

## Modeling and Pricing Cyber Insurance – Challenges and Perspectives

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(joint work with K. Awiszus, M. Scherer, G. Svindland & A. Voß)

ASTIN & DGVFM: *Aus der Wissenschaft* – November 20, 2023

## Motivation

- In the context of insurance, **cyber** is an umbrella term for all risks in the context of computer systems, hardware, software, data, the internet or other digital networks, any kind of Information Technology (IT) or Operational Technology (OT)
- While the number of **connected devices** was estimated at around 30 billion at the end of the last decade, around 125 billion such devices are expected by 2030
- Operational technologies, the Internet of Things, and also the spread of digital work within networks, e.g. in the home office, increase such risks
- The **Allianz Risk Barometer 2022** ranks cyber risks as the top global business risk for 2022 (cited by 44% of respondents), ahead of business disruption (42%), natural disasters (25%), pandemics (22%) and legal and political risks (19%)<sup>1</sup>
- Estimated<sup>2</sup> annual damage caused by cyber risks worldwide increases with USD 445 billion in 2014, USD 600 billion in 2018, and USD 1000 billion in 2020
- MunichRe estimates global **insurance premiums** at USD 5 billion in 2018 with an increase to USD 20 billion in 2025, with 50% in the USA and 25% in Europe

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<sup>1</sup>The 6th to 10th places are occupied by climate change, fire & explosions, market uncertainty, a shortage of skilled labour and macroeconomic developments.

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# Dimensions of Cyber Risk

## 1 Risks

- ▶ Lost, stolen or corrupted data
- ▶ Disruption of processes / operations / critical infrastructure
- ▶ Physical damage, injury to people and fatalities

## 2 Causes

- ▶ Human errors
- ▶ Technical failures
- ▶ Insider or hacker attacks

## 3 Risk Management

- ▶ Protection of computers and networks
- ▶ Contingency plans
- ▶ Insurance of residual risks

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## Cyber Insurance



Coverage is offered<sup>3</sup> in the following areas:

- 1 **Loss or theft of data**
- 2 **Privacy breach protection**
- 3 **Cyber extortion**
- 4 **Property damage**
- 5 **(Contingent) business interruption**
- 6 **Product liability**
- 7 **Reputational damage**
- 6 **Loss of intellectual property**

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<sup>3</sup>Source: MunichRe, 2021



# Outline

- 1 Actuarial Challenges
- 2 The Role of the Network – Illustrative Toy Models
- 3 Future Research

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# Actuarial Challenges of Cyber Risk

## 1 Data

- ▶ Data are **not yet available** in the desired amount or granularity

## 2 Non-Stationarity

- ▶ Technology and cyber threats are evolving fast and are **constantly changing**

## 3 Dependence, Contagion in Networks & Externalities

- ▶ The classical insurance independence assumption does not hold. Moreover, there is **no simple geographical distinction** between dependent groups – as, for example, in the case of NatCat
- ▶ In contrast, some forms of cyber risk are contagious and governed by **complex interactions in networks**
- ▶ Individual investments in cyber security affect the cyber security of the system; for certain risks, these externalities might be substantial

## 4 Information Asymmetries

- ▶ Insurers cannot fully observe investments in cyber security and risk levels
- ▶ In particular, due to **moral hazard** of policy holders in combination with network externalities, cyber insurance might decrease the overall level of cyber security

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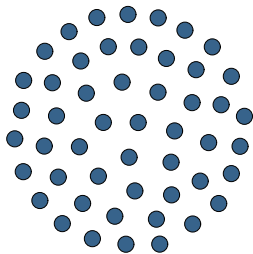
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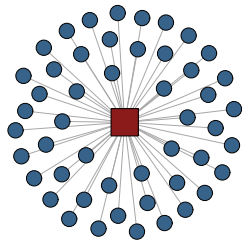
## Types of Cyber Risk

The suitability of a modeling approach depends on the **type of cyber risk**



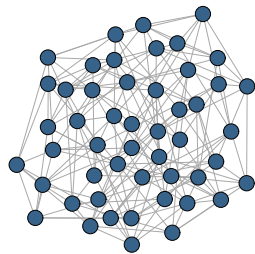
### idiosyncratic

(individual risks,  
e.g., targeted hacker attacks, errors,  
distortions)



### systematic

(common risk factor,  
e.g., attacks on widely used software or  
hardware)



### systemic

(propagation risks,  
e.g., viruses, worms,  
Trojans)

## Selected Approaches

### 1 Frequency-Severity-Models

#### ▶ Characteristics

- 1 Conditional on risk factors, frequency-severity models can also be applied in the area of cyber risks; however, usually not enough data are available
- 2 Suitable for idiosyncratic and systematic risks, but not for systemic risks without further modifications

★ Zeller, G., Scherer, M. (2022): A comprehensive model for cyber risk based on marked point processes and its application to insurance, *European Actuarial Journal*, 12(1), 33-85

### 2 Information Asymmetries

#### ▶ Core topics

- 1 Strategies to reduce information asymmetries, for example, by optimizing offerings and contract design (menu of contracts, cyber assistance)
- 2 Regulation to strengthen physical cybersecurity in the face of network externalities (see also below)

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### ③ Systemic Cyber Risks

#### ▶ Local interaction

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- ★ K. Awiszus, Y. Bell, J. Lüttringhaus, G. Svindland, A. Voß & S. Weber (2023): Building Resilience in Cybersecurity – An Artificial Lab Approach. To appear in: *Journal of Risk and Insurance*

#### ▶ Feedback in point processes

- ★ Y. Bessy-Roland, A. Boumezoued & C. Hillairet (2020): Multivariate Hawkes process for cyber insurance, *Annals of Actuarial Science*, 15(1), 1-26
- ★ C. Hillairet, A. Reveillac & M. Rosenbaum (2023): An expansion formula for Hawkes processes and application to cyber-insurance derivatives, *Stochastic Processes and their Applications*, 160, 89-119

#### ▶ Interaction on a macroscopic level

- ★ C. Hillairet & O. Lopez (2021): Propagation of cyber incidents in an insurance portfolio: counting processes combined with compartmental epidemiological models, *Scandinavian Actuarial Journal*, 8, 671-694

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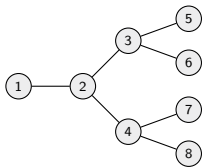
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## The Role of the Network

- **Systemic cyber risk** is significantly influenced by the underlying network; important “covariate”
- Examples include **cryptoworms like WannaCry**
- We take a closer look at the role of **security investments** in cyber networks and **modifications of the network**
- **Welfare-optimal actions** are often not achieved by the rational behavior of individual agents in the presence of **externalities**
- **Regulatory requirements** or **requirements in insurance contracts** may trigger additional security investments; in our paper, we evaluate and compare — in cooperation **with legal experts** (Y. Bell, J. Lüttringhaus) — cyber lab case studies to current insurance practice and regulation
- Suitable **centrality measures** for entities in networks evaluated by questionnaires can also enter **insurance pricing**



$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \end{pmatrix}$$

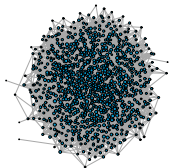
## Random Network Models

### Random Graphs Erdős-Rényi Model, 1959

$N$  nodes in which each of the possible  $N(N-1)/2$  edges is independently present with the **same probability**  $p$   
 → **Binomial distribution** of node degrees  $K$ , approximately **Poisson** for large  $N$  in the limit of fixed average degree  $(N-1)p \approx Np =: \mathbb{E}[K]$ :

$$P(K = k) = e^{-\mathbb{E}[K]} \frac{\mathbb{E}[K]^k}{k!}$$

→ **homogeneous** topology with nodes of comparable degrees



### Scale-Free Networks Barabási-Albert Model, 1999

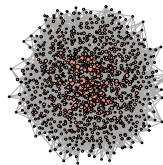
Modelling **growing** networks under **preferential attachment** (world wide web, IT networks, social and biological networks)

→ Distribution of node degrees  $K$  follows a **power-law**:

$$\mathbb{P}(K = k) \sim k^{-\lambda}, \quad \lambda \in \mathbb{R}_+$$

Special case  $\lambda = 3$  can be modeled using the Barabási-Albert model

→ **heterogeneous** topology with few nodes of high degree (called **hubs**), and a vast majority of less connected nodes



## Network Contagion: SIS and SIR Model

For a network of  $N$  nodes, the spread process at time  $t$  can be described by a *state vector*

$$X(t) = (X_1(t), \dots, X_N(t)) \in E^N$$

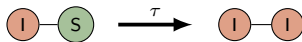
- **Node states:** at each point in time, individuals are either *susceptible* ( $S$ ) to an infection, *infected* ( $I$ ), or have *recovered* ( $R$ )  
 → **SIS Model:**  $E = \{S, I\}$ , **SIR Model:**  $E = \{S, I, R\}$
- Models differ in terms of **immunity:** multiple infections for the same node possible for SIS, ruled out in case of SIR
- Markov process with the following rates for **infection** and **recovery** of single nodes  $i$ :

$$X_i : S \rightarrow I \quad \text{with rate} \quad \tau \sum_{j=1}^N a_{ij} \mathbb{1}_{\{X_j(t)=I\}}$$

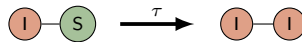
$$X_i : I \rightarrow Z \quad \text{with rate} \quad \gamma_i,$$

where  $Z = S$ , for the SIS, and  $Z = R$  for the SIR model, respectively

→ **Modeling parameters:** **infection rate**  $\tau$ , **recovery rates**  $\gamma_i$



(a) SIS Model



(b) SIR Model

## Security Investments and Strategic Interactions

- We study the interplay of **security investment decisions of network agents** and the overall **systemic risk exposure**  
→ Individual recovery rate  $\gamma_i$  is interpreted as **security level** of node  $i$
- **Investment decision of network agent  $i$**  based on **total expenses** of node  $i$ :

$$\mathcal{E}_i(\gamma_1, \dots, \gamma_N) = C_i(\gamma_i) + L_i(\gamma_1, \dots, \gamma_N)$$

- ▶  $C_i(\gamma_i)$  is the cost of implementing security level  $\gamma_i$  → choice:  $C_i(x) = \exp(kx) - 1$ ,  $x \in (0, \infty)$ ,  $k > 0$  const
- ▶  $L_i(\gamma_1, \dots, \gamma_N) = \mathbb{E}[\int_0^\infty I_i(t) dt]$  expected amount of time node  $i$  will be infected → **interdependence**

$\gamma_i$  is **individually optimal** for node  $i$ , if it minimizes the total expenses  $\mathcal{E}_i$ :

$$\gamma_i^{\text{ind}}(\gamma_{-i}) := \underset{\gamma_i \in [0, \infty)}{\operatorname{argmin}} \mathcal{E}_i(\gamma_1, \dots, \gamma_N) \quad \gamma_{-i} := (\gamma_1, \dots, \gamma_{i-1}, \gamma_{i+1}, \dots, \gamma_N)$$

- A **steady state (Nash equilibrium)** of individually optimal security levels is a choice of security levels  $\gamma \in (0, \infty)^N$  such that

$$\forall i = 1, \dots, N : \quad \gamma_i^{\text{ind}}(\gamma_{-i}) = \gamma_i$$

Steady states of individually optimal security levels exist



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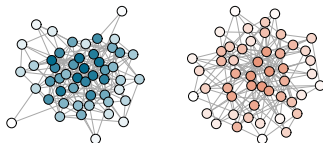
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## Public and Private Regulation



Visualization of steady states for exemplary networks drawn from the Erdős-Rényi (left) and Barabási-Albert (right) classes. Nodes are colored according to their chosen level of security after round 50 of the security investment game: the darker the color, the higher the chosen security level (for Erdős-Rényi: minimum: 0.3780, maximum: 0.6526; for Barabási-Albert: minimum: 0.4719, maximum: 0.7598).

- A Nash equilibrium is not necessarily Pareto optimal
- System perspective: **total network expenses** given by

$$\mathcal{E}(\gamma_1, \dots, \gamma_N) = \sum_{i=1}^N \mathcal{E}_i(\gamma_1, \dots, \gamma_N) = \underbrace{\sum_{i=1}^N C_i(\gamma_i)}_{\text{total cost of sec.}} + \underbrace{\sum_{i=1}^N L_i(\gamma_1, \dots, \gamma_N)}_{\text{total exp. infection time}}$$

- **Question:** Given a steady state of individually optimal security levels, is it possible to reduce the total expenses by increasing the total security investments  $\sum_{i=1}^N C_i(\gamma_i)$ , and thus in particular the total expected infection time?
- **Answer:** In the considered case, **yes!**

## Allocation of Additional Security

- **Idea:** Given a steady state  $(\gamma_1^{stead}, \dots, \gamma_N^{stead})$  of individually optimal security levels, distribute **additional** security  $\beta > 0$  among the nodes
- **Untargeted allocation** new security levels  $\gamma_i^{stead} + \beta/N$
- **Targeted allocation:** importance of node  $i$  corresponds to centrality of node  $i$ , e.g.,
  - ▶ **Degree centrality:** Nodes are ranked by the number  $C^{deg}(i)$  of neighbors
  - ▶ **Betweenness centrality:** Node as “bridge” between different network regions:

$$C^{bet}(i) = \sum_{j,h} \frac{\sigma_{jh}(i)}{\sigma_{jh}}, \quad i = 1, \dots, N,$$

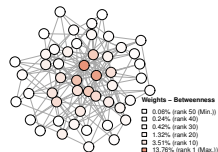
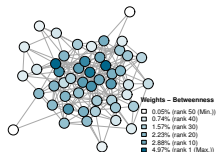
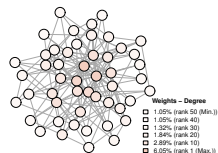
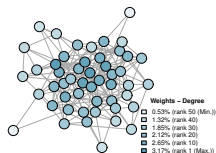
where  $\sigma_{jh}$  denotes the total number of shortest paths between nodes  $j$  and  $h$ , and  $\sigma_{jh}(i)$  is the cardinality of the subset of those paths that go through node  $i$

Choose a centrality measure  $\mathcal{C}$  and determine the **allocation weights**

$$w_i := \frac{\mathcal{C}(i)}{\sum_{j=1}^N \mathcal{C}(j)}, \quad i = 1, \dots, N$$

Budget  $\beta$  is allocated proportionally to the centrality, i.e.,  $\gamma_i^{all} := \beta \cdot w_i$

## Allocation of Additional Security (2)

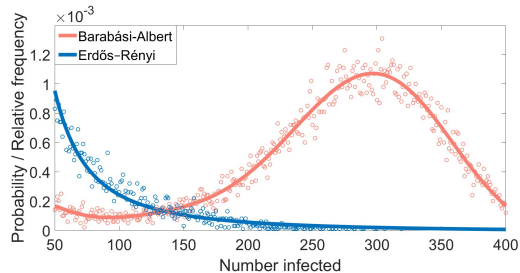


$c^{deg}$		$c^{bet}$		untargeted	
10.6%	11.3%	10.8%	12.3%	9.9%	9.0%

Percental reduction of accumulated total expenses  $\mathcal{E}$  after the allocation of the additional budget  $\beta = 5$  among all network nodes. Erdős-Rényi network is colored in blue, Barabási-Albert network in red.

## Cyber Pandemic Risk in Large-Scale Systems

- In large-scale networks, the frequency distribution of epidemic outbreak sizes in the SIR model can typically be characterized by the presence of two peaks (see, e.g., Kiss et al. (2017): *Mathematics of Epidemics on Networks*):
  - ▶ **small outbreaks**, affecting only a very small fraction of network nodes, and
  - ▶ **epidemic outbreaks** or **pandemics**, where a large number of nodes becomes infected
- The **network topology** has a major effect on the occurrence of pandemic outbreaks



**Figure:** Final outbreak size frequencies given an infection of a single network node for Barabási-Albert and Erdős-Rényi networks with  $N = 1,000$  and other parameters such that a similar number of total edges is generated. Epidemic parameters are chosen as  $\tau = 0.1$  for the infection rate, and  $\gamma_i = 1$  for all recovery rates.

# Topological Interventions and Network Functionality

- **Topological Interventions**

- ▶ **edge removal**

- ★ *physical deletion of certain connections*, or if not possible,
- ★ *edge hardening*, which corresponds to strong protection of network connections via firewalls, the closing of open ports, or the monitoring of data flows using specific detection systems

- ▶ **node splitting** to separate critical contagion channels replacing them by multiple nodes with the same operational task

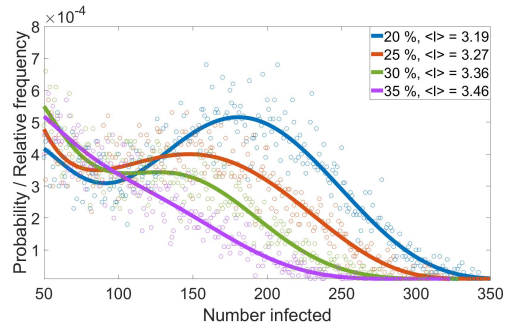
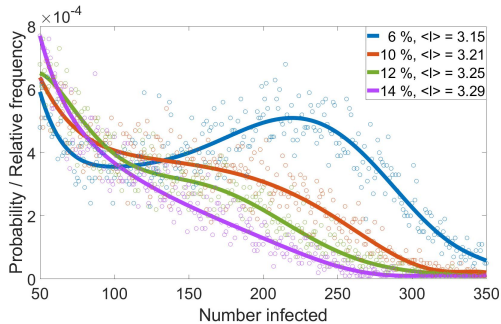
→ Topological interventions affect both the **risk exposure** and the **functionality** of the network

- **Network Functionality** could be measured by the **average shortest path length**:

$$\langle l \rangle = \sum_{i \neq j} \frac{1}{N(N-1)} l_{ij}$$

where  $l_{ij}$  is the minimum number of edges connecting  $i$  and  $j$  → small  $\langle l \rangle$  corresponds to fast and efficient data flow

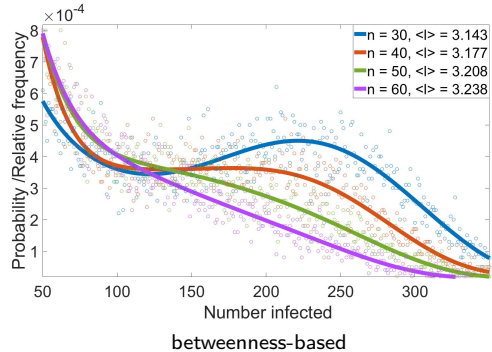
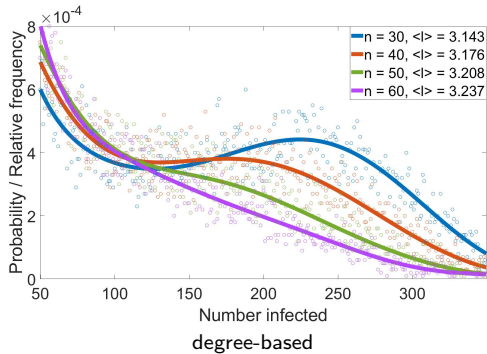
## Effect of Edge Removal



**Figure:** Final outbreak size frequencies given an initial infection of a single node in a Barabási-Albert network with  $N = 1,000$ , over 100,000 simulations for different percentages of deleted edges. The results for **edge centrality-based** removals are depicted in the **left figure**, and the percentage of critical links is found to be about 14%. In contrast, **random edge removals** are shown in the **right figure**, and this procedure is clearly less effective: Approximately 30-35% of edges need to be removed here to eliminate the risk of cyber pandemics. **The initial  $\langle I \rangle$  was 2.95.**



## Effect of Node Splitting



**Figure:** Final outbreak size frequencies given an initial infection of a single network node in the previously considered Barabási-Albert network, over 100,000 simulations for different numbers of splitted nodes. For degree-based splittings, the number of critical splits is found to be about  $n = 60$  which corresponds to 6% of the nodes. Similar results in case of betweenness centrality based splits. **The initial  $\langle I \rangle$  was 2.95.**

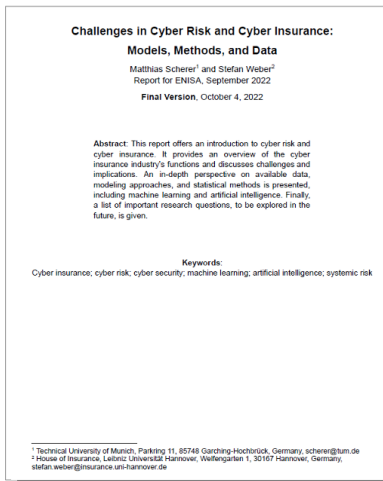
## Lessons Learnt from the Toy Examples

- Cyber security and resilience is significantly influenced by contagious transmission channels in digital networks
- Substantial externalities are observable in cyber network toy models
- Besides governments, also insurance companies might act as private regulators
- Centrality measures are important covariates for cyber pricing
- Qualitative implications are:
  - ▶ Cybersecurity measures can mitigate cyber losses:
    - ★ GOV: size-cap rule (in good agreement with EU-NIS2), supply chain protection (beyond most central entities)
    - ★ INS: assistance services (identification when important, effective resource allocation), patch management and backup (centrality captures when to invest more than individually rational amount)
  - ▶ Topological cyber resilience measures can reduce the risk of contagious scenarios:
    - ★ GOV: incident response and reporting (focus on central entities, early warning systems), critical supply chains (risk of contagion, improving resilience)
    - ★ INS: contact liability premiums, insurance backstop mechanism (incentives for more resilient network structures)

# Outline

- 1 Actuarial Challenges
- 2 The Role of the Network – Illustrative Toy Models
- 3 Future Research**

# Research Challenges and Perspectives for Cyber Insurance



The following research opportunities are detailed in Chapter 8 of the ENISA report mentioned above

## Research Challenges and Perspectives for Cyber Insurance

- 1 Improving the process of cyber risk assessment
- 2 Identifying relevant covariates
- 3 Modeling & estimating loss frequency & severity
- 4 Modeling of systemic risk in network models
- 5 Modeling dynamic strategic interaction
- 6 Understanding multilayer networks
- 7 Pricing idiosyncratic, systematic, & systemic risk
- 8 Data for systemic cyber risk
- 9 Adapting existing ML methods to the specific stylized facts of cyber
- 10 Estimation of models for cyber risk (e.g. combining statistical estimation and expert opinion)
- 11 Cyber assistance
- 12 Hedging accumulation risks
- 13 Cyber risk as an asset class
- 14 Closing the cyber-insurance gap
- 15 Optimal contract design
- 16 Behavioral challenges
- 17 Cyber insurance for private customer segment
- 18 Resilience of systems
- 19 Robustness of models
- 20 Data collection
- 21 Welfare and regulatory implications
- 22 Explainable AI for cyber risk
- 23 Vision: Autonomous cyber risk management

## Selected Challenges

### Data

- To date, only limited amounts of data are accessible for research, and their quality also has to be enhanced
- We advocate government incentives and regulatory interventions to enable a database that can allow Europe to be competitive in cybersecurity

### Models

- Innovative models need to be developed – both pragmatic models that can be used as proxies in practice and models that capture the main classes of cyber risk, idiosyncratic, systematic and systemic risks

### Insurance products and markets

- Coupling cyber insurance with cyber assistance and optimal contract design are important topics, as are strategies to close the cyber insurance gap
- How to design standardised cyber insurance for private customers is an open question

### Societal and regulatory implications

- The impact on welfare needs to be explored in more detail
- Guided by research results, governmental actors should select the guardrails in a manner that strengthens both the functionality and security of cyber networks and establish resilient structures; insurance companies can in addition function as private regulators

## References

### This qualitative cyber network analysis is based on

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- 2 Auxiliary references
  - ▶ M. Fahrenwaldt, S. Weber & K. Weske (2018): Pricing of Cyber Insurance Contracts in a Network Model, *ASTIN Bulletin*, 48(3), 1175-1218
  - ▶ A. Barabási & M. Pósfai (2016): *Network Science*, Cambridge University Press
  - ▶ I.Z. Kiss, J.C. Miller & P.L. Simon (2017): *Mathematics of Epidemics on Networks*, Springer
  - ▶ M. Newman (2018): *Networks*, 2nd ed., Oxford University Press

### Survey Papers

- 1 K. Awiszus, T. Knispel, I. Penner, G. Svindland, A. Voß & S. Weber (2023): Modeling and Pricing Cyber Insurance – Idiosyncratic, Systematic, and Systemic Risks, *European Actuarial Journal*, 13(1), 1 - 53
- 2 M. Dacorogna, & M. Kratz (2023): Managing cyber risk, a science in the making. *Scandinavian Actuarial Journal*
- 3 M. Scherer & S. Weber (2023): Challenges in Cyber Risk and Cyber Insurance: Models, Methods and Data. To appear in: *Annual Research and Innovations Briefs*, ENISA

**Thank you for your attention!**