Risky Business: Assessing Security with External Measurements

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ABSTRACT

Security practices in large organizations are notoriously difficult to assess. The challenge only increases when organizations turn to third parties to provide technology and business services, which typically require tight network integration and sharing of confidential data, potentially increasing the organization's attack surface. The security maturity of an organization describes how well it mitigates known risks and responds to new threats. Today, maturity is typically assessed with audits and questionnaires, which are difficult to quantify, lack objectivity, and may not reflect current threats.

This paper demonstrates how external measurement of an organization can be used to assess the relative quality of security among organizations. Using a large dataset from Bitsight1, a cybersecurity ratings company, containing 3.2 billion measurements spanning nearly 37,000 organizations collected during calendar year 2015, we show how per-organizational ‘risk vectors’ can be constructed that may be related to an organization’s overall security posture, or maturity. Using statistical analysis, we then study the correlation between the risk vectors and botnet infections. For example, we find that misconfigured TLS services, publicly available unsecured protocols, and the use of peer-to-peer file sharing correlate with organizations that have increased rates of botnet infections. We argue that the methodology used to identify these correlations can easily be applied to other data to provide a growing picture of organizational security using external measurement.

1. INTRODUCTION

In an increasingly connected world, organizations frequently partner with third parties. A 2014 report by the Institute for Internal Auditors found that 91% of organizations partnered with technology vendors, 76% with business service providers, and 40% formed strategic partnerships with third parties [66]. These partnerships often entail sharing confidential data and integrating network infrastructure, potentially increasing an organization’s attack surface and risk. One high profile example was the 2014 Target breach, which exposed credit card information about 40 million customers [30] when attackers stole a third party vendor’s credentials and used them to infiltrate the network [47].

Traditional approaches to managing the risk in such partnerships use risk assessment questionnaires [4, 8] and audits [14]. The results are then interpreted with cyber threat matrices [42], which provide a rough, qualitative snapshot of risk. Such strategies are time consuming, expensive, and it is unclear how effective they are. Although some efforts have been made at standardization [4], there is currently no standard quantitative and objective approach to assessing risk in these environments. Finally, although assessments, audits, and compliance standards can point to vulnerabilities (potential avenues of attack), they do not link these vulnerabilities to actual outcomes. Thus, there is a need for a different approach to the problem of understanding and mitigating security risks in organizations. Ideally, such an approach will be objective (not subject to self-interpretation), non-invasive, quantitative, and it will reflect actual risk, rather than hypothetical threats.

This paper addresses the need by presenting a rigorous, data-driven methodology for assessing organizational risk vectors. The methodology can inform an organization about the risks posed by third-party partnerships, and it can help it better understand its own risk profile, ultimately providing guidance on how to improve the security of its internal networks. The methodology consists of three components: 1) a mapping of network (IP) space to individual organizations 2) measurement of possible avenues of attack which we dub ‘risk vectors’ and 3) measurement of externally observable security incidents.

We focus on risk vectors that can be measured externally and objectively and show how they correlate with actual security incidents. We investigate three broad classes of risk vectors: peer-to-peer file sharing, incorrect configuration of Transport Layer Security (TLS) services, and the presence of publicly available insecure communication protocols. For simplicity, we focus on assessing risk using one type of security incident, the presence and prevalence of botnet infections within an organization. While there are myriad possi-
ple security incidents to measure, botnets are a critical part of the cybercrime infrastructure, and cost users upwards of $10 billion in cleanup costs alone [3]. Because our method is statistical in nature, it doesn’t identify root causes of any particular security incident. Rather, it provides an overall assessment of the security maturity of an organization, in the same spirit as assessments and audits.

To investigate the link between risk vectors and botnet infections, we begin with a large dataset consisting of over 3.2 billion network events measured across almost 37,000 organizations throughout 2015 (Section 2.C). IP addresses are associated with specific organizations through a rigorous and unique mapping process (Section 2.A). The mapping allows us to use large-scale scans of the Internet and associate specific kinds of events with a particular organization. Combining these data with information about an organization’s size and other properties (Section 2.B) allows us to normalize measures of risk and botnet infection, study different types of organizations, and make comparisons across similar organizations.

With these data in hand, we show how they can be leveraged to develop statistical models to establish quantitative relationships between risk vectors and botnet infections. We find that each of the three categories of risk vector correlates with the prevalence and presence of botnets within an organization. We also study how the effects of each risk vector varies with the type of organization, finding significant differences between different organization types.

We do not claim that the link between risk vectors and botnet infections is causal. However, we do suggest that they have a common cause—security immaturity. Failure to configure TLS services correctly, making known insecure protocols publicly available, and allowing employees to download files that are likely infected with malware, are all indicative of poor network security practices. Similarly, the failure of an organization to detect and remove botnet infections suggests that it probably lacks a systematic and thorough approach to security. In this way, the paper shows how security maturity can be effectively assessed through external measurements of risk vectors and infections.

Our results only focuses on a handful of risk vectors which are externally observable, and one type of security incident. However, our methodology is general and could easily be expanded to more risk vectors and different security incidents, e.g. data breaches and service interruptions. We believe that moving towards a more quantitative data-driven view of risk assessment will be crucial in the future. Not only will provide a clearer picture of cyber risk, but will help to assess whether specific security lapses are associated with incidents. This in turn will help security practitioners assess and triage emerging threats for their specific organization.

In summary the paper makes several contributions:

1. A methodology for collecting security data about organizations using external measurements.
2. A demonstration of how to analyze the collected data to gain insight about the relative security of organizations
3. Insights from the data including: a strong relationship between peer-to-peer sharing activity and botnet infections, and differentiation of risk vectors across different industries.
4. A thorough discussion of how the methodology could be expanded and used to cover other types of incidents and risk vectors.

The rest of the paper is organized as follows: Section 2 elaborates on our process for data collection, organization, and aggregation. Next section 3 provides an initial analysis of the data and examines some of it’s basic properties. Section 4 builds several models of risk vectors and botnet infections. Section 6 cover related work. We conclude with a discussion of the implications of our results and opportunities for future work in section 5 and some final remarks in section 7.

2. DATA COLLECTION AND PROCESSING

This section describes the data collection and processing that were used in this study. The dataset was collected throughout 2015 by BitSight for use in their commercial service. We discuss how the data was used to develop the mapping of IP space to organizations, the measurement of risk vectors, and the measurement of security outcomes.

2.1 Identifying an Organizations Network Footprint

The first step to measuring an organization’s security practices is to identify its overall network presence. Over the past four years, BitSight has developed a process for identifying the IP addresses associated with individual organizations, which they use for in their commercial service. In this section we give an overview of our process. A variety of methods could be used to construct a mapping of IP space to organizations, but it is crucial to make this mapping as accurate as possible. Given the heavy tailed nature of security incidents [?, ?], misc attribution of a security incident could alter the assessment of an organization.

For this reason the process presented here utilizes a manual verification step. Specifically, individual researchers construct mappings for each organization, which is then independently checked by another researcher. This process presented here is an improvement over the one used in [?] as it uses additional information sources and completed and verified manually.

Organizations are selected because they are economically prominent (such as the Fortune 500 companies) or are referred for mapping through industry partners. A researcher starts the mapping process by first identifying an organization’s web presence and main company domain. Next, a company’s presence on social media as well as other public sources are examined and information about the company is gathered. This includes the industry in which the organization operates and its number of employees. The number of employees gives a rough estimate of the organization’s size, which we use to normalize some of our other measurements so meaningful comparisons between different organizations can be made. This is an imperfect measure of size however, and we discuss some consequences in section 3 and suggest how it might be improved in [?]. Next, media sources and financial fillings are used to identify any fully owned subsidiaries of an organization. After this organizational information is gathered, a manual search of BGP routing information, regional internet registries, and other proprietary services are consulted to identify IP addresses which are allocated to that organization and its subsidiaries.
We believe this represents a best-effort approach to accurately identifying organizational ownership of IP addresses and thus observed events and services. At the time these data were collected, BitSight has mapped 1.8 billion IPv4 addresses (42% of the IPv4 Internet), enabling us to observe 36,982 distinct organizational entities in 2015. This includes all of the Fortune 500 companies. However, any methodology which endeavors to associate IP addresses to organization will face many challenges, such as the deployment of DHCP and NAT and the increasing use of cloud services. We believe our approach improves on previous similar mapping techniques [39] by consulting multiple additional sources, manual identification of IP ranges, and includes a manual verification step.

2.2 Risk Vectors

Here we describe a handful of externally observable events and system states, which we refer to as “risk vectors” (also known as risk factors). Most are unlikely to directly cause malware infections in and of themselves (though peer-to-peer activity might be an exception); rather, they are indicators of conditions in an organization that may lead to malware infection or other security problems. That is, risk vectors relate to an organization’s security maturity. We consider three classes of risk vectors: peer-to-peer file sharing, transport layer security, and network services.

2.2.1 Peer-to-Peer File Sharing

Peer-to-peer file sharing protocols are well-known security risks. Research has shown that as many as 35% of torrent files are infected with malware [15], and the infrastructure itself can be used to propagate worms [31]. Since peer-to-peer file sharing has only limited use in most enterprises, many security-conscious organizations block BitTorrent by default within their networks or prevent their users from installing and running torrent clients. While other peer-to-peer file sharing protocols exist we focus on BitTorrent because it is the most popular protocol [51].

We identify peer-to-peer file sharing by collecting torrent tracker lists from two of the largest open and public trackers. For each torrent in the tracker list we collect a list of IP addresses that are ‘seeding’ the file, meaning the IP addresses that have downloaded the complete file and made it available for download by others. The IP addresses are then mapped to organizations as described above. This provides a count of the number of files actively shared by each organization, which we normalize by the number of employees to produce a per employee concentration. By counting the total number of files rather than IP addresses sharing, we believe we obtain a more accurate representation of the prevalence of file sharing than would be obtained by raw IP counts.

2.2.2 Transport Layer Security

Transport Layer Security (TLS) is the backbone of encrypted internet communication and is often the target for new attacks and vulnerabilities.

We track two different types of possible errors in the TLS protocol, software configuration weaknesses and certificate weaknesses. Software weaknesses are caused either by out-of-date software or an administrative error in the configuration of the service. Out-of-date software leaves the network susceptible known vulnerabilities such as Heartbleed [21] and FREAK [6], while the use of weak versions of the Diffie-Helman key exchange could lead to eavesdropping [2]. It is unlikely that TLS weaknesses would lead directly to malware infections at any measurable scale. More commonly, the result is that some data are no longer communicated confidentially. However, TLS issues provide an excellent indicator of the state of an organization’s security maturity.

We derive data on the number, type, and configuration of TLS services from Internet wide scans of IPv4. These scans probe all of IPv4 space and attempt to identify any running services across a number of ports utilized for common services [22]. 250 different ports commonly used for a variety of services were scanned. We limit our investigations to ports offering TLS and 21 ports commonly associated with popular services (see section 2.2.3). Scans were completed roughly once per month, and if a TLS service was present, a connection was established with the server, and the certificate presented as part of the process was saved for analysis. While faster scanning processes exist [22], our approach utilizes more in-depth scanning, for example it tests all possible encryption suites and protocol versions when establishing a TLS connection. This less frequent scanning also reduces the chance that the scans will be perceived as malicious and blocked. Since we find little variance in the total number of TLS services for each organization each month, we believe that the scans are accurate enough for our purpose.

Certificate errors refer to problems with the certificates used for authentication and the Public-Key Infrastructure. The collected certificates were examined to determine if they used keys created using weak cryptographic protocols, were signed using cryptographically weak hash functions, or had a suspicious chain of trust. Specifically, we collect information on chain of trust issues including expired certificates, certificates that were issued for a future date, self signed certificates, and certificates whose chain of trust is broken. Any of these errors alone could be benign, but all are potentially exploitable by a determined attacker and relatively easy to fix, and therefore a good candidate indicator of the maturity of the organization.

Specifically, we looked for the following errors in software configuration:

- TLS version less than or equal to SSLv3;
- The presence the Heartbleed or FREAK bugs;
- The presence of weak Diffie-Helman Key exchange, either keys with less than 2048 bits or with commonly used prime numbers;

and certificate errors, including:

- Self signed certificates, expired certificates, certificates that were issued in the future, certificates with non-standard roots, and certificates with a broken chain of trust;
- Certificates with weak keys, specifically using RSA or DSA with 1024 bits or less, or ECC with less than 224 bits;
- Certificates with weak signatures, including those signed with SHA1, MD5, and MD2.

Larger organizations are likely to have a higher number of TLS services. To be able to make comparisons across organizations, we calculate the fraction of TLS services that have configuration and certificate errors. Each of these fractions is used as a separate risk vector in our analysis.

2.2.3 Services

Finally, we measure how many and what kind of network
services the organization makes publicly available. While scanning for TLS services we also scanned for other types of services on other ports. Although any external communication service increases the attack surface of an organization, some services are safer than others. For example, remote terminal access through SSH is encrypted and supports key-authentication, so it is preferred over terminal access through Telnet, which transmits all data through plain text, leaving an organization susceptible to eavesdropping and interception of passwords and data.

We scanned 250 different services and categorized 21 frequently used services into risky, neutral, and reasonable. These services account for just under 95% of all services seen in the scans and were selected because they were popular or posed significant security risks. Reasonable services are those that can be exposed to the Internet with relative little fear of easy exploit such as SSH, while risky services should not be open to public access (telnet). Neutral services are those which may be exploited given misconfiguration or unpatched software, but are not inherently dangerous or are required to be exposed to the outside world to be useful, for example HTTP. These services are summarized in table 1.

For each organization we normalize by calculating the fraction of known services that were classified as reasonable, neutral and risky.

### 2.3 Botnet Infections

The above measures identify the network properties of an organization, but do not directly measure security incidents. In this paper we examine a common security incident: botnet infections. In this section, we describe how data from a diverse number of botnets is collected as a measure of security incidents within a company.

Botnet infection data is collected through Anubis Networks. Anubis Networks uses several techniques to infiltrate botnet command and control structure so measurements of individual infections can be taken. First, samples of malware are obtained and are reverse engineered to identify how a particular bot communicates with its command and control infrastructure. Many botnets communicate through randomly generated domains, created using Domain Generating Algorithms (DGA) which are controlled by the botnets master. By reverse engineering the DGA used to create these random domains, Anubis is able to register domains consistent with the algorithm. Communications from the infected client to these domains allows for the monitoring of IPs associated with infections.

Some botnets have attempted to circumvent this type of infiltration by using a peer-to-peer architecture to communicate with the botnet master. In these cases, a machine controlled by Anubis executes the malware and communicates with other members of the botnet is monitored. These bot peers can then be queried to further investigate the peer-to-peer structure.

Using this methodology, the activity of 120 different botnets was monitored in 2015. In this period over 650 million unique infection days were identified, where an infection day is a unique IP address infected on a specific day. For each organization we measure this count of infection days on a monthly basis. For example, if an organization has a single IP address which is infected for a single day in a month, its infection day count is 1. Whereas if that single IP address is infected for a week its infection day count is 7. This measure allows us to measure the severity of infection by both the total number of infected IP addresses and the duration of infections. We then normalize these counts by employee count to obtain a concentration of infection days per employee per month. Because of the presence of NATs and DHCP, these measurements represent a lower bound on infection concentrations. We discuss how we might address this in the future in section 5.

### 2.4 Data Aggregation

While it is conceivable that some of these data could be collected continuously, for example the botnet data could be collected in real time, most collection requires longer time scales. Scanning available services requires roughly a month to scan all the possible IPs associated with the organizations we are monitoring. Therefore, we aggregate the data by month, producing monthly counts and rates for each organization. We found little variation in any of the measures over time, so we averaged the values of the measured quantities over the entire year. Future research could investigate the impact of time, for example, how risk vectors and infections change after major security incidents such as data breaches.

### 3. ANALYSIS OF RISK VECTORS AND INFECTIONS

This section examines the data aggregated in section 2. First, we investigate some of the basic properties of the data. Next, we ask whether our risk vectors (peer-to-peer file sharing, TLS errors, and publicly accessible services), correlate with botnet infections. We find that risk vectors are correlated with botnet infections in ways we would expect.

#### 3.1 Risk Vectors

We begin the analysis by visualizing the distribution of
analyze both the presence and prevalence of botnet infections and peer-to-peer file sharing in our analysis. Figure 3 also shows a large percentage of the measured values of certificate and service errors are either zero or one. That is, for many organizations either all of their TLS services were misconfigured or none were. In between these two values we see a relatively smooth distribution. A similar property can be seen in risky and reasonable services, though it is not as pronounced, with both types of services experiencing relatively high density at one. We discuss the implications of this type of distribution in section 5.

3.2 Identifying Correlations Between Risk Vectors and Infections

To establish whether a relationship exists between risk vectors and security outcomes we use three statistical methods. When both measures are continuous, we use Spearman’s $\rho$, a nonlinear measure of correlation [19]. We use Spearman’s $\rho$ instead of the traditionally used Pearson’s correlation coefficient, because some of the relationships may be nonlinear and we would like to capture any dependence between the values.

When one value is continuous and the other is discrete, for example the presence the existence of botnets and the fraction of services which employ encryption, we use Mann-Whitney-Wilcoxon rank-sum test [41]. This test is similar to the Student’s $t$-test in that it tests whether one particular distribution is larger than another, except it does not rely on an assumption of normality for the underlying distributions. Finally, when both values are discrete, we use a $G$-test, which is a measure of statical dependence in discrete variables. It is recommended that the $G$-test be used in situations where the $\chi^2$-test was traditionally used, as the $\chi^2$-test was conceived as an easily calculable approximation of the likelihood ratio test [58].

3.3 Risk Vectors and Infections

Because a large number of organizations experience no botnet activity, we first test whether any of the risk vectors are associated with the presence of bots in an organization. To do this, we consider the distribution of each of the risk vectors for organizations which we have measured botnet activity and those which we have not. The results can be seen in figure 2.

A very clear relationship can be seen in panel A) of figure 2 for organizations with peer-to-peer activity tend to have some botnet activity, while those without peer-to-peer activity tend to lack botnet activity ($p < 10^{-12}$). For the other risk factors the results are not easily visually discernible; however, we can establish the difference using statistical tests. For three of the five remaining risk vectors, the relationship between botnet infections and the risk vector is what we would expect, organizations with bots generally have higher levels of TLS certificate errors (D), risky services (E) and lower levels of reasonable services (F). These differences are statistically significant using the Mann-Whitney-Wilcoxon rank test ($p < 10^{-4}$).

Counter-intuitively the prevalence (shares per employee) is slightly higher for organizations without bots ($p < 10^{-12}$). This is also the case in the difference in the distribution of

![Histograms of risk vectors and botnet infections.](image)

Figure 1: Histograms of risk vectors and botnet infections. Note that plots of botnet infections per employee (A) and peer-to-peer file sharing per employee (B) are plotted on log scales, as they span several orders of magnitude. All others are on linear scales. (A) appears as a slightly different color as it is an outcome as opposed to the other variables which are risk vectors.

To account for the large number of zeros in the data we...
Figure 2: A) shows the percentages of organizations with and without bots and the relative number of those organizations that have peer-to-peer activity. B) C) D) E) and F) are violin plots of the distributions of risk vectors in organizations measured to have botnet activity and those without botnet activity. Each subplot contains a violin plot which is a representation of the underlying distribution of values as represented by a Kernel Density Estimate. Box and Whisker plots are also included showing the 25% 50% and 75% quartiles(Box) and 1.5 times the inner quartile range (Whiskers).

3.4 Botnet and Risk Vector Correlation

The relationship between the count of IP addresses associated with botnets per employee and various risk vectors is plotted in Figure 3. Values of the Spearman’s Correlation Coefficients can be seen in table 2.

We can see that peer-to-peer sharing has a strong positive relationship to botnet infections. In particular we note that it appears roughly linear on a log-log scale\(^4\). This may indicate the existence of a power-law relationship. The other variables have weak, but statistically significant linear relationships to botnet infection rates.

The other risk vectors show weak but significant correlations. The negative correlation between reasonable services and botnet infections may at first seem counterintuitive, as running any services, even if they are reasonable, would increase an organizations attack surface, increasing the potential for infections. However, because we are measuring the fraction of services which are reasonable, organizations with a high fraction of reasonable services (and necessarily a lower fraction of risky services), are likely to have a smaller attack surface than those with a high fraction of risky services.

4. MODELING BOTNET INFECTIONS

This section examines the effect of the organizational risk vectors on botnet infections. We start by constructing a model that quantifies how the risk vectors are correlated with botnet concentration. Next, we consider how these correlations vary across different industries.

4.1 Modeling Approach

We use simple linear regression to model the effect of the various risk vectors presented in sections 2 and 3 on botnet
Table 2: Correlation Coefficients between risk vectors and botnet count per employee. All correlations are significant at the \( p < 10^{-12} \) level.

| Variable                        | Spearman’s \( \rho \) |
|--------------------------------|------------------------|
| Concentration of Peer-to-Peer  | 0.725                  |
| TLS Configuration Errors       | 0.176                  |
| TLS Certificate Errors         | 0.174                  |
| Risky Services                 | 0.138                  |
| Reasonable Services            | -0.151                 |

The relationship between peer-to-peer sharing and botnet infections appears to be linear in figure 3. This suggests that a linear multiple regression with appropriately transformed variables is a reasonable method for studying the effect of each risk vector on botnet infections [12].

4.1.1 Variable Transformation

Beginning with the peer-to-peer file sharing data shown in section 3, the apparent linear relationship with botnet infections a log/log scale suggests a type of power-law relationship. To incorporate this variable into our linear regression, we would expect to log-transform the data first. However, this would entail removing the 13.5% of organizations with zero peer-to-peer file sharing and non-zero concentrations of botnet infections, possibly biasing our results. To avoid this problem, we separate the peer-to-peer data into two variables [22]: 1) an indicator random variable (binary variable) that is one if the peer-to-peer file sharing value is zero and 2) a transformed variable calculated as \( \log(\text{concentration of peer-to-peer shares}) \). Specifically, if \( t \) is the number of files being shared per employee, we calculate the indicator random variable, \( t_0 \), as

\[
t_0 = \begin{cases} 
1, & \text{if } t = 0 \\
0, & \text{otherwise} 
\end{cases} \tag{1}
\]

and the transformed variable \( t \) as

\[
t = \begin{cases} 
\log(t), & \text{if } t > 0 \\
0, & \text{otherwise} 
\end{cases} \tag{2}
\]

This transformation is useful in two ways. First it allows us to incorporate the observed log/log relationship while including all of data points. Second, it allows us to measure both the effect of both presence and prevalence of file sharing.

4.1.2 Regression Model

Because the rest of the variables presented in section 3 do not span multiple orders of magnitude and have a roughly linear relationship with botnet infections, we can include them as linear terms in the regression. Our final regression model is

\[
\log(b) = \beta_0 t_0 + \beta_1 t + \beta_2 T_{CF} + \beta_3 T_{CT} + \beta_4 S_{Ri} + \beta_5 S_{Re} + \beta_6 N(0, \sigma)
\tag{3}
\]

where \( b \) is botnets per employee, \( t_0 \) and \( t \) are the transformed variables from equations 1 and 2 respectively; \( T_{CF} \) is the fraction of TLS services with configuration errors; \( T_{CT} \) is the fraction of TLS certificates with certificate errors; \( S_{Ri} \) is the fraction of risky services; \( S_{Re} \) is the fraction of reasonable services; \( \beta_0 \) is the intercept; and \( N(0, \sigma) \) is the normal distribution of residuals with mean 0 and standard deviation \( \sigma \).

4.2 Regression Results

We determined the coefficients \( \beta_i \) in equation 3 using ordinary least squares. Post-regression diagnostics indicate that it is unlikely our coefficients estimates are biased. The exact coefficients are shown in table 3 and depicted visually in Figure 4.

The results of the regression indicate that the measured risk vectors affect the concentration of bots in the expected way. Organizations with high concentrations of peer-to-peer sharing, risky services, and configuration and certificate errors, tend to have higher concentrations of botnet infections.

![Figure 4: Plot of the regression coefficients from equation 3. An estimate of each coefficient’s distribution is given as a Kernel Density estimate on each line. Solid lines below represent 98% confidence intervals and dark blue lines are significant at \( p < 0.01 \).](image)

Table 3: Estimated Coefficients for the model described in 3. All value are statistically significant at the \( p < .005 \) level, except for the Intercept which is significant at the \( p < 0.1 \) level.

| Variable                        | Coefficient | Estimate |
|--------------------------------|-------------|----------|
| Peer-to-Peer Blocked (\( t_0 \))| \( \beta_1 \) | -5.763   |
| Peer-to-Peer Concentration (\( t \))| \( \beta_2 \) | 0.841    |
| TLS Configuration Errors (\( T_{CF} \))| \( \beta_3 \) | 0.512    |
| TLS Certificate Errors (\( T_{CT} \))| \( \beta_4 \) | 0.638    |
| Risky Services (\( S_{Ri} \))| \( \beta_5 \) | 0.509    |
| Reasonable Services (\( S_{Re} \))| \( \beta_6 \) | -0.493   |
| Intercept                      | \( \beta_0 \) | -0.167   |

\( R^2 \) is 0.458
Figure 4 illustrates the difference in effect size between each of the variables. Interestingly, we see that the indicator variable for peer-to-peer sharing has the largest effect. In particular, we calculate using the model (equation 1) that organizations that allow peer-to-peer file sharing have, all other things being equal, more than 318 times the number of bots per employee. We explore the reasons for this large effect in the next section and the section 5. We can calculate the effects for other variables, for example, organizations with 10% higher peer-to-peer file sharing per employee have an 8.3% higher rate of botnet infections. Organizations with no TLS certificate errors have 14% lower botnet infections than those with a 25% misconfiguration rate.

The variation in the estimates for each variable seen in figure 4 is also interesting. The narrow variation in the concentration of peer-to-peer sharing indicates a consistent effect across different organizations, while the wider variation seen in risky services indicates an inconsistent effect which perhaps varies significantly across different organization types. For example, we hypothesize that the reason for the weak effect is that in some organizations, risky services might be necessary and appropriately handled, even if in general this risk vector is associated with higher levels of botnet infections. We explore how the effect of different industries influences these relationships in the next section.

4.3 Industry Effects

Next, we ask whether or not the risk vectors have different effects in different industry types. For example, telecommunications companies and universities typically have less control over the computers connected to their networks and this may lead to higher botnet infection rates. This effect can be seen in figure 4, where the distribution of botnet infections for various industries is plotted. As a more rigorous test, we conducted a pairwise comparison of botnet infection distributions between all industries using a Kolomogorov-Smirnov (K-S) test. Among the 231 possible industry comparisons, 63% indicated that botnet distributions between industries differed. We discuss more refined groupings of industries in section 5.

This suggests that the model in equation 3 captures only some of the relevant behavior and that more detailed industry-specific models may be appropriate. There are several possible approaches that could be used, e.g., we could include an indicator random variable for each industry (fixed effect model), we could allow a different intercept for each industry (random effect model), or we could refit the regression model once for each industry (an un-pooled model). Each of these approaches will result in a more accurate representation of the data, but at the expense of potentially unnecessary complexity. We use Akaike Information Criteria (AIC) to select among different possible models. AIC considers the model’s goodness of fit and penalizes its complexity. We found that the most complex model, a separate regression for each industry, gives the minimum (preferred) AIC despite the large number of variables (154). The results are shown in figure 4.

The above plot shows how the effect of risk vectors varies across industries. The only consistent effect across all industries is peer-to-peer file sharing (Columns A and B). This indicates that the large effect observed in section 4.2 is not confined to organizations with a large number of hosts per employee, e.g., telecommunications and education. In particular, Column A has one of the smallest effects for educational organizations. And, Column B (concentration of peer-to-peer file sharing) is one of the most consistent across industries, with comparatively low variation compared to the other coefficients.

Among industries, the effect of the other variables is mixed. For most variables and most industries, when significant effects are present, they affect botnet infections in the direction we would expect. TLS configuration, certificate errors, and risky services all increase botnet infections, while infection rates decrease as the fraction of safe services increases. There is one possible exception to this trend, in Column E (risky services). The presence of a large fraction of risky services decreases botnet infections within the real-estate industry. This effect is not significant at the p < 0.01 level but is at the (p < 0.015) level. This puzzling finding is warrants

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When the dependent variable is log-transformed, a one unit change in an independent variable results in an \( e^{\beta} \) change in the dependent variable. Organizations that block peer-to-peer sharing have \( e^{-5.76} = 0.00314 \) times lower botnet infections rate, or inversely \( 1/0.00314 = 318 \) higher botnet infection rate.

For brevity, we do not give the exact values of all 154 coefficients and their standard errors here; however, we will make them available before publication.
Figure 6: Visual representation of coefficients for the un-pooled regression model. Each panel (A-G) shows the coefficients for each industry in the vertical axis. Each bar represents the 98% confidence interval around the coefficient estimate. Estimates which are statistically significant at the $p < 0.01$ level are blue. Non-statistically significant estimates are in grey.

further investigation.

Finally, for most industries not all risk vectors have a significant effect on botnet infections. For example, having a high fraction of reasonable services is significant in only Government/Politics, Business Services, and Telecommunications industries. Similarly, TLS configuration and certificate errors only affect a handful of industries.

5. DISCUSSION

In this section we highlight some of the more interesting results arising from our analysis, and we discuss threats to the validity of the results. We conclude by exploring a number of possible future research opportunities suggested by this rich data set and the analysis.

Figure 2 showed, counterintuitively, that organizations with bots tend to have lower concentrations of peer-to-peer file sharing as opposed to those with no botnet activity. A second surprising result is organizations with botnet infections do not have more TLS configuration errors than those without bots. Although we do not have a definitive explanation for these two unexpected results, we speculate that they could be caused by having set an unrealistic threshold of zero for low botnet activity. It is unlikely that over the course of an entire year any organization would be completely free of botnet infections. Other more reasonable thresholds for errors may provide a clearer and more intuitive picture.

Among the risk vectors we studied, the presence and prevalence of peer-to-peer file sharing through BitTorrent had the largest effect on botnet concentrations among organizations that showed signs of infection. Initially we hypothesized that this was an artifact of normalizing organization size using employee counts rather than number of computers. If true, we would expect to see differences in the un-pooled regression study. However, peer-to-peer file sharing had a consistent effect across all industries. Research on file sharing has focused on the performance and security of the protocol itself, rather than on the security risks it creates as a side effect (see section 6).

We reiterate that our analysis has identified correlations and that the risk vectors are not necessarily causal. For example, it is unlikely that an expired TLS certificate would lead directly to a botnet infection. However, given the prevalence of malware present in files shared through BitTorrent[15], it is possible that some of the infections we measured are the direct result of file sharing. The most likely cause for the relationships we see is that both risk vectors and botnet infections arise from the same common cause: security immaturity. For example, organizations that don’t prevent the use of peer-to-peer file sharing may also have difficulty identifying and cleaning up botnet infections.

When we created the un-pooled regression model by industry we found only one surprising result: in the real estate industry, a high fraction of risky services is associated with lower levels of botnet infections. This anomalous result does not have an obvious explanation.

Many of the risk vectors did not have significant statistical effects in the un-pooled regression. This could be an artifact of how we defined the risk vectors originally. For example, we give equal weight to all TLS errors, but some errors may be more indicative than others. A second possibility is that there are real differences in risks in different industries. For example, correct TLS configuration may be less important in the aerospace industry because its main business does not involve communicating customer data. In the future, an organization might use the kind of analysis presented here to prioritize which security issues to address first.

5.1 Caveats and Threats to Validity

As with any large-scale study, our data might be incomplete or biased. Variation in monthly scans was small, but even this small amount of variation may indicate that we are missing some data. We mitigate this issue by aggregating monthly data into a single yearly measure for each organization. In the future, higher resolution data might provide
additional insights.

As discussed earlier, we measure organization size in terms of employee counts, assuming that this is a good proxy for of the actual number of computers within the organization. What we actually care about is the number of computers connected to each organization’s network. However, to our knowledge there is no straightforward way to obtain such a count. We know, for example, that employee count is not particularly accurate for Telecommunications companies (because employee counts miss all the customers and their computers). We also know that in educational institutions, students are not included in employee counts. A potential alternative would be to estimate organization by counting the total number of IP addresses associated with it. We have experimented with this measure informally with similar results.

Any measurement that assesses network properties based on IP addresses will be inexact. The presence of NATs and DHCP and cloud service technology will affect the accuracy of our mapping. For example, the extensive use of cloud services may shrink the perceived network footprint of an organization while inflating that of the cloud service provider. Network volatility, specifically the reallocation of IP addresses, also make identifying the exact network boundaries of an organization difficult. We did our best to mitigate the effects caused by these network practices. For example, file sharing was measured on a per file basis rather than a per IP basis and infections were measured on an infection per day basis. In both cases our measurements provide a lower bound on the measurement of interest. In the future, some of these measurements could be refined. Indirect methods for measuring botnet size have been proposed [24], and some botnets utilize unique identifiers for individual infections which could separate infections on a single IP address [59]. Additionally, data on the internal structure of organizational networks may provide more accurate measures of risk vector and infection concentrations.

One of our main results indicates that peer-to-peer communication has a strong correlation with botnet infections. Previous work has demonstrated that some botnets have adopted peer-to-peer communication in attempts to grow more robust [28]. It has also been shown that the BitTorrent protocol itself can be used as a covert channel [13], though no study has observed this channel used in a botnet in the wild. However, our measurement of peer-to-peer file sharing focuses on IP addresses that are advertising popular files for download, and we believe it is unlikely that these popular files are being used for covert communication.

We use linear modeling in section 4 because our preliminary analysis (section 3) indicated that for most risk vectors linearity (under transformation) was a reasonable assumption. However, we note that in figure 1 many of the variables have a multi-modal distribution, which implies more complexity than we have captured in our linear regressions. However, figure 3 suggests that these extrema are unlikely to bias our results. We also explored using multiple variables to represent these multimodal distributions (similar to the way we handled peer-to-peer sharing with equation 1), but models with these transformed variables did not improve the fit of the model and yielded equivalent results to those seen in section 4.

5.2 Future Work

Future work could address the completeness of the data set by using statistical techniques to identify the true population size, both for risk vectors and for outcomes. Mark and recapture methods, originally developed for estimating species populations in ecology, have already been used to estimate the true size of botnets [67]. These methods could be used to improve our estimates of botnets and risk vectors.

We have simplified some risk vectors, for convenience and ease of interpretation. For example, we weight all TLS software errors equally, although it is unlikely that they are all equally risky. For example, an organization that uses the theoretically weak 1024-bit Diffie-Helman key exchange may not actually experience more attacks. Similarly, we made a rough classification of services into risky and reasonable. Services we did not investigate may be strong indicators of negative organizational outcomes. These nuances may explain the multi-modal distributions observed in figure 4. However, separating out these effects is challenging because of concerns about statistical independence. More complex modeling approaches, such as hierarchical models, could help identify more precise relationships.

While the current set of risk vectors can explain nearly half the variation we see in botnet infection rates ($R^2 = 0.49$), there are certainly other measures of security maturity that could be included to give a more complete picture of security maturity. We analyzed 21 different services and roughly categorized them into risky, neutral and reasonable. Other services and a finer categorization may provide more detailed results. Additionally, internal organizational practices are likely a good measure of security maturity. For example, password policies, security training, and internal access control policies are likely to reflect the security maturity of an organization and correlate with outcomes like botnet infections. Quantifying these properties and identifying their effect is rich ground for future work.

Although we examined several different methods to account for difference across industries, there are many more possibilities. Figures 3 and 4 show botnet infections and the effect of risk vectors vary across industries. However, it is possible that better groupings of industries could provide more insight on how risk vectors affect security outcomes.

In this paper, we focused on botnets as a measure of negative outcomes for organizations. However, the methodology can easily be applied to other security problems, such as data breaches or blacklists (for sending spam, port scanning, or hosting malware). Our preliminary results on these other outcomes are consistent with those presented for botnets.

As one example of generalizing to other problems, we examined a small set of data breaches experienced by the organizations in our study. The data were collected in a variety of ways, such as scraping news articles, Freedom of Information Act requests, and some private data streams. We considered two possible risk factors (peer-to-peer or botnet activity), and found that organizations with data breaches are likely to also have these risk factors (Figure 1). This effect is statistically significant according to the G-test ($p < 10^{-12}$). This preliminary work is promising but requires additional study and validation before we can draw firm conclusions.

6. RELATED WORK

Although botnet activity is an outcome in the earlier sections, here we treat it as a risk factor itself.
In this section we review work related to that presented in this paper. We find that research as focused on identifying vulnerabilities and elaborating on why they might put organizations at risk, there has been surprisingly little work linking risk vectors to actual outcomes such as botnet infections.

Work on BitTorrent has primarily focused on measuring the use of the protocol as a method for peer-to-peer file distribution [50], its performance [7], the security of its distributed hash table algorithm [61], and studies of attacks against the protocol [36, 31]. However, there has been little work studying the potential danger of the use of the protocol in the wild. To our knowledge, only one paper by Cuevas examined the dangers of BitTorrent identifying that 35% of files shared on through BitTorrent are fake, and of those more than 99% contain malware or phishing attempts [15]. Our work is the first which actually examine this correlation between the use of peer-to-peer file sharing in organizations and botnet infections.

In contrast, the Transport Layer Security protocol, and its predecessor the Secure Socket Layer protocol, have been widely known to be a source of vulnerabilities. One recent and widely publicized was the "Heartbleed" vulnerability which allowed attackers to remotely read protected memory on servers hosting vulnerable websites [27]. Other research has shown that many of the available cryptographic protocols used to communicate, and hash functions used to sign certificates are vulnerable to a variety of attacks [6, 2, 26, 65, 20, 53]. There have also been work suggesting that the certificate infrastructure itself is a target for hackers, in particular one of the major certificate authorities, Verisign, was the subject of numerous successful attacks in 2010 [43]. While this work speaks to the insecurity of various implementations and configurations of TLS, and the certificate infrastructure in general, it does provide a direct link between the problems of TLS and outcomes for organizations.

Reports have linked exploitation of the Heartbleed bug to the compromise of 4.5 million patient records in an attack against Community Health Systems [58], an unknown number of records against the website "Mumsnet" [51], and a compromise of an unknown number of records from Canadian Revenue Agency [55]. However, no work to our knowledge has investigated the relationship between vulnerable TLS services and botnet infections.

The case is similar for various types of services. As we outline in section 2, there has been extensive research on developing attacks for a number of the protocols we collect data on including FTP [40], TELNET [34], and Microsoft SQL [10]. Moreover, techniques have been developed for automatically generating attacks against a variety of protocols [29]. However, as of now we find no work linking the presence or use of these services to negative outcomes, as we do in this paper.

Botnets are recognized as a costly part of the cybercriminal infrastructure [3], and a good deal of research has been devoted to detecting [25], measuring [11, 18], classifying [17] and fighting them [63, 5]. Similar to the research presented in this paper, some work focuses on measuring relative botnet infections within various types of organizations. For example Stone-Gross et al. focused on ISPs with persistent malicious behavior [60]. Edwards et al. studied the concentration of spam sending IP addresses within Internet Service providers, and examined some risk vectors(including economic, geographic, and connectivity) for high levels of spam concentrations [23]. Other work has focused identifying high concentrations of infected IP addresses in certain parts of the Internet [36, 52, 13]. Yen et al. explored malware infections in a single large enterprise, and identify possible entry points for infection on individual hosts, but do not provide a comparison across a large number of organizations as we do here [69].

Little work linking the network characteristics of organizations with security incidents across a broad number of organizations. Zhang et al. found that higher concentrations of different types of network mismanagement such as open DNS resolvers and SMTP relays lead to high concentrations of infected PCs within different Autonomous Systems [70]. Our work focuses on an organizational level, and considers a broader scope of risk vectors which are correlated with network infections. Liu et al. use a similar but much larger set of network features (258) of organizations and machine learning to predict data breaches [39]. While they make some effort to rank features on their relative importance, using a random forest limits their ability to directly quantify the impact of risk vectors as we do here.

In the past there have been calls to better understand security at the organizational level [65]. However, research developing qualitative models of organizational security have been difficult to validate [37, 56]. Others have tried to investigate organizations security culture. Merete et al. study common information security practices across organizations in Norway [44], and Furnell et al. investigate how organizational culture can be utilized to increase security [27]. Recent work has tested organizations response to being told informed about spam sending infections, both publicly and privately [52]. However, none of this work makes a direct connection to organizational maturity and the likelihood of incident such as botnet infections.

7. CONCLUSIONS

The ability to assess security risks in organizations is critical, both internally and externally. Internally, those who are most responsible for a company’s performance, e.g., the CEO or Board of Directors, often lack the technical skills to assess their own IT systems, especially for security risks. The evidence-based approach described in this paper pro-
vides an objective and quantitative method that goes beyond self-reporting or qualitative audits. From an external perspective, these methods could be used by one organization to guide decisions about outsourcing or partnerships, and they could potentially be used in settings like insurance where quantifying risk is essential. Current approaches provide only the most general idea of exactly what practices and vectors expose organizations to minor incidents such as malware infection or major incidents such as data breaches, business interruptions, and financial and intellectual theft. Although the results in this paper represent a first cut at developing a robust quantitative approach to assessing security risks, the methods could readily be applied to other data sources, other risk vectors, and other security problems.

Even as a first cut, our results are promising. We found that 90% of organizations have low levels of botnet infections (fewer than 1 botnet infection per 12 employees) however, infection rates can span many orders of magnitude. Using a simple, linear regression approach, we found that the presence and prevalence of peer-to-peer file sharing through the BitTorrent protocol, TLS errors, and publicly available services are all correlated with concentrations of botnet infections. In particular we find that organizations which have peer-to-peer activity have, on average, 318 times higher concentrations of bot. When we evaluate different industries separately, a similar large effect was consistently observed all different industries; however, other risk vectors are only significantly related to botnet infections in a handful industries.

In conclusion, we argue that a data-driven, statistically principled approach is the best way to identify objective risks within an organization. Identifying what risk vectors and minor incidents are correlated with major incidents such as data breaches is an important next step in understanding security maturity.

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9. REFERENCES
[1] Moheeb Abu Rajab, Jay Zarfoss, Fabian Monrose, and Andreas Terzis. A multifaceted approach to understanding the botnet phenomenon. In Proceedings of the 6th ACM SIGCOMM conference on Internet measurement, pages 41–52. ACM, 2006.
[2] David Adrian, Karihikeyan Bhargavan, Zakir Durumeric, Pierrick Gaudry, Matthew Green, J Alex Halderman, Nadia Heninger, Drew Springall, Emmanuel Thomé, Luke Valenta, et al. Imperfect forward secrecy: How diffie-hellman fails in practice. In Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security, pages 5–17. ACM, 2015.
[3] Ross Anderson, Chris Barton, Rainer Böhme, Richard Clayton, Michel JG Van Eeten, Michael Levi, Tyler Moore, and Stefan Savage. Measuring the cost of cybercrime. In The economics of information security and privacy, pages 265–300. Springer, 2013.
[4] Shared Assessments. Standardized information gathering questionnaire. viitattu 23.5 2014, 2010.
[5] Michael Bailey, Evan Cooke, Farnam Jahanian, Yunjing Ju, and Manish Karir. A survey of botnet technology and defenses. In Conference For Homeland Security, 2009. CATCH’09. Cybersecurity Applications & Technology, pages 299–304. IEEE, 2009.
[6] Benjamin Beurdouche, Karihikeyan Bhargava, Antoine Delignat-Lavaud, Cédric Fournet, Markulf Kohlweiss, Alfredo Pirotton, Pierre-Yves Strub, and Jean Karim Zinzindouhoue. A messy state of the union: Taming the composite state machines of tls. In Security and Privacy (SP), 2015 IEEE Symposium on, pages 535–552. IEEE, 2015.
[7] Ashwin R Bharame, Cormac Herley, and Venkata N Padmanabhan. Analyzing and improving botnet performance. Microsoft Research, Microsoft Corporation One Microsoft Way Redmond, WA, 98052-2005-03, 2005.
[8] J Brock, J Boltz, E Doring, and M Gilmore. Information security risk assessment practices of leading organizations. Director, USGAO [online] http://www.gao.gov/special.pubs/as00033.pdf (accessed 20 March 2009), 1999.
[9] Kenneth P Burnham and David R Anderson. Model selection and multimodel inference: a practical information-theoretic approach. Springer Science & Business Media, 2003.
[10] Cesar Cerrudo. Manipulating microsoft sql server using sql injection. Application Security, Inc, 2002.
[11] CERT. Simple network management protocol (snmp) vulnerability frequently asked questions(faq), https://www.cert.org/historical/tech_tips/snmp_faq.cfm, 1999.
[12] Ronald Christensen. Log-linear models and logistic regression. Springer Science & Business Media, 2006.
[13] M Patrick Collins, Timothy J Shimell, Sidney Faber, Jeff Janies, Rhiannon Weaver, Markus De Shon, and Joseph Kadane. Using uncleanness to predict future botnet addresses. In Proceedings of the 7th ACM SIGCOMM conference on Internet measurement, pages 93–104. ACM, 2007.
[14] CEB Audit Leadership Council. 2015 audit plan hot spots. 2014.
[15] Rubén Cuevas, Michal Kryczka, Roberto González, Angel Cuevas, and Arturo Azcorra. Torrentguard: Stopping scam and malware distribution in the bittorrent ecosystem. Computer Networks, 59:77–90, 2014.
[16] Mathieu Cunche, Mohamed Ali Kaafar, and Roksana Boreli. Asynchronous covert communication using bittorrent trackers. In High Performance Computing and Communications, 2014 IEEE 6th Intl Symp on Cyberspace Safety and Security, 2014 IEEE 11th Intl Conf on Embedded Software and Syst (HPCC, CSS, ICESS), 2014 IEEE Intl Conf on, pages 827–830. IEEE, 2014.
[17] David Dagon, GuoFei Gu, Christopher P Lee, and Wenke Lee. A taxonomy of botnet structures. In Computer Security Applications Conference, 2007. ACSAC 2007. Twenty-Third Annual, pages 325–339. IEEE, 2007.
[18] David Dagon, Cliff Changchun Zou, and Wenke Lee. Modeling botnet propagation using time zones. In NDSS, volume 6, pages 2–13, 2006.
[19] Wayne W Daniel et al. Applied nonparametric statistics. 1990.
[20] Hans Dobbertin. The status of md5 after a recent attack. CryptoBytes, 2(2), 1996.
[21] Zakir Durumeric, James Kasten, David Adrian, J Alex Halderman, Michael Bailey, Frank Li, Nicolas Weaver, Johanna Amann, Jethro Beekman, Mathias Payer, et al. The matter of heartbleed. In Proceedings of the 2014 Conference on Internet Measurement Conference, pages 475–488. ACM, 2014.
[22] Zakir Durumeric, Eric Wustrow, and J Alex Halderman. Zmap: Fast internet-wide scanning and its security applications. In Usenix Security, volume 2013, 2013.
[23] Benjamin Edwards, Steven Hofmeyr, Stephanie Forrest, and Michel van Etten. Analyzing and modeling longitudinal security data: Promise and pitfalls. In Proceedings of the 31st Annual Computer Security Applications Conference, pages 391–400. ACM, 2015.
[24] MARJZ Fabian and Monrose Andreas Terzis. My botnet is bigger than yours (maybe, better than yours): why size estimates remain challenging. In Proceedings of the 1st USENIX Workshop on Hot Topics in Understanding Botnets, Cambridge, USA, 2007.
[25] Maryam Feily, Alireza Shahrestani, and Sureswaran Ramadass. A survey of botnet and botnet detection. In Emerging Security Information, Systems and Technologies, 2009. SECURWARE’09. Third International Conference on, pages 268–273. IEEE, 2009.
[26] FoxIT. Rsa-512 certificates abused in the wild. [http://blog.fox-it.com/2011/11/21/rsa-512-certificates-abused-in-the-wild/]. November 2011.
[27] Steven Furnell and Nathan Clarke. Organizational security culture: Embedding security awareness, education, and training. Proceedings of the IFIP TC11 WG, 11:67–74, 2005.
[28] Julian B Grizzard, Vikram Sharma, Chris Nunnery, Brent ByungHoon Kang, and David Dagon. Peer-to-peer botnets: Overview and case study. HotBots, 7:1–7, 2007.
[29] Kowsik Guruswamy. Portable program for generating attacks on communication protocols and channels, June 7 2011. US Patent 7,958,560.
[30] Elizabeth Harris and Nicole Perlroth. For target, the breach numbers grow. New York Times, page B, 1, 2014.
[31] Sinan Hatahet, Abdelmadjid Bouabdallah, and Yacine Challal. A new worm propagation threat in bittorrent: modeling and analysis. Telecommunication Systems, 45(2-3):95–109, 2010.
[32] Shu He, Gene Moo Lee, John Quarterman, and Andrew Whitinston. Designing cybersecurity policies. Workshop on the Economics of Information Security, 2015.
[33] David W Hosmer Jr and Stanley Lemeshow. Applied logistic regression. John Wiley & Sons, 2004.
[34] Laurent Joncheray. A simple active attack against tcp. In USENIX Security, 1995.
[35] Ken Kelley and Kristopher J Preacher. On effect size. Psychological methods, 17(2):137, 2012.
[36] Marlon A Konrath, Marinho P Barcellos, and Rodrigo B Mansilha. Attacking a swarm with a band of liars: evaluating the impact of attacks on bittorrent. In Peer-to-Peer Computing, 2007. P2P 2007. Seventh IEEE International Conference on, pages 37–44. IEEE, 2007.
[37] Andrew G Kotulic and Jan Guynes Clark. Why there aren’Äôt more information security research studies. Information & Management, 41(5):597–607, 2004.
[38] John Leyden. Heartbleed implicated in us hospital megahack. The Register (August 20, 2014), 2014.
[39] Yang Liu, Armin Sarabi, Jing Zhang, Parinaz Naghizadeh, Manish Karir, Michael Bailey, and Mingyan Liu. Cloudy with a chance of breach: Forecasting cyber security incidents. In 24th USENIX Security Symposium (USENIX Security 15), pages 1009–1024, 2015.
[40] Pratyusa Manadhatara, Jeannette Wing, Mark Flynn, and Miles McQueen. Measuring the attack surfaces of two ftp daemons. In Proceedings of the 2nd ACM workshop on Quality of protection, pages 3–10. ACM, 2006.
[41] Henry B Mann and Donald R Whitney. On a test of whether one of two random variables is stochastically larger than the other. The annals of mathematical statistics, pages 50–60, 1947.
[42] Mark Mateski, Cassandra M Trevino, Cynthia K Veitch, John Michalski, J Mark Harris, Scott Maruoka, and Jason Frye. Cyber threat metrics. Sandia National Laboratories, 2012.
[43] Joseph Menn. Key internet operator verisign hit by hackers. Reuters (February 2, 2012), 2012.
[44] Janne Merete Hagen, Eirik Albrechtsen, and Jan Hovden. Implementation and effectiveness of organizational information security measures. Information Management & Computer Security, 16(4):377–397, 2008.
[45] Microsoft. Ms09-001: Vulnerabilities in smb could allow remote code execution. [https://technet.microsoft.com/en-us/library/security/ms09-001.aspx]. 2009.
[46] Giovane Cesar Moura. Attacking a swarm with a band more information security research studies. Information & Management, 41(5):597–607, 2004.
[47] Nicole Perlroth. Heartbleed hacking bug. The Guardian (April 14, 2014), 2014.
[52] Anirudh Ramachandran and Nick Feamster. Understanding the network-level behavior of spammers. In ACM SIGCOMM, volume 36. ACM, 2006.

[53] N Rogier and Pascal Chauvaud. Md2 is not secure without the checksum byte. Designs, Codes and Cryptography, 12(3):245–251, 1997.

[54] Inc ULC SANDVINE. Global internet phenomena report, 2015.

[55] Dave Seglins. Cra heartbleed hack: Stephen solis-reyes facing more charges. Canadian Broadcast Service (December 3, 2014), 2014.

[56] Mikko T Siponen. A conceptual foundation for organizational information security awareness. Information Management & Computer Security, 8(1):31–41, 2000.

[57] Nickolay Smirnov. Table for estimating the goodness of fit of empirical distributions. The annals of mathematical statistics, 19(2):279–281, 1948.

[58] Robert R Sokal, F James Rohlf, et al. The principles and practice of statistics in biological research. WH Freeman and company San Francisco:, 1969.

[59] Brett Stone-Gross, Marco Cova, Lorenzo Cavallaro, Bob Gilbert, Martin Szydlowski, Richard Kemmerer, Christopher Kruegel, and Giovanni Vigna. Your botnet is my botnet: analysis of a botnet takeover. In Proceedings of the 16th ACM conference on Computer and communications security, pages 635–647. ACM, 2009.

[60] Brett Stone-Gross, Christopher Kruegel, Kevin Almeroth, Andreas Moser, and Engin Kirda. Fire: Finding rogue networks. In Computer Security Applications Conference, 2009. ACSAC’09. Annual, pages 231–240. IEEE, 2009.

[61] Juan Pablo Timpanaro, Thibault Cholez, Isabelle Chrisment, and Olivier Festor. Bittorrent’s mainline dht security assessment. In New Technologies, Mobility and Security (NTMS), 2011 4th IFIP International Conference on, pages 1–5. IEEE, 2011.

[62] Olzak Tom. The problem with netbios. http://www.techrepublic.com/blog/it-security/the-problem-with-netbios/, 2007.

[63] Michel Van Eeten, Johannes M Bauer, Hadi Asghari, Shirin Tabatabaie, and David Rand. The role of internet service providers in botnet mitigation an empirical analysis based on spam data. TPRC, 2010.

[64] Robert Wagner. Address resolution protocol spoofing and man-in-the-middle attacks. The SANS Institute, 2001.

[65] Xiaoyun Wang, Yiqun Lisa Yin, and Hongbo Yu. Finding collisions in the full sha-1. In Advances in Cryptology—CRYPTO 2005, pages 17–36. Springer, 2005.

[66] Patrick D Warren. Closing the gaps in third-party risk management: internal audit can add value by assessing risk around the organization’s business relationships. Internal Auditor, 71(1):37–42, 2014.

[67] Rhiannon Weaver. A probabilistic population study of the conficker-c botnet. In Passive and active measurement, pages 181–190. Springer, 2010.

[68] Michael E Whitman. Enemy at the gate: threats to information security. Communications of the ACM, 46(8):91–95, 2003.

[69] Ting-Fang Yen, Victor Heorhiadi, Alina Oprea, Michael K Reiter, and Ari Juels. An epidemiological study of malware encounters in a large enterprise. In Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security, pages 1117–1130. ACM, 2014.

[70] Jing Zhang, Zakir Durumeric, Michael Bailey, Mingyan Liu, and Manish Karir. On the mismanagement and maliciousness of networks. In NDSS, 2014.