# Cyber-insurance: an actuarial approach

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18 mars 2019



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#### Cyber-risk and insurance

- CESIN (annual barometer for cyber-security):
  - 80% of organisations were targeted by at least one cyber-attack in 2018,
  - with damages (like business interruption) more significant than in 2017.
- Cyber-insurance (Opinion Way for CESIN in 2017):
  - 40% of organisations had subscribed (25% in 2016),
  - 37% were in the process of subscribing or willing to (17% in 2016).



# How to evaluate risks for cyber-insurance ?

 Basics of insurance pricing: if we want to equalize (in expectation) the engagements of the policyholder (premium π) and of the insurer,

$$\pi = E[N]E[X],$$

where N is the number of claims (E[N] = "frequency") and X is the cost of a claim ("severity"), assuming that X and N are independent.

■ If we want to perform reserving, we must understand the whole distribution of *N* and *X*.



## Adverse selection, moral hazard

- Asymmetry of information: (potential) policyholders have better knowledge of their risk than the insurer.
- More precisely :
  - People who already experienced the risk are more likely to buy insurance.
  - Existence of potential changes of behaviors after subscription (the policyholder replaces a "physical" protection by an insurance protection).
- Also absence of reporting of some claims.



# Specificities of cyber-risk

- With cyber-risk, these phenomena are aggravated and are more complex than for traditional risks.
- Examples:
  - absence of reporting of small claims (because they are undetected or with small impact)...
  - ... but also potential absence of reporting of large claims (because of reputation issues).



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  - ... but also potential absence of reporting of large claims (because of reputation issues).
- Changes through time in the reporting behavior, due to regulation and evolutions in the perception of the risk.
- Missing information is particularly important because of the relative lack of data on a new risk.



#### Data

- Internal data must be completed by external data because of the novelty of the risk.
- Problem: the number of registered events in the database depends on the exposure.
- In other words, increase of the number of cyber events may be caused by the increase of entities reporting, but not by a true evolution of the risk.



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- Problem: the number of registered events in the database depends on the exposure.
- In other words, increase of the number of cyber events may be caused by the increase of entities reporting, but not by a true evolution of the risk.
- Exposure is hard to track for public databases.



# Outline

#### 1 Introduction

- 2 Presentation of Privacy Rights Clearinghouse (PRC) database
  - Structure of the database
  - Cost of data breaches
  - Extreme value theory
- 3 Frequency and severity analysis
  - Changes in the exposure
  - Annual frequency assessment
  - Heterogeneity of the severity variable
  - Severity assessment



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## Presentation of the PRC database

- Aim to raise awareness about privacy issues
- Chronology of data breaches maintained from 2005
- Focus on the number of records affected: can be known or unknown
- Gathering events information from multiple sources:

| Source                 | Share in PRC | Share in PRC<br>known |  |
|------------------------|--------------|-----------------------|--|
| Nonprofit organization | 39%          | 37%                   |  |
| US GA - HIPAA          | 27%          | 36%                   |  |
| US GA - State          | 22%          | 17%                   |  |
| Media                  | 12%          | 10%                   |  |
| Total                  | 8860         | 6641                  |  |

25% of data breaches have an unknown number of records



Cyber-Insurance

PRC Data

└─ Structure of the database

#### Data contained in the PRC database

| Exposition data | Organization's name                |  |  |
|-----------------|------------------------------------|--|--|
|                 | Organization's type                |  |  |
|                 | Organization's geographic position |  |  |
| Event data      | Release's source                   |  |  |
|                 | Release's date                     |  |  |
|                 | Breach's type                      |  |  |
|                 | Number of records affected         |  |  |
|                 | Description of the event           |  |  |



-Structure of the database

## Data contained in the PRC database

| Type of organization      |
|---------------------------|
| Banking and Insurance     |
| Retail (including online) |
| Education                 |
| Government                |
| Healthcare                |
| Business (Other)          |
| Nonprofit organization    |

Type of breach

Hacking or Malware

Physical Loss

Portable Device

Stationary Device

Unintended Disclosure

Payment Card Fraud

Insider



# Cost of data breaches

Main costs:

- Incident investigation cost
- Customer notification and regulatory sanctions cost
- Post data breach response
- Loss business

Assessment of costs:

- Ponemon Institute LLC
  - Data collection
  - Yearly report: "Cost of a data breach study" (CODB)
- Jacobs' formula
  - Based on 2013 and 2014 CODB reports
  - $\bullet log(Costs) = 7.68 + 0.76 \times log(Records)$



# Volatility of cyber-events

- An important disparity exists between cyber-events.
- Illustration on the PRC database:



 Also necessity to plan for events even worse than what was already observed.



Extreme value theory

# Extreme value theory

#### Generalized Pareto Distribution

A random variable X with Generalized Pareto Distribution of parameters  $(\gamma, \sigma)$  is characterized by its survival function

$$S_{\gamma,\sigma}(x) = \mathbb{P}(X \ge x) = \left\{ egin{array}{ccc} rac{1}{\left(1+rac{x\gamma}{\sigma}
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**Approximation beyond a threshold:** Pickands (1975): for a random variable Y, let  $S_{u_n}(y) = \mathbb{P}(Y \ge y | Y \ge u_n)$ , there exists  $(\gamma, \sigma_n)$  such that

$$\lim_n |S_{u_n}(y) - S_{\gamma,\sigma_n}(y)| = 0,$$

where  $u_n$  tends towards  $\tau_S = \sup \{x : S(x) > 0\}$ .





#### Analysis on extreme cyber events

- Edwards B., Hofmeyr S. and Forrest S. (2016), "Hype and heavy tails: A closer look at data breaches." *Journal of Cybersecurity*, vol. 2 (2057-2085), pp. 3-14.
- Eling M. and Loperfido N. (2017), "Data breaches: Goodness of fit, pricing, and risk measurement." *Insurance: Mathematics and Economics*, vol. **75** (0167-6687), pp. 126-136.
- Wheatley S., Maillart T. and Sornette D. (2016), "The extreme risk of personal data breaches and the erosion of privacy." *European Physical Journal B*, vol. **89** (1434-6036), pp. 7.



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- Frequency and severity analysis
  - Changes in the exposure

# Heterogeneity of the PRC chronology





Frequency and severity analysis
Changes in the exposure

#### Evolution of the frequency

• The heterogeneity caused by the evolution of data collection makes difficult temporal evolution.





Annual frequency assessment

# Frequency analysis

- How many times a company have been affected by a data breach ?
- Work with count data
- The 8860 events have affected 7737 different companies

| Total | 1    | 2   | 3   | 4  | 5  | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|-------|------|-----|-----|----|----|---|---|---|---|----|----|----|
| 7737  | 6929 | 634 | 103 | 41 | 12 | 6 | 7 | 3 | 1 | 0  | 0  | 1  |

Issues:

- 0-truncated data because of the PRC chronology can be viewed as a claim database
- 1-inflated data: a lot of companies have been only affected one time



Annual frequency assessment

### Hypotheses and results

- Restriction with count data above 2
- 8 years window of data because of the instability of sources
- Risk factor: the type of organization
- We deduce yearly rate

| Type of organization      | $\lambda$ |
|---------------------------|-----------|
| Unknown                   | 0.27      |
| Education                 | 0.23      |
| Banking and Insurance     | 0.15      |
| Business (Other)          | 0.13      |
| Retail (including online) | 0.13      |
| Health                    | 0.10      |
| Government                | 0.07      |
| Nonprofit organization    | 0.01      |



- Frequency and severity analysis
  - -Heterogeneity of the severity variable

# QQ-plots





Heterogeneity of the severity variable

# Clustering And Regression Trees (CART)

- Introduced by Breiman (1984). Many extensions: Su (2004), Hothorn (2006), Loh (2014),...
- Consider a random variable Y (here the "size" of the breach) and X some covariates.
- Regression trees:
  - combining clustering with regression (that is evaluation of the impact of covariates on a variable).
  - regression trees aim to estimate a function m(x) (characterizing the distribution of Y when X = x, for example m(x) = E[Y|X = x]) by

$$\hat{m}(x) = \sum_{j=1}^{K} m_j R_j(x),$$

where  $R_j$  are called a "rule," that is  $R_j(x) = 0$  or 1, and, for all x, only one  $R_j(x)$  is nonzero.



- Frequency and severity analysis
  - -Heterogeneity of the severity variable



CART : Step 0



- Frequency and severity analysis
  - Heterogeneity of the severity variable





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# The splitting rule

Most classical version of regression trees use a "quadratic" splitting rule, that is, we look for a split such that, the following quantity is minimal:

$$\sum_{j=1}^{\kappa} \sum_{i:R_j(X_i)=1} (Y_i - \bar{Y}_j)^2,$$

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- Such a procedure produces an estimation of the target m(x) = E[Y|X = x].
- Potential problem: quadratic loss is very sensitive to high volatility.
- Changing the splitting rule changes the target function and can also be used to improve robustness of the estimation.



Heterogeneity of the severity variable

# Median trees and GPD Trees

Replace the quadratic loss by the absolute loss leads to estimate the conditional median, that is the quantity med(x) such that

$$\mathbb{P}(Y \leq med(x)|X = x) = \mathbb{P}(Y \geq med(x)|X = x) = 1/2.$$

Median regression is less influenced by large observations.



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- We used median regression trees to analyze the "center" of the distribution.
- To look at the tail of the distribution, we use GPD-log likelihood as a splitting rule.
- In this way, the tail of the distribution is approximated by a GPD, with parameters depending on x.



-Severity assessment

## Median tree illustration



# GPD tree illustration





-Severity assessment

### QQ-plots on some GPD tree leafs







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- Important difficulty with public databases: determining the exposure.
- We identified instability and heterogeneity in estimating the frequence due to a changing exposure.
- A similar impact (less obvious) is identified on the severity...
- ... although not so obvious for large events.



#### Thank you for your attention!



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