Heavy-Tailed Data Breaches in the Nat-Cat Framework & the Challenge of Insuring Cyber Risks

Annette Hofmann¹, Spencer Wheatley² and Didier Sornette³

Abstract

Considering cyber risk as a (man-made) natural catastrophe (Nat-Cat) systematically clarifies the actuarial need for multiple levels of analysis, going beyond claims-driven statistics to forecast losses, and necessitating ambitious advances in scope, quality, and standards of both data and models. The prominent human component and dynamic and multi-type nature of cyber risk makes it uniquely challenging when compared with other Nat-Cat type risks. Despite noted limitations of data standards and models, using updated U.S. breach data, we show that this extremely heavy-tailed risk is getting significantly worse - both in frequency and severity of private information items (ids) exfiltrated. The median predicted number of ids breached in the U.S. due to hacking, for the last 6 months of 2018, is about 0.5 billion, but there is a 5% chance that it exceeds 7 billion – doubling the historical total! In view of this extreme loss potential, insurance principles indicate a need to reduce ambiguity through research and to provide a sufficient basis for writing sustainable insurance policies. However, as demand for extended insurance coverage exists, premium differentiation is deemed attractive to incentivize self-protection and internalize externalities.

¹Assistant Professor, School of Risk Management, Insurance and Actuarial Science, The Peter J. Tobin College of Business, St. John's University, New York, USA. Email: hofmanna@stjohns.edu

²Senior Scientist, Chair of Entrepreneurial Risks, ETH Zurich, Switzerland. Email: swheatley@ethz.ch

³Professor, Chair of Entrepreneurial Risks, ETH Zurich, Switzerland. Email: dsornette@ethz.ch
1. Introduction

The 3rd and 4th industrial revolutions have brought rapid coupling of the physical and digital (i.e., cyber) worlds, and increasing reliance on the Internet and other networked cyber-technologies.\(^1\) Increasingly sophisticated criminals (and state actors), seeking profitable illicit opportunities and using various attack strategies, have contributed to a wide range of cyber-events that we observe in today’s extreme risk landscape.\(^2\) Cyber risk, in brief, consists of the possibility that sensitive information be exfiltrated, and operations of information systems, or even critical physical infrastructures (Zetter, 2014; Greenberg, 2017) disrupted.\(^3\)

Data breaches\(^4\) at firms/organizations constitute the bulk of current cyber-insurance, a growing class of insurance coverages, but pricing models are still immature (RMS, 2017). Rough estimates of the cost of breaches indicate global losses of above one hundred billion US dollars per year (Eling and Schnell, 2016b), and cost on the order of hundreds of US dollars per item breached - varying by country, sector, event type, and year (Ponemon, 2017; Eling and Wirfs, 2015). Remarkably, while heavily regulated industries (i.e., health, financial, services and life science) have per capita data breach costs substantially above the overall mean; the public sector, research, hospitality and entertainment companies have per capita cost well below the overall mean value.\(^5\) Heavy tails in breach severity have been reported and discussed early by Maillart and Sornette (2010), and some later studies (Edwards et al. (2016), Wheatley et al. (2016), Eling and Wirfs (2016)). For instance, with current data, one out of ten breaches containing more than ten thousand pieces of private information (ids) will exceed one million ids – and three breaches in excess of one billion ids have been reported. Clearly, data breaches constitute an extreme financial risk to firms. Early efforts to differentiate data breach risk include considering sector and organization size (Wheatley, Maillart and Sornette, 2016), as well as event type.\(^6\)

As estimated by Wheatley et al. (2016), it seems that cyber risk is getting worse, with plausible factors being: more digital data available worldwide and more users connected each day, growing fleets of mobile devices, and increasingly concentrated data pools on cloud services; the rapidly evolving and hard-to-catch cyber-criminals differ substantially from the relatively complacent\(^7\) and unsophisticated population that they prey upon; and finally, a software business model allowing for the sale of buggy software, all of which that the inertial legal and insurance apparatus struggles to keep up with. However, there are major business and protection incentives that drive development of cyber defense and risk mitigation. For instance, the median time for the detection of a breach shows a downward trend.\(^8\) Edwards et al. (2016) argues that the breach size distribution is not getting heavier tailed. So, who is winning this cyber arms race, and can insurance better respond to the needs of the market and the public in

---

\(^1\) The term “cyber” refers to the “cyberspace”, which is a general description of the Internet-based domains and networks used to store, modify and exchange information between users.

\(^2\) See Appendix A1 for a broad classification of the various attack strategies that are used today.

\(^3\) A definition of cyber risk, typical of the operational risk literature, by Cebula and Young (2010) is “The operational risk to information and technology assets that have consequences affecting the confidentiality, availability or integrity of information and information systems.” It is a contemporary, multi-type, and rapidly evolving risk that requires special methods of evaluation and tailored concepts for insurance pricing.

\(^4\) A subset of cyber risks, where large amounts of personal information (name, social security number, address, email, date of birth, credit card numbers, usernames and passwords, etc.) are exfiltrated from firms/organizations. Data exfiltration is achieved by diverse modes (so-called vectors) such as the Internet, private networks, social engineering attacks, theft of hardware, and other strategies – typically for the use in identity fraud.

\(^5\) See Appendix A1.

\(^6\) E.g., software versus network based events (Boehme and Schwartz (2010), Oeguet et al. (2011), Mukhopadhyay et al, 2013); and data loss or unauthorized modification, data breach, and data abuse including insurance or banking fraud (Cebula et al. (2010), Biener et al. (2015), Eling and Schnell (2016)).

\(^7\) This routinely delays the following of basic security best practices, namely prompt installation of outdated versions. Based on 75% of worldwide browser traffic on the Internet, Maillart et al. (2011) document a massive “law of procrastination” in the form of a general class of power law behavior of the waiting times between available new versions and updates. See also Saichev and Sornette (2010).

\(^8\) See Cisco (2017) and Figure A1 in the Appendix.
A specific objective of this study is to resolve this fundamental issue. We address this by performing a rigorous frequency-severity statistical analysis of the most comprehensive open scientific database for data breaches in the USA. In particular, merging Privacy Rights Clearinghouse data with that of the former Open Security Foundation Data loss Data Base, results in 1,713 breach events with breach size severity in excess of 10,000 individual identities items compromised between 01/2005 and 09/2017. We provide summary statistics for data breach risk by sector and event type. Importantly, we identify that a certain event type that is dominating the risk, and which risk is growing.

To clarify the scope, limitations, and applicability of these results, we compare cyber risk with the insurance Nat-Cat framework. This assumes that cyber risk can be seen as a type of man-made catastrophe, the man-made equivalent of natural catastrophes (Nat-Cats), which are very consequential yet rare events, whose statistical characteristics tend to be relatively uncertain. Examples of Nat-Cats are floods, huge fires or earthquakes. We justify this analogy by breaking down cyber risk in terms of Nat-Cat modules: hazard (threat intensity), vulnerability, damage (breach size), and resultant financial loss. In this young field, these different modules are poorly understood – they are rapidly evolving and depending upon difficult-to-measure organizational features, with a lack of standards and information. We propose here that the number and type of IDs (information items) breached is an appropriate measure for damage severity, indicating the partial contribution of our statistical analysis to overall characterization of cyber risk and cyber risk insurance.

This article is structured as follows. The next section offers an analysis of cyber risk in Nat-Cat terms. Section 3 deals with statistical quantification of the frequency and severity of U.S. data breaches. Section 4 evaluates how insurance principles can be used to price cyber insurance policies. The last section summarizes our findings, discusses implications and concludes.

2. Putting cyber risk in the Nat-Cat framework

To support marketable and sustainable insurance pricing a sufficiently detailed quantitative characterization is needed. To support a complete view of the risk, we analogize data breaches as a Nat-Cat, with the following modules:

Hazard(s): The combined rate of the many diverse processes that may lead to data breach, including intentional and accidental events, as well as technical and/or human causes.

Exposure: The quantity, type, and value of sensitive information at risk.

Vulnerability: The susceptibility of the firm to breach, depending on people, processes, technology, and structure.

Damage: The amount of data that is breached, which depending on the circumstances, is mapped to loss.

Loss: being the defined measure of negative consequences, or liabilities in the contract.

From this exercise, it is clear that data breach risk can be decomposed into these modules. This also responds to the suggestion of Boehme et al. (2017) and Edwards et al. (2016) that one should look at multiple levels rather than just

---

9 This calls for a need for cyber insurance products, which typically will provide an IT forensic investigator as well as legal and public relations assistance and thereby offer competence in evaluating and covering these risks. However, the cyber insurance market might face similar insecurities when it comes to evaluating and pricing cyber security risks.

10 See Grossi and Kunreuther (2005).

11 See chapter 4.4 of Chernov and Sornette (2016).

12 E.g., it is well known, based on surveys, that even the majority of data breaches may not be reported (Ponemon, 2017).
a financial measure of loss. For instance, working with breached identity items (ids) as the measure of severity of damage instead of cost offers many advantages: ids are objectively defined, typically known quite precisely, relatively widely available, and independent of the (also evolving) factors that map the breach size in ids to cost. Note that, of course, the types of id(s) should also be considered, e.g., breaching triples of name, social security number, and credit card number could be very severe. Cost, on the other hand, is often not known and itself requires a more subjective definition and justification, unless one simply defines it as the cost of the related insurance claim. A full social cost is difficult to estimate given the cumulative erosion of privacy, reporting issues, lack of standards, etc. Then the mapping from damage to cost can be calibrated, exploiting the more limited and subjective cost information, and as done in Edwards et al. (2016), the relevant cost information can be extrapolated to the broader sample of breach events. Finally, past Nat-Cat lessons can be applied. For instance, common modes of failure should not be underestimated, and in particular, for a given hazard and exposure, the mapping to damage and subsequently to cost should allow for uncertainty that is representative of the wide range of different observed outcomes.

However, it is also clear that cyber risk is more diverse, complex, and detailed than a typical Nat-Cat. For instance, the hazards/threats are multiple, with some rapidly co-evolving with cyberspace and being a set of socio-technical phenomena rather than purely physical. That is, human behavior is identified as a major factor on the sides of both the victim and the attacker (Eling and Wirfs, 2015). Furthermore, the hazard itself depends on the characteristics of the target that make it attractive to be attacked. Importantly, risks are interdependent not only because of physical, cyber, and social networks, but also because of common software or hardware that is used by multiple firms. Thus, each hazard type has its own graph/network, mapping the scope of a mode of failure common to multiple firms—which can be extensive. Important is the cumulative effect of combining latent/already breached data, with fresh breaches – especially severe for firms that are repeat victims or are connected to victims – which may complicate attribution of liability. Finally, all of the above modules are evolving, with limited and hard-to-measure information, and a lack of standards. In particular, no models relating vulnerability to all relevant factors mentioned above have been published. A deep analysis of hazard/threat, vulnerability and damage, extending far beyond our current data, would require analysis of data breach precursors, up to near-misses: where an attack failed at some level due to a remaining line of defense; or by luck that a long-term vulnerability was never discovered and exploited by hackers. Such events are referred to as precursors (see e.g., Kunreuther, Bier, and Phimister, 2004).

Considering other difficulties, cyber risks involve contagion effects and thus individual firms’ investments in protection implicitly benefit others because one party’s investment decision will have an impact on the utility of the other parties connected to it (Kumar et al., 2007). One of the many examples is the Target data breach in 2013, which was caused by an unprotected source that spread to other sources. Second, many cyber events exploit vulnerabilities in systems used by multiple users. The consequences of risks not being independent but positively correlated, like risks resulting from natural catastrophes, are well known: a reduced risk pooling effect, contagion effects, and suboptimal economic market outcomes. In contrast to floods, fires, or earthquakes, the risks of cyber

---

13 The mapping from breach size to cost is also quite noisy, so it is more precise to study breach sizes directly.
14 Such as the concentration of semiconductor manufacturing in a region of high flood risk in Thailand, e.g., see Romero, J. “The Lessons of Thailand’s Flood”, IEEE Spectrum, 1 Nov 2012.
15 Although, e.g., trends and complex weather dynamics are of course included in high quality Nat-Cat models, these dynamics are tame when compared with the blistering evolution of cyber risk.
16 For instance, in November 2017, it was confirmed that millions of Intel chips have a major vulnerability, potentially allowing arbitrary remote code execution and privileged information access. [https://www.us-cert.gov/ncas/current-activity/2017/11/21/Intel-Firmware-Vulnerability].
17 Another way would be to study the developments of threats (e.g., hacker activity) as opposed to just the vulnerability of firms. See, for instance, https://lockheedmartin.com/content/dam/lockheed/data/sgs/documents/Threat-Driven%20Approach%20Whitepaper.pdf.
18 This would require integration of databases on threats, vulnerabilities, damage (the focus here), and cost. All such databases exist, but likely require detailed event study and additional annotations to realize their full value.
attacks are correlated globally rather than locally, which makes it even more difficult for local insurers to pool these risks. In these cases, the reinsurance market must support primary insurers to competently insure these risks. Interestingly, the reinsurance market excluded cyber risk explicitly in their policies in the 2000s; this may have been the case because of the important difference to the conventional risks that cyber events are planned and executed (either intentionally or by accident) by humans, which requires exploiting the complex positive dependence structure of these risks potentially leading to “correlated failure”. The economic system behind this network issue originates from game theory and is known as Interdependent Security (IDS): For each potential data breach source, the probability of an attack does not only depend on its own protection level, but also on the degree of protection of all connected sources (Kunreuther and Heal, 2003), which presents a challenge for insurance pricing.

3. Quantification of Data Breach Risk

3.1 Data Overview

We consider the risk of data breaches for U.S. firms, decomposed into frequency and severity, focusing primarily on “damage” as quantified by the number of ids breached. Taking frequency as the number of breach events at U.S. firms per year, we do not normalize for the number of firms, quantity of data stored, or other measures of exposure, as done in Wheatley et al. (2016). We use the latest data from the Privacy Rights Clearinghouse merged and harmonized with events from the former Open Security Foundation Dataloss Data Base, resulting in a set of 1’713 breach events with severity in excess of 10’000 ids, compromised between 01/2005 and 09/2017. To our knowledge, this is the most comprehensive open scientific dataset for breaches, but it still has a number of limitations.19

For the United States, we observe an average of 135 events per year having in excess of 10^4 ids, between 01/2005 and 09/2017. Statistics also differ by state.20 The cumulative total breach amounts to 1.4x10^10 ids, of which the largest, being 3x10^5, is 30 percent of the total! Given a breach has size in excess of 10^4, it has a 10% chance of being above 10^6, and a 1% chance of being above 10^8. Clearly, data breaches are heavy tailed (see Fig 1). And given that the U.S. is ¼ of global GDP (gross domestic product), a rough estimate for cumulative global breached ids from firms is almost 6 x 10^10, approaching 10 for every human on the planet. Naïvely applying an average per id cost of about $200 to the U.S. events gives a massive average annual cost of $1.7 x 10\(^{11}\) – being almost 1 percent of the U.S. GDP. However, this neglects that the relationship between breach size and cost should be noisy, depending on multiple factors, and -- most importantly -- sublinear, which could easily see the real number being orders of magnitude smaller. Overall, these alarming numbers raise concerns, since such events are not only costly to businesses, but their full costs are poorly known, and inflict external costs onto the public.21

---

19 See http://www.privacyrights.org/data-breach. The usual limitation of data incompleteness applies, however, here more severely as many events may fail to be reported or even discovered. In addition, there are thousands of additional events with unknown size. Next, breach events are treated inconsistently, as sometimes multiple organizations are targeted by a single attacker.

20 Not surprisingly, the highest frequencies are seen in the States of New York and California; the highest severities are in Nebraska, Nevada, and the District of Columbia. See Appendix A3.

21 Stolen identities have been used for fake comments online, distorting the appearance of important dialogues, and “hacking consensus”. See, for example, the information on Hackernoon: https://hackernoon.com/more-than-a-million-pro-repeal-net-neutrality-comments-were-likely-faked-e9f0e3ed36a6
Figure 1 Probability density and histogram of cyber events up to (a) 1,000,000 and (b) 100,000 ids compromised.

Figure 2 12-year frequency and median severity by type of breach.

For insurance purposes, we aim to be as specific as the data reliably allows. In particular, we consider five breach event types:

- **HACK**: is any unauthorized exfiltration of ids by an outsider, typically including software media, and a range of attack strategies, excluding physical theft of devices.
- **HW**: is for all physical devices, i.e., hardware, either lost or stolen.
- **DISC**: is accidental disclosure via software media.
- **INSD**: is a HACK performed by an insider.
- **NA**: is not further specified, unknown, and/or does not fall into the above categories.

This available classification is rough, and we acknowledge that a better one would be mutually exclusive and more precise. In the absence of data about fundamental factors, we let victim organizations be grouped into sectors, limited to: 1. financial, 2. non-financial business from which we distinguish 3. large web-based businesses/services, and social networks/communities, 4. medical, 5. educational, and 6. governmental.

Summary statistics by sector and breach type are given in Tables 1 and 2, and Figure 2, of which hack events tend to be the largest (especially at web-based companies) and most frequent (especially in the business sector). However, accidental disclosure is also significant. Inference about risk based on sector Tables 1 and 2 requires normalizing for the number and size of firms in each sector (see Wheatley et al. (2016)).

---

22 Useful categories could include: External/internal actor, data media (hard or software), attack strategy mode, intentional or accidental, actual effect or potential (i.e., egregious vulnerability not exploited), data type, aggregating factors (e.g., distributed online), “cost” (e.g., total fraud, total liability, etc.).
Table 1. Annual breach frequency for events in excess of $10^4$ ids, and quantiles, by sector for firms in the US.

| Quantile    | 50%   | 75%   | 90%   | 100%  | Annual Frequency |
|-------------|-------|-------|-------|-------|------------------|
| Business    | 60,000| 200,000| 867,800| 250.0 x10^6| 26.1             |
| Educational | 34,000| 80,750| 185,100| 7.5 x10^6   | 18.7             |
| Financial   | 90,881| 609,301| 3.5 x10^6 | 145.5 x10^6| 19.2             |
| Government  | 72,000| 250,000| 1.3 x10^6 | 76.0 x10^6| 12.4             |
| Medical     | 29,082| 79,750| 327,359| 78.8 x10^6| 53.2             |
| Large Web   | 6.0x10^6 | 57x10^6 | 150x10^6 | 3.0x10^9 | 5.1              |

0.78          0.28          0.61          0.26          0.21          7.3

Table 2. Total breached ids at U.S. firms, by sector and breach type, since 2005. In particular: a hack breach of 1 Billion ids in 2014 is not attributed to a sector, and overall 0.38 Billion are not attributed to an event type, due to lack of information.

|        | Business | Educational | Financial | Governmental | Medical | Large Web | Sum (Bil.) |
|--------|----------|-------------|-----------|--------------|---------|-----------|------------|
| HACK   | 5.04x10^8 | 1.18x10^7   | 5.17x10^8 | 6.18x10^7   | 1.39x10^8 | 5.70x10^9 | 7.0        |
| DISC   | 2.45x10^8 | 2.21x10^6   | 2.22x10^6 | 3.25x10^7   | 9.15x10^6 | 1.46x10^9 | 1.8        |
| INSD   | 7.48x10^6 | 1.21x10^6   | 4.18x10^7 | 3.33x10^7   | 4.20x10^6 | 0         | 0.088      |
| HW     | 2.33x10^7 | 2.80x10^6   | 3.62x10^7 | 1.31x10^8   | 5.89x10^7 | 2.80x10^5 | 0.25       |
| Sum (Bil.) | 0.78       | 0.28        | 0.61      | 0.26         | 0.21     | 7.3       | 10.4       |

3.2 Frequency: are breaches becoming more frequent?

In Wheatley et al. (2016), it was claimed that the rate of breaches in excess of 50k ids was constant, and this continues to be the case. That is, GLM (generalized linear model) regressions give an insignificant slope over time. However, the most recent two years have only suffered about 80% of the historical mean frequency of events. But this is a spurious decrease, because this is around the amount expected when considering the typical delay between an event occurring and being in the database. E.g., consider the case of Uber, which concealed a breach of 57 million ids from October 2016, only to have the event become known to the public in Nov, 2017.\(^{23}\) To be robust against this we employ smooth models, although more sophisticated methods could control for the missing data.

On a more specific basis, looking at hack type events, we find a significant increase quantified by a log-linear negative binomial regression (see Figure 3 and Table 3). Annual growth ranges from 8 percent for breaches in excess of $10^4$ up to 19 percent per year for breaches larger than $10^6$, having significantly faster growth for larger

\(^{23}\) Uber Breach, Kept Secret for a Year, Hit 57 Million Accounts. The New York Times. November 22, 2017. See https://www.nytimes.com/2017/11/21/technology/uber-hack.html
breaches. The distribution of counts at any given time is well described by a negative binomial, with mean \( \mu \), and variance \( \sigma^2 = \mu + \mu^2/\theta \). The fit is significantly over-dispersed relative to the Poisson: e.g., for the \( 10^4 \) threshold, the variance-to-mean ratio grows from 2 to 3.5 over the almost 13 years.

Figure 3 6-month counts of hacking events from 01/2005 to 9/2017 (left with size above \( 10^4 \), right with size above \( 10^6 \)). The dashed lines provide the quartiles of the estimated negative binomial distribution, roughly consistent with the fluctuations observed around the regression line.

| \( u \) | \( n > u \) | Intercept \( \beta_0 \) | Growth rate \( \beta_1 \) | \( \theta \) | \( P \) |
|---|---|---|---|---|---|
| \( 10^4 \) | 623 | 2.65 (0.13) | 0.08(0.02) \( 10^{-5} \) | 14.8(7.0) | 0.0003 | 0.28 |
| \( 10^5 \) | 242 | 1.45 (0.19) | 0.11(0.02) \( 10^{-6} \) | 11.9(7.5) | 0.05 | 0.38 |
| \( 10^6 \) | 88 | -0.23 (0.36) | 0.19(0.04) \( 10^{-5} \) | 4.6(3.3) | 0.15 | 0.21 |
| \( 10^7 \) | 41 | -0.79 (0.48) | 0.17(0.06) | 0.001 | 3.2(2.8) | 0.47 | 0.35 |

Table 3 Log-linear negative binomial regressions (log link GLM fit by maximum likelihood), as a function of years 0 to 12.75 (01/2005 to 9/2017). Table quantities are: 1) lower threshold (\( u \)), 2) number of points above it, 3) estimated intercept with SE (standard errors), 4) growth rate with SE and \( p \)-value for test with null being \( \beta_1 = 0 \) all of which are highly significant, 5) \( \theta \) is the negative binomial dispersion parameter with SE and likelihood ratio test \( p \)-value against Poisson null, indicating significant over-dispersion, and 6) “\( p \)” is the chi-square test \( p \)-value on deviance residuals (model diagnostic), indicating that the overall fits cannot be rejected.

\(^{24}\) One sided Z test of the growth rates of the \( u=10^6 \) and \( u=10^4 \) fits gives \( p=0.007 \), indicating significantly faster growth of more extreme breaches.
3.3 Severity: are big breaches getting bigger?

As demonstrated above, there is a strong trend towards increasing severity of particularly high-impact cyber events in our data, which is not present for all cyber events. This suggests that the answer to the above question is yes. Another view is to examine the full event size distribution over time. As can be seen in Figure 6, one can distinguish a clear and significant increasing trend for hack events – consistent with the regressions in Table 3, whereas other event types are roughly stationary and less extremal. The results here and in 3.2 are likely to be robust to common data completeness issues due to the natural tendency for large events to be observed and recorded, regardless of law.

![ Scatterplot of breach sizes over the years, by type (HACK black, DISC red, INSD blue, HW green). The trend is clear for hacks but not for others, as quantified by the log-linear regression of the 0.9 quantile (Koenker, 2001). For the HACK data, the slope is significant with p-value < 0.01. ]

Without assuming a dynamic model for the growth of hacking events, the Pareto distribution,

\[ Pr\{X > x\} = \left(\frac{x}{u}\right)^{-\alpha}, x > u > 0, \alpha > 0 \]

is fitted on a moving window of 50 events to capture the non-stationary behaviour. As shown in Figure 7, a major decrease of the tail index \( \alpha \) took place, from the range 0.6-0.7 before 2007 to a roughly stable value in the range 0.3-0.4 post 2015, as the tail has become heavier and significantly bent-down for the largest values. To consider alternative tail models, a lower-truncated lognormal\(^{26}\) and an upper-truncated Pareto are also considered, where the truncated CDF (cumulative distribution function),

\[ T(x) = Pr\{X \leq x|u < X \leq m\} = \frac{F(x) - F(u)}{F(m) - F(u)}, 0 < u < m, T(u) = 0, T(m) = 1, \]

---

\(^{25}\) See Appendix A3.
\(^{26}\) The distribution such that the natural logarithm is the lower-truncated Normal distribution with parameters \((\mu, \sigma^2)\). See Malevergne et al. (2011) for examples, and the uniformly most powerful unbiased test against the Pareto tail.
is derived from its un-truncated CDF, F(x). The tail fits shown, and summarized in Table 4, indicate that both a lognormal and an upper-truncated Pareto\(^{27}\) tail fit well, and are statistically indistinguishable.\(^{28}\) Naturally, a maximal breach size exists, on the order tens of billions, where 3-billion global Internet users exist, and breaches in excess of 1 billion ids have already occurred. Further, this maximum is likely to grow with the increasingly networked and growing population. In this case, only the upper truncated Pareto imposes a finite maximum.

| U    | N>u | α        | logL | α₁   | logL     | µ       | σ²     | logL |
|------|-----|----------|------|------|----------|---------|--------|------|
| 25k  | 167 | 0.35(.03)| -341.4| 0    | -338.1   | -12.8(13)| 7.14(3)| -340.3|
| 100k | 101 | 0.35(.03)| -207.6| 0.3   | -203.9   | -2.9(4.0)| 4.7(1.3)| -205 |
| 1Mil | 47  | 0.40(.05)| -90.1 | 0.3   | -87.4    | -4.1(7.4)| 4.5(2.1)| -89.2|

Table 4. Tail fits of hack breach sizes since 2014 with Pareto (left), upper-truncated Pareto (middle, parameter α₁), and Lognormal distributions (right). The lower threshold (u), maximum likelihood parameter estimate, standard error, sample size, and log-likelihood value are given for all fits.

![Figure 7](image)

**Figure 7:** Main: Empirical survival distributions for the breach types for all time by color: DISC in red, INSD in blue, and HW in green. HACK (in black) is split into pre-2010 data and post-2014 data, being the heavier tailed of the two. Maximum likelihood fits to the post-2014 hack data plotted: Pareto with upper truncation (black solid), and Lognormal (red dashed). Inset: Estimated parameter α of the Pareto tail (u=25’000), from 2005 to Q4 2017 on a moving window of 50 points, for the HACK events, including one and two standard deviations of the maximum likelihood estimate.

\(^{27}\) The Pareto distribution with upper truncation, being the largest value given non-zero mass, set to be the size of the largest HACK event: \(3\times10^9\).

\(^{28}\) According to a chi-square likelihood ratio test, only the un-truncated Pareto is significantly worse (\(p < 0.01\)).
3.4 Risk: An Aggregate Compound Process

Focusing on the dominant and worsening breach risk, caused by hack events, we propose a model for the U.S. in the near future. The incidence is well modeled by a highly dispersed negative binomial distribution with exponentially growing mean (Table 3). However, a linear mean model is not significantly worse,\(^{29}\) which yields lower future predicted values. For severity, a Pareto distribution with lower bound \(u=10^4\), maximum value \(m=10^{10}\) and estimated \(\alpha = 0.35\) is proposed – being between the best Pareto and lognormal fits (see Figure 7). Accounting for model and parameter uncertainties, the aggregate distribution is summarized, for the last 6 months of 2018, in Table 4, which predicts a median of around 0.5 Billion hacked ids in the last 6 months of 2018. However, in that same time, it also allows for more than 7 Billion ids to be breached with about a 5% chance – being about equal to the total data already breached due to all past hacks (see Table 2). Despite the imposed finite maximum, the tail is exceptionally heavy, resulting in the potential for massive fluctuations in aggregate loss. This is not unrealistic given that a breach of 3 Billion took place at Yahoo in 2016.

These figures for the near future are briefly compared with the aggregate distribution for the last 6-months of 2012, summarized in Table 6. In particular, \(\alpha = 0.4\) is selected based on Figure 7, a maximum breach event of \(m=10^9\) is assumed, and frequency is again taken according to the GLM model. On this basis, the mean and quantiles are about ten times less than their counterparts in Table 5, quantifying an order of magnitude worsening of risk over the past five years.

\[\begin{array}{|c|c|c|c|c|c|c|} \hline
\text{Quantile} & \text{Mean} & \text{SD} & 0.5 & 0.9 & 0.95 & 0.99 \\
\hline
0.25 & 1.5 & 2.5 & 0.41 & 4.9 & 7.3 & 11 \\
0.5 & 1.6 & 2.6 & 0.5 & 5.4 & 7.8 & 11.4 \\
0.75 & 1.9 & 2.8 & 0.61 & 5.8 & 8.2 & 12.1 \\
\hline
\end{array}\]

*Table 5:* Summary of aggregate distribution for total number of billions of ids hacked in the last six months of 2018 (out of sample at time of writing with data sample studied ending at 09/2017). A lower threshold of ten thousand was taken. The mean, standard deviation, and tail quantiles (VaR) are given. The rows are the median and quartiles of these quantities accounting for model uncertainty (equal weighting for the exponential and linear mean model for frequency) and parameter uncertainty (by parametric bootstrap).

\[\begin{array}{|c|c|c|c|c|c|c|} \hline
\text{Quantile} & \text{Mean} & \text{SD} & 0.5 & 0.9 & 0.95 & 0.99 \\
\hline
0.25 & 0.18 & 0.26 & 0.06 & 0.54 & 0.77 & 1.11 \\
0.5 & 0.19 & 0.27 & 0.07 & 0.57 & 0.81 & 1.18 \\
0.75 & 0.20 & 0.28 & 0.08 & 0.61 & 0.85 & 1.25 \\
\hline
\end{array}\]

*Table 6:* The same as table 5, also given in billions of ids, but for the in-sample period of the first 6 months of 2013.

\(^{29}\) With intercept 13.1 (2.3), slope 1.7 (0.4), and NB dispersion parameter 14.3 (6.65), e.g., predicting a level of 13.1 events per 6 months in 2005, and approx. 35.2 by Q3 2017, where the exponential model predicts 38.4.
4. Applying Insurance Principles to Cyber Risk

Cyber insurance refers to insurance policies addressing first- and third-party losses that result from a computer-based attack or malfunction of a firm’s/individual’s information technology systems (Romanosky et al., 2017). Most property and general liability policies do not cover data breaches, and policies either exclude cyber (non-physical) IT risk or remain silent on which cyber events would be covered under the policy. As a consequence, the cyber insurance market is small; it is most developed in the U.S. with Europe being the second main market. In 2016, U.S. cyber insurance premiums have increased 30% up to US$ 1.34 billion for a total of 138 insurers, including 29 new entrants (Shetty et al., 2018).

In the U.S., insurance is regulated at the state level and thus insurance companies need to file notices to state insurance commissions describing each new insurance product that they want to offer. As of 2013, the annual gross prices for cyber insurance in the United States were US$ 1.3 billion, the majority growing annually around 10–25% on average; a few very large writers reported premiums in excess of US$ 50 million; carriers that have been significant players in the cyber risk insurance market for several years already indicated premium growth ranging from 25% to over 100% (Betterley, 2013). Risk assessments take into account the number of records/ids and the types of sensitive/confidential data managed by a firm/individual. A challenge in this insurance market is the non-standardization of contract specification of covered items. Insurance products and their coverage options tend to vary between competitors and change rapidly over time.

Numerous studies have evaluated the question whether cyber risks are insurable, mainly using prominent insurability criteria based on Berliner (1982), which results in the insight that cyber risk is difficult to insure given the important and challenging-to-model role of human behavior on both the threat (attacker) and vulnerability (victim) sides.

4.1 The need for a stronger base of information

The analysis of historical cyber risk events for insurance pricing may be misleading given that the underlying risk is highly dynamic, and difficult to relate to institutional features. As a consequence, technical measurements – such as quantity and type of data, and other features summarizing the technology, processes, and human role in data storage and access, which determine exposure and vulnerability -- should be used in addition to claim history. Such a measurement approach can only be usefully applied to a network as a whole. In this way, an aggregated-risk-database (ARD) seems needed that includes all risk information on all cyber events within the network. Although such an aggregated-risk network would contribute to make cyber risk more transparent and more easily calculable

30 This lack of coverage led in the 1990s to the emergence of cyber security insurance as a stand-alone insurance product. Frequency and severity of cyber losses were relatively small before 2000, taking on a substantial part in all operational risks companies face today. The growth of the cyber risk insurance market is hindered by the high correlation of losses, general lack of data, and limited information available to carriers.
31 Romanosky et al. (2017) evaluate 180 of those filings submitted 2007-2017 in New York, California and Pennsylvania.
32 There are, however, a significant amount of exclusions and limitations in these policies, which makes it difficult to evaluate the policies and make an informed purchase decision on the demand side. An example for stand-alone cyber insurance is data breach insurance, protecting the policyholder against losses due to information leakage. Coverage options include asset damage, business interruption losses, costs of restoration in case of denial of service attacks, network security claims, privacy liability, post-incident public relations, and crisis management services.
33 See Gordon and Sohail (2003), Baer and Parkinson (2007), Opadhyay and Rao (2009), Shackelford (2012), Mukhopadhyay et al. (2013), Eling and Wirfs (2015) as well as Eling et al. (2016a, 2016b).
by insurance companies it may not be sustainable due to incentives for firms to conceal sensitive information. The 
problem might be solved by a legal or other obligation to report an incident to the ARD. This regulatory intervention 
in the form of a reporting obligation, however, calls for controlling firms and imposing cost of regulation. 
Interestingly, some jurisdictions in the EU already plan mandatory reporting and sanctioning of non-compliance, 
referred to as the EU Cybersecurity Act. In the U.S., mandatory reporting of data breaches in terms of size exists 
in most states; forty-six states have already passed laws requiring disclosure, starting with California in 2002, but 
these laws vary significantly in terms of when and how notice must be given, allowing often for delays to investigate 
the intrusion.

However, an ARD of data breach events alone will still fail to provide important technical information, leaving it 
to be inferred. In particular, lack of technical information is a major problem in identifying networks and their risk 
exposures Disclosure of such information would allow for identification of network hubs and vulnerabilities, and 
support a rational consideration of where to concentrate protection efforts, regulation based on networks structure, 
external costs, and liabilities.

This need for more systematic and transparent technical information relates to the issues of moral hazard and 
adverse selection. To prevent/reduce these two common types of demand-side problems, insurance companies 
require virtual information security audits. After such an audit has been performed, a firm may need to pay a 
surcharge (premium loading) or may be given a higher deductible, or an incentive to invest in improved security.

4.2 Elements of the current cyber-insurance market

It has been established that cyber risks, and data breaches in particular, are extreme, uncertain, and potentially strong 
correlated risks, making pricing as well as diversification difficult. This is further complicated by the currently small 
risk pools, and heterogeneous cyber security regulation which differs state-by-state within the U.S.

Considering regulation and the IDS problem, it can be shown that the Nash equilibrium is associated with higher 
social welfare than under a regulated network in which all firms are required to protect themselves against cyber 
attacks (Hofmann and Ramaj, 2011). This insight reveals that regulation in the form of requiring safety 
investments for all firms seems to be the wrong strategy here: This is because such a regulation would require those 
with relatively high protection cost to protect themselves, which is likely to be difficult to enforce or control. 
A better way to increase the protection level in the cyber network may be to subsidize some firms in such a way 
that cyber risk protection becomes less costly for them to implement. Liability rules as well as cheaper insurance 
protection for companies with enhanced cyber protection seem to be good control mechanisms here. Indeed, this 
may create sufficient economic incentives for all other firms to invest in improved protection, as well. This is an 
example of a behavioral change by a small subpopulation of players that may cause a massive shift in the overall 
population behavior (Schelling, 1978). Heal and Kunreuther (2007) show that, in an IDS game, a critical coalition

---

34 See https://www.enisa.europa.eu/news/enisa-news/european-commission-proposal-on-a-regulation-on-the-future-of-enisa. 
35 Organizations with a high degree of cyber risk exposure are more likely to purchase coverage 
36 Organizations that have been victim of an attack are more likely to purchase insurance (Rothschild and Stiglitz, 1976) 
37 For instance, the Fair Credit Reporting Act and the Gramm-Leach-Bliley Act (both 2000) include a cyber security component but regulation 
   is mainly done retrospectively; and the Identity Theft and Assumption Deterrence Act (1998) gives the Federal Trade Commission the right 
   to investigate cases of identity theft. Due to the heterogeneity in cyber security regulation, cyber risk and its pricing can only be determined 
   on the state level. 
38 Indeed, only an insurance monopoly may be in a position to fully internalize protection externalities and maximize social welfare 
   (Hofmann, 2007, and Hofmann and Ramaj, 2011). 
39 However, given the external impacts of data breaches, it seems unlikely to have these fully captured via liability, and thus perhaps it can 
   be seen as a public interest to have public resources support cyber protection in firms.
of players may be sufficient to induce such a tipping phenomenon. As discussed by Hofmann and Ramaj (2011), this implies that a suboptimal Nash equilibrium may be converted into one with full cyber risk by incentivizing only a critical subset of the players to change their policies, which will tip the entire network to full protection. Determining a critical coalition is then the main challenge. Alternatively, and probably less sophisticated, a tipping phenomenon may also be initiated by subsidizing research and development in cyber risk protection, deterrence and mitigation. Once an affordable and effective protection strategy is found and maintained for the network, the attackers can be deterred.

Given the young risk and relatively small size of the cyber insurance market, efficient risk pooling and diversification cannot easily be achieved. Underwriting practices rely on judgement and experience. So far, cyber risk assessment techniques are generally not very sophisticated. As shown in Romanosky et al. (2017), many insurance providers use very simple Flat Rate pricing methods, defined as a single rate for each first- and third-party coverage to all policyholders, which is based on past loss history. A more sophisticated pricing strategy is Base Rate pricing, where a base premium is calculated as a function of the policyholder’s annual revenues/assets; the base premium is then adjusted according to variables relating to standard insurance factors (i.e., policy limits or deductibles) and industry-related factors (i.e., type of industry such as non-profit, government, or health care). The factor that assigns the greatest influence on the premium is the base revenue/asset of the applicant. The most sophisticated approach used is Information Security Pricing that also accounts for characteristics of the insured’s information security control mechanisms and protection level when determining the final premium (Romanosky et al., 2017). The pricing strategy will depend on the risk pool and the information the insurer has available for pricing.

At the end of the day, the small risk pools imply that a well-functioning cyber insurance market will need the opportunity of having enough reinsurance capacity available to better spread the risk exposures over a larger pool, i.e. worldwide. The small size of the market implies that cyber risk insurance policies with high limits are rarely available given that insurers try to avoid high exposures (Shetty et al. (2018)). In order to get enough cyber risk protection, policyholders will need to stack up multiple cyber policies — to form so-called tower policies — “which is usually a suboptimal solution because the coverages provided by different policies are misaligned most of the time”.

5. Summary, Implications and Conclusion

This paper places cyber risk within the Nat-Cat framework, as a man-made catastrophe, providing guidelines for the assessment and quantification of cyber risk, which we think may be useful for the insurance industry to appropriately price these extreme heavy tailed risks. The Nat-Cat framework requires analysis at many modules/levels — responding to the suggestion of Boehme et al. (2017) and Edwards et al. (2016), that focusing just on a financial measure of loss is insufficient. Much of this work is not yet possible, as it would rely on ambitious increases in event and technical information. An important and relatively tractable module to analyze is data breach severity. A statistical analysis of data breaches at U.S. organizations identified a highly significant increase in the frequency of large breaches, measured in id items exfiltrated caused by hack events, which dominates the overall data breach risk; in detail, not only is the frequency of hack breaches highly over-dispersed and growing about 8 percent per year, but the breach sizes are becoming increasingly heavy tailed, well described by an extremely heavy tailed truncated Pareto, or a lognormal. Characterization of the other modules will enable additional and more complete and useful insights. The role of human error is a major cause here – accidental disclosures can be severe.

---

40 Shetty et al. (2018), p. 4.
and human error often plays a role in a hack being successful – which may serve as a bottleneck to specific and precise risk assessment. Lessons should be learned from success and limitations of other mature fields.41 Further, rather than using average cost values per breached id, a multivariate stochastic model for should be developed.

Existing cyber event data suffer from a number of limitations. First, we did not analyze all event types in detail but instead concentrated on hack type events, which form 80% of all breached ids. Furthermore, we see this as the risk type that evolves more as we transition more into the cyber world, especially relative to theft of hardware and insider breaches, which take place in the more slowly evolving and constrained physical world. Second, while most U.S. companies today need to report cyber events, different states have different laws and thus reporting differences may be reflected in the data. Our data may represent only the tip of the iceberg given that many cyber events are simply not reported or revealed by their individual victims. And then there are thousands of additional events with unknown size.

However, given that data breaches are an extremely heavy-tailed risk, small events contribute little to the overall risk level. Further, as usual, applying a lower threshold as we have done credibly minimizes the aforementioned issues of reporting and data completeness, as large breaches tend to be profoundly consequential and difficult to suppress (witness Uber, 2017)42. Only a much more detailed study, perhaps aiming to capture multivariate dependencies, or a study for insurance focusing on small breaches only, would warrant an effort to bring the threshold down for better insight. However, data reliability and completeness issues would be far more severe there.

Fourth, we did not discuss in detail the potential delay in reporting cyber events and how it may affect the loss distribution. Our analysis of breach data indicates that about 80% of breaches were reported within 2 years of their occurrence. Ponemon 2017 estimate that it takes about 6 months on average to identify a breach. This will tend to bias downwards the estimate of event frequency in recent times, as can be seen in Figure 3 near the end of the data window (mid 2017). Despite this, we get a clearly significantly increasing frequency of big hacks43. There is also no meaningful impact of delay on the severity distribution expected.

Another relevant aspect is that breach events are often treated inconsistently, as sometimes multiple firms are targeted simultaneously by a single attacker. Recommendations were made for more mutually exclusive and exhaustive data standards. Notably, in the absence of disclosure of technical information by firms, future work should include and relate knowable fundamental variables to cyber risk (firm size, quantity of data, organizational structure, etc.), which define what size of a breach is possible (exposure), as well as hazard, and vulnerability. Such an analysis is necessary for an effective clustering into risk classes to support competitive and sustainable underwriting. In other terms, before a standard risk aggregation can be reliably implemented, substantial multivariate analysis needs to take place, identifying the key relationships among the between different firms, attack types, and data types, which current open data does not allow.

It was shown that cyber risk can be treated as a man-made natural catastrophe, but there are still important differences between cyber and natural catastrophes: The pricing of insurance policies is traditionally based on claims history. In case of natural catastrophes like earth quakes, the geographical location often determines the probability and severity of an event, while in case of cyber risk, the location in the cyber network determines this probability and severity. Although both risk types share the similarity of a heavy tail, the interdependent risk

41 E.g., In nuclear safety where efforts have been made to account for human error and limitations experienced, and more generally where largely realistic probabilistic safety models exist (see Kröger and Sornette, 2013).
42 To test empirically, one could look at data breaches in each state separately and see if there was a change-point when a new cyber law was introduced. This could be an interesting way forward but goes beyond the current paper.
43 Although we might technically control for this in estimation and obtain a slightly higher growth rate estimate, it won't make any meaningful difference, inter alia because the GLM regression model itself is only “approximately true” (i.e., model error likely dominates estimation error). However, if one were relying on a histogram estimator for frequency, one would have to be more careful.
structure of cyber risks, and the fact that cyber losses are not – as compared to the relatively stationary natural catastrophes data – as easily predictable since they evolve very quickly over time, the forecasting of cyber losses and thus their pricing for insurance purposes is more difficult. The three main problems with developing sound insurance policies -- which are based on enough history of actuarial data, taking current industry trends as well as new technology and human factors into account -- are (1) the high dynamics of cyber risk, (2) the lack of independence and (3) the extremely heavy tail of the loss distribution. A particular danger for risk pooling is the cumulative effect, where some breached information already exists latently, and when combined with a new breach allows for a rather costly event.

Finally, from a regulatory and social welfare viewpoint, cyber insurance should be used as an incentive to increase the level of investment in self-protection in the network, thereby potentially triggering a high protection level within the whole network (i.e., tipping points should be reached). In particular, premium differentiation and monetary incentives should be used to influence prevention efforts of policyholders. Setting appropriate incentives for protection from cyber risk can then also benefit other participants in the network via externality effects.

---

44 The insurer may, for instance, require policyholders to proactively enhance their cyber-security using other risk mitigation strategies such as encrypting important data, using regular backups, or using air gapping systems that disconnect them (temporarily) from the public internet (Shackelford, 2012).
References

Berliner, B. (1982), Limits of Insurability of Risks, Englewood Cliffs, NJ: Prentice-Hall.

Betterley, R. (2013), Cyber/Privacy Insurance Market Survey 2013: Carriers Deepen Their Risk Management Services Benefits - Insureds Grow Increasingly Concerned with Coverage Limitations, online edition, 2013, available online at: http://betterley.com/samples/cpims13_nt.pdf.

Boehme, R., Laube, S., and Riek, M. (2017): A Fundamental Approach to Cyber Risk Analysis, Variance Journal, www.variancejournal.org, online edition, 2017. Available online at: http://www.variancejournal.org/articlespress/articles/Fundamental-Boehme.pdf

Biener, C., Eling, M. and Wirfs, J. H. (2015). Insurability of cyber risk: an empirical analysis. Geneva Papers on Risk and Insurance-Issues and Practice, 40(1):131-158.

Cebula, J.J., Popeck, M.E. and Young, L.R. (2010). A taxonomy of operational cyber security risks, Technical Note, CMU/SE-2010-TN-028. Software Engineering Institute, Carnegie Mellon University.

Chernov, D. and Sornette, D. (2015). Man-made catastrophes and risk information concealment (25 case studies of major disasters and human fallibility), 1st ed. 2016 edition.

Cisco (2017). Midyear Cybersecurity Report. online edition, 2017. Available online at: https://engage2demand.cisco.com/LP=5897.

Edwards, B., Hofmeyr, S. and Forrest, S. (2016). Hype and heavy tails: A closer look at data breaches, Journal of Cybersecurity, 2(1):3-14.

Eling, M., and Schnell, W. (2016a). What do we know about cyber risk and cyber risk insurance? Journal of Risk Finance, 17(5):474-491.

Eling, M., and Schnell, W. (2016b). Ten Key Questions on Cyber Risk and Cyber Risk Insurance, Geneva Association Newsletter, November 2016 Report. Available online at: https://www.genevaassociation.org/sites/default/files/research-topics-document-type/pdf_public//cyber-risk-10_key_questions.pdf.

Eling, M. and Wirfs, J. H. (2015). Modelling and management of cyber risk. Available online at: https://www.actuaries.org/oslo2015/papers/IAALS-Wirfs&Eling.pdf.

Gordon, L. A., M. P. L. and Sohail, T. (2003). A framework for using insurance for cyber-risk management. Communications of the ACM, 46(3):81-85.

Grenberg, Andy. Crash Override: The malware that took down a power grid. Wired Magazine, June 2017. https://www.wired.com/story/crash-override-malware/

Grossi, Patrici, and Howard Kunreuther (2005). "Catastrophe modeling: a new approach to managing risk." Huebner international series on risk, insurance and economic security.

Hofmann (2007). Internalizing Externalities of Loss Prevention through Insurance Monopoly: An Analysis of Interdependent Risks, Geneva Risk and Insurance Review, No. 32, 91-111, 2007.
Hofmann/Ramaj (2011). Interdependent Risk Networks, *International Journal of Management and Decision Making*, Vol. 11, No. 5/6, 312-323, 2011.

Kaplan, S. and Garrick, J. (1981). On the quantitative definition of risk, *Risk Analysis*, 1(1): 11-27.

Koenker, R. and Hallock, K.F. (2001). Quantile regression. *Journal of Economic Perspectives*, 15(4), pp.143-156.

Kröger, W. and Sornette, D., 2013. Reflections on Limitations of Current PSA–Methodology. In: International Topical Meeting on Probabilistic Safety Assessment and Analysis (PSA) 2013. International Topical Meeting on Probabilistic Safety Assessment and Analysis (PSA) 2013.

Kumar, V., Telang, R. and Mukhopadhyay, T. (2007) Optimally securing interconnected information systems and assets, *Proceedings of the Sixth Workshop on the Economics of Information Security*, 7–8 June, Carnegie Mellon University. Available online at http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.209.425.

Kunreuther, H. and Heal, G. (2003). Interdependent security, *Journal of Risk and Uncertainty*, Vol. 26, pp.231–249.

Kunreuther, H.C., Bier, V.M. and Phimister, J.R. eds., (2004). *Accident precursor analysis and management: reducing technological risk through diligence*. National Academies Press.

Lynn, W.J. (2010). Defending a new domain, *Foreign Affairs*, 89(5):97-108.

Maillart, T. and Sornette, D. (2010). Heavy-tailed distribution of cyber-risks, *European Physical Journal B*, 75(3):357-364.

Maillart, T., Sornette, D., Frei, S., Duebendorfer, T. and Saichev, A. (2011) Quantification of deviations from rationality from heavy-tails in human dynamics, *Physics Review E* 83, 056101.

Malevergne, Y., Pisarenko, V., & Sornette, D. (2011). Testing the Pareto against the lognormal distributions with the uniformly most powerful unbiased test applied to the distribution of cities. *Physical Review E*, 83(3), 036111.

RMS, 2017 Cyber Risk Landscape, RMS, 2017. http://www.rms.com/models/cyber.

Mukhopadhyay, A., Chatterjee, S., Saha, D., Mahanti, A. and Sadhukhan, S. K. (2013). Cyber-risk decision models: To insure IT or not? *Decision Support Systems*, 56:11-26.

Oeguet, H., Raghunathan, S. and Menon, N. (2011). Cyber security risk management: Public policy implications of correlated risk, imperfect ability to prove loss, and observability of self-protection, *Risk Analysis*, 31(3)

Opadhyay, T. B., V. S. M. and Rao, R. C. (2009). Why IT managers don’t go for cyber-insurance products. *Communications of the ACM*, 52(11):68{73.

Ponemon (2014). 2014 Cost of Data Breach Study, US.

Ponemon (2017). Cost of Data Breach Study, IBM/Ponemon, 2017. https://www.ibm.com/security/data-breach.

Romanosky, S., Ablon, L., Kuehn, A. and Jones, T. (2017). Content Analysis of Cyber Insurance Policies, Working Paper, RAND Justice, Infrastructure, and Environment, 2017. Available online at: https://www.rand.org/content/dam/rand/pubs/working_papers/WRI200/WRI208/RAND_WRI208.pdf
Rothschild, M., Stiglitz, J. E. (1976). Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information, *Quarterly Journal of Economics*, 90(4), 629-649.

Saichev, A., and D. Sornette (2010). Effects of diversity and procrastination in priority queuing theory: The different power law regimes. *Physical Review E* 81.1 (2010): 016108.

Schelling, T. (1978) *Micromotives and Macrobehavior*, W.W. Norton and Firm, New York.

Shackelford, S.J. (2012). Should your firm invest in cyber risk insurance?, *Business Horizons*, Vol. 55, p. 349-356.

Shetty, S., McShane, M., Zhang, L., Kesan, J.P., Kamhoua, C.A., Kwiat, K., Njilla, L.L. (2018). Reducing informational disadvantages to improve cyber risk management, *Geneva Papers on Risk and Insurance – Issues and Practice*, forthcoming.

Wheatley, S., Maillart, T., Sornette, D. (2016). The extreme risk of personal data breaches and the erosion of privacy, *The European Physical Journal B*, 89(7):1-12.

Zetter, Kim (2014). *Countdown to Zero Day: Stuxnet and the Launch of the World's First Digital Weapon*. Broadway Books.
Appendix

A.1 Attack strategies, breach costs by industry for the United States, and median time-to-detection of cyber attacks

Generic cyber-attack strategies include: *Denial-of-Service (DOS)* attacks, which shut down websites or services and are often distributed -- stemming from many different sources/computers worldwide. *Malware* (“malicious” + “software”) is used to harm the user (via email worms, viruses or trojans). *Phishing* (“password” + “fishing”) refers to false email messages designed to acquire user information, e.g. in order to gain access to certain websites. *Ransomware* programs take some virtual property or data hostage with the promise to return it given a ransom payment (often cryptocurrency, making catching hackers difficult), and may even autonomously travel between networked computers. A new threat called *business email compromise (BEC)*, exploiting illicit access to an official email account, has become extremely lucrative, with US$5.3 billion loss between October 2013 and December 2016, compared with “only” US$1 billion in ransomware loss in 2016 (Cisco, 2017). Another new strategy is *Destruction of service (DeOS)*, where the applications that users rely on to restore their systems and data following an event is destroyed.

![Figure A1: Median time to detection, i.e., window time between a compromise and the detection of a threat. Source: Cisco (2017).](image1)

![Figure A2: Per capita breach cost by industry. Source: Ponemon Institute (2017).](image2)
A.2 Cyber events in the United States by State

Figure A3 shows the 12-year frequency and median severity of information items compromised by U.S. state. As can be seen, the highest frequencies are in the States of New York and California, followed by Texas and Ohio. The highest severity, interestingly, has Nebraska, followed by Nevada and District of Columbia.

Figure A3: 12-year frequency and median severity of ids (information items compromised) by U.S. state. Notes: We use only breach events from the PRC [rather than OSF DLDB] database, where state information is readily accessible. States with ≤ 10 cyber incidents over the 12 years were omitted [i.e. Alaska, Arkansas, Delaware, Hawaii, Idaho, Kansas, Louisiana, Maine, Mississippi, New Hampshire, New Mexico, North Dakota, Rhode Island, South Dakota, Vermont, West Virginia, Wyoming]. The inset panel magnifies the cluster near the origin.
A.3 Chronology of cyber events: Is there a general trend?

There is a strong trend for increasing frequency and severity of hack data breach events, having size > 10,000k. This very strong trend is not distinguishable for overall breach events in excess of 10k (see Figures A4 and A5).

**Figure A4:** Chronology of high-impact cyber events involving ids > 25,000k compromised during 01/2005 through 9/2017. We can see a strong upward trend in severity here. *Note:* Natural logarithmic scale for ids along the ordinate axis.

**Figure A5:** Chronology of all breach events from 01/2005 through 9/2017. As can be seen, the overall picture for the severity shows a weak upward trend. A more specific view is necessary to identify trends. *Note:* Natural logarithmic scale for ids.