risk in its components as additive risks via analytical formulas or simulations
2. Able to replicate the event of a financial crisis using real data and a microstructural model.
3. Our estimates of the average banks’ PD resembles the pattern of EA banks CDS prices;
4. Systemic events are generated by amplification mechanisms in the financial sector (Adrian et al. 2017)
5. Flexible to perform counterfactual policy exercises and assess the role of each single institution in the system

❑ Policy implication – Take Away

With such high levels of interdependency among banks' economic and financial losses, regulators targeting the reduction of a bank default probability have very little effects in reducing the probability of experiencing a systemic crisis, that is banks’ joint default probability.

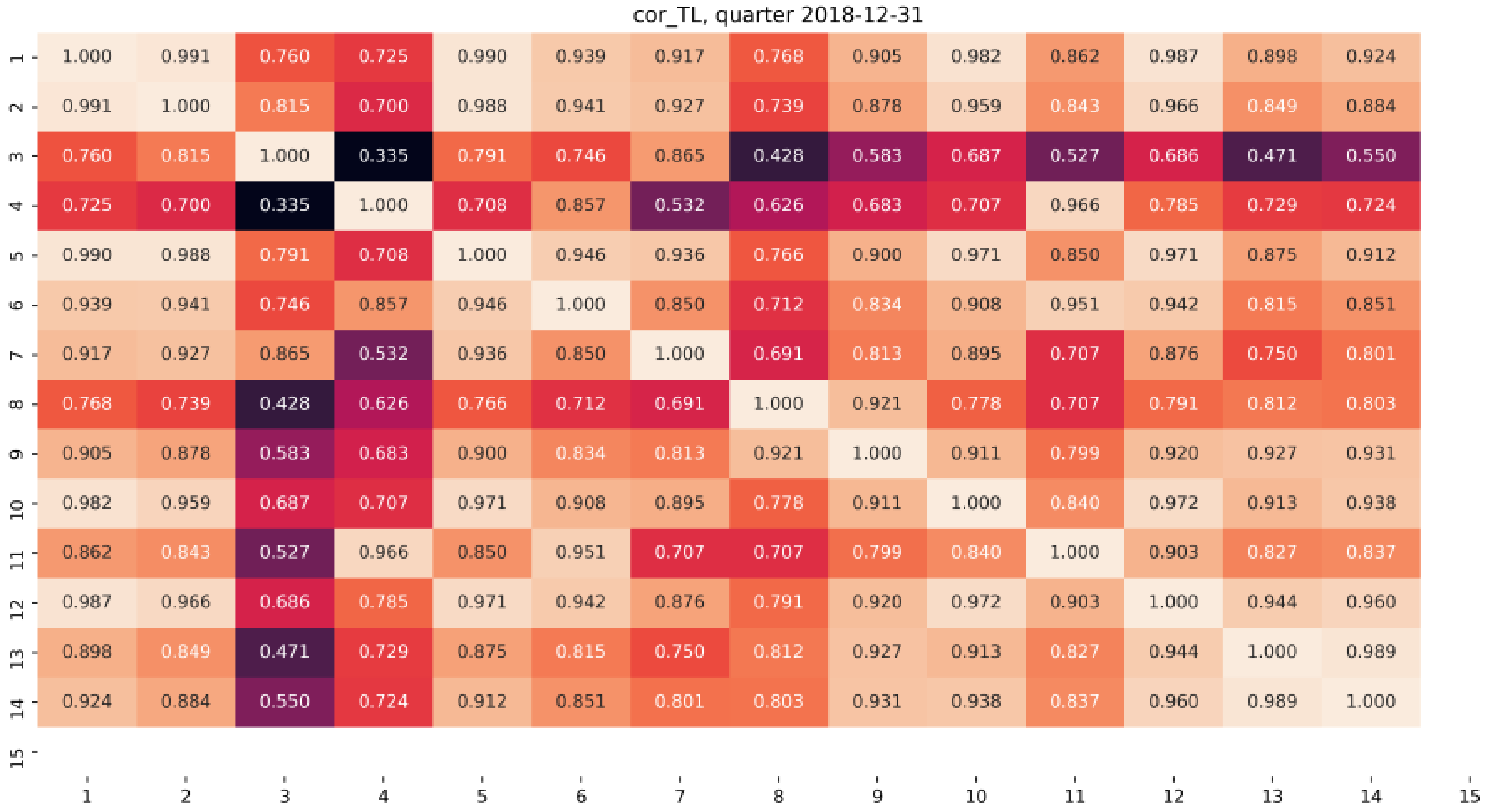
Appendix

Results (5) – Correlation among Bank Defaults

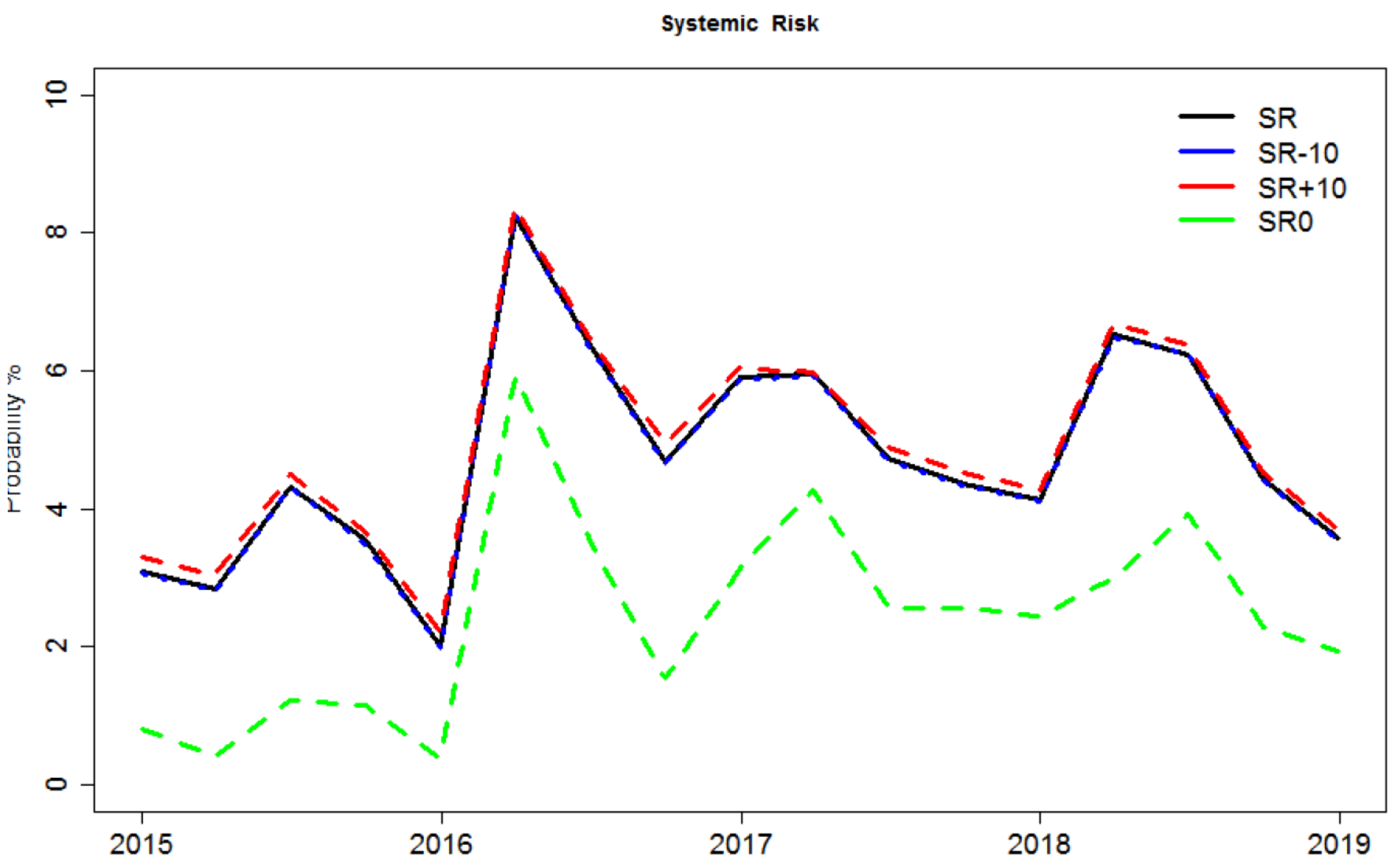
cor_TOT, quarter 2018-12-31

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1.000	0.812	0.845	0.472	0.766	0.796	0.836	0.621	0.787	0.824	0.610	0.865	0.813	0.588	0.621
2	0.812	1.000	0.755	0.429	0.680	0.722	0.726	0.592	0.725	0.726	0.506	0.784	0.726	0.508	0.601
3	0.845	0.755	1.000	0.394	0.747	0.736	0.807	0.541	0.715	0.787	0.500	0.771	0.691	0.462	0.622
4	0.472	0.429	0.394	1.000	0.429	0.638	0.404	0.423	0.461	0.440	0.567	0.534	0.546	0.396	0.300
5	0.766	0.680	0.747	0.429	1.000	0.703	0.725	0.538	0.680	0.722	0.497	0.730	0.704	0.507	0.553
6	0.796	0.722	0.736	0.638	0.703	1.000	0.733	0.598	0.728	0.741	0.653	0.795	0.774	0.553	0.572
7	0.836	0.726	0.807	0.404	0.725	0.733	1.000	0.571	0.728	0.778	0.532	0.758	0.707	0.491	0.614
8	0.621	0.592	0.541	0.423	0.538	0.598	0.571	1.000	0.646	0.568	0.470	0.657	0.676	0.508	0.424
9	0.787	0.725	0.715	0.461	0.680	0.728	0.728	0.646	1.000	0.729	0.544	0.770	0.775	0.583	0.569
10	0.824	0.726	0.787	0.440	0.722	0.741	0.778	0.568	0.729	1.000	0.560	0.792	0.761	0.544	0.582
11	0.610	0.506	0.500	0.567	0.497	0.653	0.532	0.470	0.544	0.560	1.000	0.651	0.637	0.469	0.349
12	0.865	0.784	0.771	0.534	0.730	0.795	0.758	0.657	0.770	0.792	0.651	1.000	0.871	0.650	0.569
13	0.813	0.726	0.691	0.546	0.704	0.774	0.707	0.676	0.775	0.761	0.637	0.871	1.000	0.785	0.528
14	0.588	0.508	0.462	0.396	0.507	0.553	0.491	0.508	0.583	0.544	0.469	0.650	0.785	1.000	0.359
15	0.621	0.601	0.622	0.300	0.553	0.572	0.614	0.424	0.569	0.582	0.349	0.569	0.528	0.359	1.000

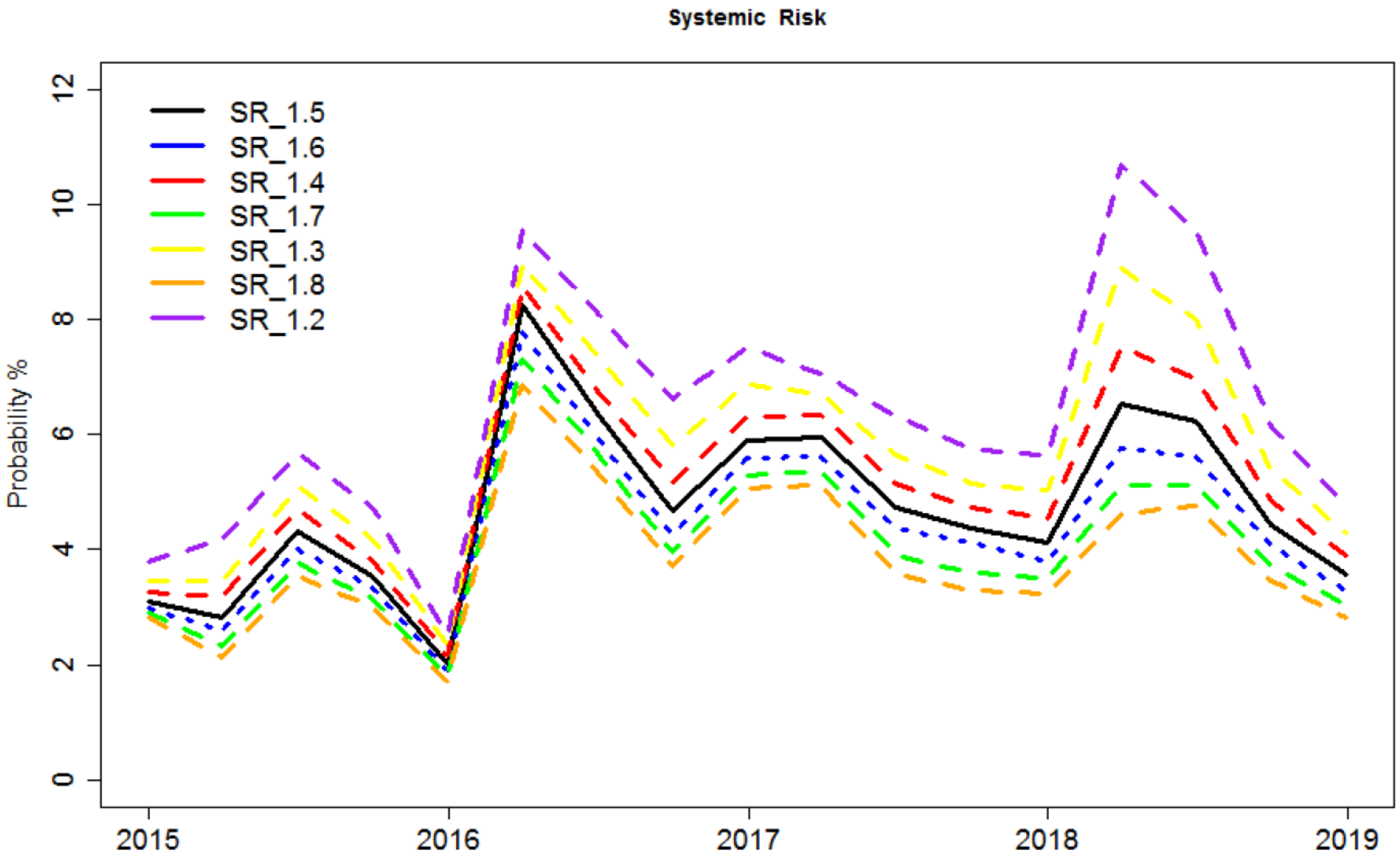
Results (6) – Correlation among Banks’ Total Losses



Robustness (1) – No Correlations among Economic Shocks



Robustness (2) – Variations of Systemic Event Threshold



Robustness (3) – Variations of Number of Simulations