Analysing The Impact Of A DDoS Attack Announcement On Victim Stock Prices

Abhishta
University of Twente
Enschede, The Netherlands
Email: s.abhishta@utwente.nl

Reinoud Joosten
University of Twente
Enschede, The Netherlands
Email: r.a.m.g.joosten@utwente.nl

L.J.M. Nieuwenhuis
University of Twente
Enschede, The Netherlands
Email: l.j.m.nieuwenhuis@utwente.nl

***Abstract*—DDoS attacks are increasingly used by 'hackers' and 'hacktivists' for various purposes. A number of on-line tools are available to launch an attack of significant intensity. These attacks lead to a variety of losses at the victim's end. We analyse the impact of Distributed Denial-of-Service (DDoS) attack announcements over a period of 5 years on the stock prices of the victim firms. We propose a method for event studies that does not assume the cumulative abnormal returns to be normally distributed, instead we use the empirical distribution for testing purposes. In most cases we find no significant impact on the stock returns but in cases where a DDoS attack creates an interruption in the services provided to the customer, we find a significant negative impact.**

***Index Terms*—Abnormal Returns, Event Study, Cyber Security, DDoS Attacks.**

I. Introduction

The trend of significant growth in the magnitude of high intensity DDoS attacks has been consistent in the past years [1] and these attacks have resulted in heavy losses for firms [2]. The rise in the number of attacks being encountered can be attributed to the ample availability of online tools for launching DDoS attacks. Booter websites have become successful in creating a market for themselves and as a consequence technical knowledge is no longer a prerequisite for launching a DDoS attack [3].

The losses encountered by firms due to these cyber assaults can be divided into direct and indirect ones [4]. Financial damages due to infrastructural downtime, loss of online traffic, paid ransom and customer compensation etc. are accounted as direct losses. Indirect losses include damage to company's reputation and impact at stock prices etc. We examine the indirect loss due to the decrease in the market value of a firm as a result of an announcement of getting hit by a DDoS attack. In Section II we discuss several studies on the impact of information security breaches on the stock prices [5].

In our study, we consider all DDoS attacks reported after 2010. We do this in order to understand the effects caused by these announcements. Unlike earlier studies we will study the impact of DDoS attack announcements only, because these attacks do not lead to any form of information leaks and do not pose any danger to customer data. Hence, in our sample we do not consider any of the events where DDoS has been used as a smoke screen.

II. Previous Work

Event studies measure the impact of company related events on the market value of the firm. MacKinlay [13] discusses the procedure for conducting an event study and also the various models that can be used for estimation of normal behaviour of the market. In the past many researchers have studied the impact of information technology related events on the market value of the firm. Santos *et al.* [14] examined the impact of information technology investment announcements on the market value of the firm and suggested that there is no significant impact of these investment announcements on the market value.

Previous studies [7, 8, 10, 11] have used a one-factor market model for the estimation of stock prices as shown in Equation 1. Where r_{it} represents the rate of return of the stock i and r_{mt} represents the rate of return of the market index on day t. For instance, r_{it} can be calculated as $(P_{it} - P_{it-1})/P_{it-1}$, where P_{it} is the price of the stock on day t.

$$r_{it} = \alpha_i + \beta_i r_{mt} + \epsilon_{it} \tag{1}$$

The parameters α and β are firm dependent coefficients. $\hat{\alpha}$ and $\hat{\beta}$ are their ordinary least square (OLS) estimators. The stochastic variable ϵ_{it} is the error term with $\mathbb{E}[\epsilon_{it}] = 0$. Gordon *et al.* [12] uses a Fama-French three factor model [15] to predict the stock prices. The three factors being company size, company price-to-book ratio and market risk. The three factor model is shown in Figure 2.

$$r_{it} = a_i + b_i r_{mt} + s_i SMB_t + h_i HML_t + \epsilon_{it}, \tag{2}$$

SMB_t is the difference between the return on the portfolio of small stocks and the return on the portfolio of large stocks on day t and HML_t is the difference between the return on a portfolio of low-book-to-market stocks and the return on a portfolio of low-book-to-market stocks on day t. The parameters a_i,b_i,s_i and h_i are Fama and French three-factor model estimated firm dependent coefficients. The stochastic variable ϵ_{it} is the error term with $\mathbb{E}[\epsilon_{it}] = 0$.

These studies [7, 8, 11] use abnormal returns (additive) and cumulative abnormal returns (additive) as a measure of

2377-5750/17 $31.00 © 2017 IEEE
DOI 10.1109/PDP.2017.82

TABLE I: Previous works on impact on victim stock prices.

	Author	Estimation Model	Sample Size	Breach Type	Conclusion	Sample Period
[7]	Hovav & D'Arcy (2003)	Market Model	23	DoS	No significant impact of DoS attacks on the capital market. Some indication of impact on firms that rely on the web for their business.	1998-2002
[8]	Campbell *et al.* (2003)	Market Model	43	Generic	Some negative stock market impact to reported information security breaches.	1995-2000
[9]	Garg *et al.* (2003)	N/A	22	Generic	Average fall in the stock price was approximately 2.9% over a 2-day and 3.6% over 3-day period.	1996-2002
[10]	Cavusoglu *et al.* (2004)	Market Model	66	Generic	Security breach announcements affect the values of the announcing firms and also the Internet security developers.	1996-2001
[11]	Kannan *et al.* (2007)	Market Model	102	Generic	Drop of 1.4% in the market valuation relative to the control group of firms.	1997-2003
[12]	Gordon *et al.* (2011)	Fama-French Model	258	Generic	Pre 9/11 information security breaches showed significant negative stock market returns but the results for the post 9/11 period were not significant.	1995-2007

event impact. Equations 3 and 4 show the relations used to compute abnormal returns and cumulative abnormal returns respectively. As they assume normal distribution for the CAR values hence they use Z statistic to test their hypothesis.

$$AR_{it} = r_{it} - (\hat{\alpha}_i + \hat{\beta}_i r_{mt}) \tag{3}$$

$$CAR_n = \sum_{t=-1}^{n} AR_{it} \tag{4}$$

Past studies have been conducted on evaluating the impact of information security breaches on the prices of the victim firm's shares. Table I lists selected works and their conclusions. In this table we also take a look on the sample size and period of the sample considered by these studies.

Previous studies had a mixed response on the impact of denial of service attacks on the stock returns of the victim firms. Some studies like Garg *et al.* [9] and Hovav & D'Arcy [7] suggest that DDoS attack announcements lead to a negative abnormal returns, while Gordon *et al.* [12] deny the effect of these attacks on the market value of the firm. Spanos & Angelis [5] conducted a systematic literature review on the impact of information security events on the stock market and concluded that the events examined created a significant impact on the stock price of the firms.

III. Method

To analyse the impact of DDoS attack announcements on stock returns we use the method as shown in Figure 1. We can broadly divide the method into two sections:

1) Data collection.
2) Analysis

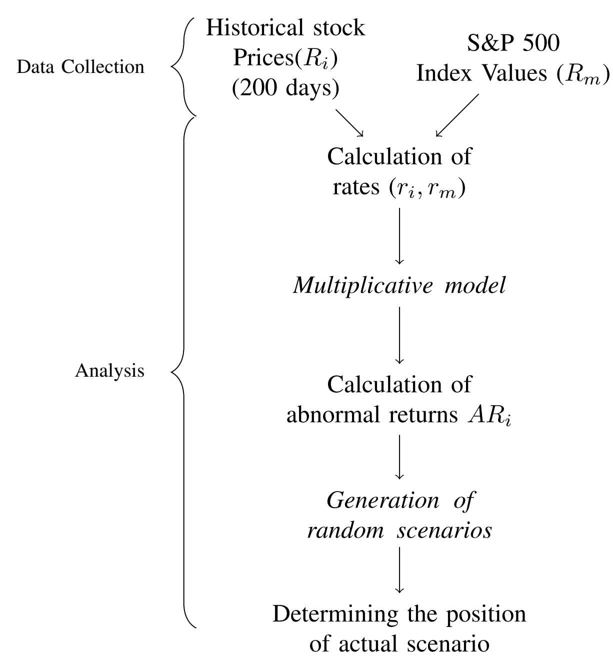

Fig. 1: Method for event study. (Our contribution in *Italics*.)

Our contribution to the analysis is at two instances. Firstly, we use a *multiplicative model* for the estimation of return rates and secondly, we use the empirical distribution of abnormal returns by *generation of random scenarios* for the analysis. In Section III-A we explain the approach for data collection. Section III-B deals with the identification of the impact caused by the announcements.

TABLE II: Sample of DDoS attack events.

Organisation	Announcement Date	Source	Infrastructure	Firm Type
Master Card	8-12-2010	spiegel.de	Website	Financial Services
Visa	8-12-2010	spiegel.de	Website	Financial Services
Bank of America	27-12-2010	infosecisland.com	Website	Financial Services
Vodafone	5-10-2011	infosecurity-magazine.com	None	Telecommunications
Apple	29-5-2012	att-iphone-unlock.com	Website	IT
AT&T	16-8-2012	pcworld.com	None	Telecommunications
Wells Fargo	20-12-2012	technologybanker.com	DNS	Financial Services
JP Morgan Chase	13-3-2013	scmagazine.com	Website	Financial Services
TD Canada Trust	21-3-2013	thestar.com	E Services	Financial Services
American Express Company	28-3-2013	bankinfosecurity.com	Website	Financial Services
International Netherlands Group	9-4-2013	nrc.nl	Payment Services	Financial Services
Linkdin	21-6-2013	news.softpedia.com	Website	Social Networking
Microsoft	27-11-2013	scmagazine.com	DNS	IT/Gaming
Royal Bank of Scotland	4-12-2013	theguardian.com	Banking Services	Financial Services
JP Morgan Chase	30-1-2014	bobsguide.com	Online Banking Services	Financial Services
Bank of America	30-1-2014	bobsguide.com	Online Banking Services	Financial Services
Facebook	21-2-2014	nos.nl	Messageing Services	Social Networking
Activision Blizzard	29-3-2014	ign.com	Gaming Services	Gaming
Danske Bank	10-7-2014	ddosattacks.net	Website	Financial Services
Storebrand	10-7-2014	ddosattacks.net	Website	Insurance Company
Gjensidige Forsikr	10-7-2014	ddosattacks.net	Website	Insurance Company
Sony Corporation	24-8-2014	techcrunch.com	Gaming Services	IT
Amazon	27-8-2014	shacknews.com	Twitch Streamers	E-commerce
Activision Blizzard	14-11-2014	eurogamer.net	Gaming Services	Gaming
Sony Corporation	26-11-2014	wiwo.de	Gaming Services	IT
Rackspace	22-12-2014	welivesecurity.com	DNS	Hosting
Microsoft	24-12-2014	krebsonsecurity.com	Gaming Services	IT/Gaming
Sony Corporation	24-12-2014	krebsonsecurity.com	Gaming Services	IT
Alibaba Group	25-12-2014	ddosattacks.net	Cloud Services	E-commerce
Nordea Bank	4-1-2015	ddosattacks.net	Online Banking Services	Financial Services
Facebook	27-1-2015	gizmodo.com.au	Website	Social Networking
Amazon	16-3-2015	scmagazineuk.com	Twitch Streamers	E-commerce
EA Sports	18-3-2015	ibtimes.com	Gaming Services	Gaming
Ziggo	18-8-2015	emerce.nl	DNS	Telecommunications
Overstock.com	3-9-2015	ddosattacks.net	DNS	E-commerce

A. Data Collection

In this study we consider all DDoS attack announcements that were made on the web since ‘Operation Payback’, launched by Anonymous in December, 2010. Table II shows the final list of all announcements that we analysed. For each attack we collected the date of announcement, the company type and also the services disrupted. The initial list consisted of 43 announcements.

We further filtered the list using the following criteria:

1) If multiple announcements were made on consecutive days, then the earliest date was considered.
2) All announcements regarding companies that were not publicly traded at the time of attack were eliminated.
3) All attack announcements in which DDoS attack was coupled with information theft were also not considered for analysis. This was done in order to be able to see the isolated effect of a DDoS attack announcements on the firm’s stock price.

The stock prices for all the firms in the sample were collected by using the Yahoo! finance API. For measuring the market rate we collected the S&P 500 index values.The final sample consisted of 35 announcements.

B. Analysis

We depart from the familiar research strategy for event studies for the following reasons. We wish to avoid the widespread practice of approximating multi-day returns by simply adding up the corresponding single-day returns[1] and instead use the exact ones. Secondly, we want to avoid the equally wide-spread assumption about short-term returns being (approximately) distributed according to a normal, i.e., Gaussian, distribution. We refrain from imposing as an alternative one of the better known distributions such as the Weibull or the Erlang distributions, as the problem generally is not only skewness (asymmetry) but fatness of both tails, i.e., realisations quite far from the average are more common than for instance in the normal distribution with the same mean and variance. Another route not taken is to use the data consisting of a sample of returns for a period of 200 days prior to the event, and tone of these alternative distributions to the data. Instead we assume that the one-day returns follow an unknown distribution which we are going to approximate

[1]Note that a 10% increase, followed by a 10% decrease imply a total decrease of 1% according to the multiplicative formula $(1.1)(0.9) = 0.99$. The additive approximation would yield a 0% change, an overestimation of 1%.

by the empirical distribution, i.e., the distribution of the 200-day-sample returns.

We acknowledge the considerable merits of the widespread research strategy involving these two approximations as they subsequently allow the construction of test variables which follow the Student's t-distribution in order to engage in the testing of hypotheses.

As we do not use the approximations central to this research strategy, we are faced with the challenge of establishing a pertinent distribution for similar hypothesis testing. We do this by the technique of bootstrapping (e.g., Efron [17]) which in our case involves generating a sufficiently large number of multi-day returns by drawing from the empirical distribution a number of consecutive one-day returns corresponding to the number desired. With such a series of one-day returns we compute the exact multi-day returns, and proceed in the same fashion to obtain a large number (in our case 5 million) of such multi-day returns. The relative frequencies of this large population of exact multi-day returns are then employed as the relevant distribution for hypothesis testing. Note that the standard approach in event studies is to take as the null hypothesis that the event has no influence at all, meaning in statistical terms that the distribution of returns before the event and the one after the event are identical. So, under this assumption the sample returns can be indeed used to generate the relevant distributions of multi-day returns.

We consider a multiplicative model to represent the normal behaviour of the market. According to the model if r_{it} represents the rate of return of the stock i on day t and r_{mt} represents the rate of return of the market index on day t, then the model can be represented mathematically by Equation 6. Rate of return can be calculated as shown in Equation 5, where R_{it} and R_{mt} represent the stock price and market index for day t. The value of the market index shows the average of returns of all the firms included in the market index.

$$\begin{aligned} r_{it} &= \frac{R_{it} - R_{i(t-1)}}{R_{i(t-1)}} \\ r_{mt} &= \frac{R_{mt} - R_{m(t-1)}}{R_{m(t-1)}} \end{aligned} \tag{5}$$

$$(1 + r_{it}) = \alpha_i (1 + r_{mt})^{\beta_i} \tag{6}$$

A multiplicative model[1] is used to estimate the returns on a firm's stock. In this study we use the Standard and Poor's (S&P) 500 as the index of the market. S&P 500 has been used as a market study in many of the previous event studies. The parameters α_i and β_i are firm dependent and will be estimated.

Equation 6 is linearised in Equation 7. The stochastic variable ϵ_{it} is the error term with $\mathbb{E}\left[\epsilon_{it}\right] = 0$. We use ordinary least square (OLS) estimation to obtain estimations $\widehat{\ln \alpha_i}$ and $\hat{\beta}_i$ for $\ln \alpha_i$ and β_i by considering daily returns over a period of 200 days. This period starts 201 days before the date of announcement and ends 2 days before the announcement. In this study we will call this the *estimation period*. This length of the estimation period is consistent with the previous event studies [7, 12, 14].

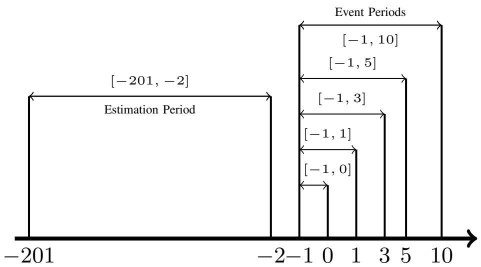

Fig. 2: Estimation and Event Periods.

$$\ln(1 + r_{it}) = \ln(\alpha_i) + \beta_i \ln(1 + r_{mt}) + \epsilon_{it} \tag{7}$$

The abnormal return measures the deviation that the stock shows from the model we calculate. AR is calculated for the estimation period and is given by Equation 8. Hence, abnormal returns can be calculated by using Equation 9.

$$\ln(1 + AR_{it}) = [\ln(1 + r_{it}) - [\widehat{\ln(\alpha_i)} + \hat{\beta}_i \ln(1 + r_{mt})]] \tag{8}$$

$$AR_{it} = \frac{(1 + r_{it})}{\hat{\alpha_i}(1 + r_{mt})^{\hat{\beta}_i}} - 1 \tag{9}$$

The estimator[2] $\widehat{\ln(\alpha)}$ is good for $\ln(\alpha)$ but cannot be used to estimate $\hat{\alpha}$. Hence, for estimating $\hat{\alpha}$ we make use of Equation 10, that is derived using Equation 7.

$$\hat{\alpha_i} = \frac{\sum_{t=1}^{T} (1 + r_{it})}{\sum_{t=1}^{T} (1 + r_{mt})^{\hat{\beta}_i}}, \tag{10}$$

where T is the total number of days in the estimation period. In order to measure the impact of the announcements on the stock return we define five event periods as shown in Figure 2. These are:

1) One day prior to the announcement to the day of announcement $[t-1, t]$.
2) One day prior to the announcement to 1 days after it $[t-1, t+1]$.
3) One day prior to the announcement to 3 days after it $[t-1, t+3]$.
4) One day prior to the announcement to 5 days after it $[t-1, t+5]$.
5) One day prior to the announcement to 10 days after it $[t-1, t+10]$.

We consider the starting point of the event period one day prior to the announcement so as to accommodate for information leaks. We randomly draw 2,3,5,7 and 12 abnormal

[1] If the returns r_{it} and r_{mt} are extremely small a linear relationship between these variable will give a good approximation.

[2] Note that $\hat{\alpha}$ is not $e^{\widehat{\ln(\alpha)}}$ as $\mathbb{E}\left[\alpha\right] \neq \mathbb{E}\left[\ln \alpha\right]$.

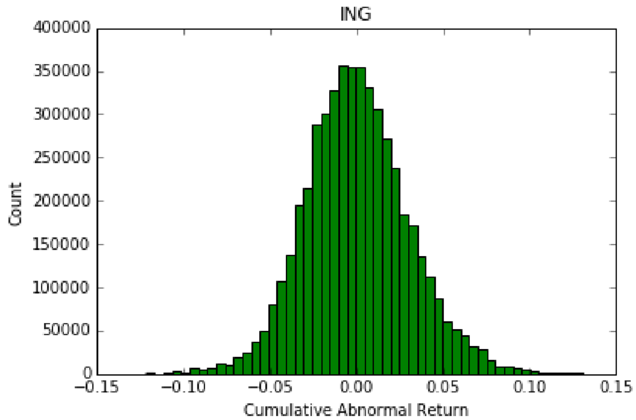

Fig. 3: Empirical distribution of two-day CAR values for ING.

returns from the estimation period to represent the abnormal returns for event periods $[-1, 0], [-1, 1], [-1, 3], [-1, 5]$ and $[-1, 10]$ respectively. We generate five million possible random scenarios for the event periods. Recall, we do not assume the abnormal returns to be normally distributed at any point. This is done to improve the accuracy of our results. We consider short event periods of 2 days, 3 days, 5 days, 7 days and 12 days respectively in accordance with the results of previous studies [7, 9, 12].

For evaluating the combined effect over a certain number of days we also calculate cumulative abnormal returns for the randomly generated scenarios. CAR is calculated using relation shown in Equation 11. Where, N_1 and N_2 represent the start and ending days of the event period. The actual ARs and CARs for the event period are calculated using Equations 8 and 11 respectively on the real stock data for the event periods. It is important to note that previous studies have assumed these cumulative abnormal returns to be normally distributed for strategic convenience. We use the empirical distribution of CAR for analytical purposes, i.e. for hypothesis testing.

$$CAR = \prod_{t=N_1}^{N_2} (1 + AR_{it}) - 1 \tag{11}$$

Finally, to determine the effect of the announcement on the daily stock return rates we check where do the cumulative actual abnormal returns lie in the distribution of simulated cumulative abnormal returns (multiplicative). Figure 3 shows an example of the distribution two-day CAR values for *International Netherlands Group*. A highly unlikely negative CAR value will represent a negative impact of the announcement and the actual scenario will fit to the extreme left of the probability distribution. For our analysis we consider 10 percentile of the scenarios on the left to be representative of a negative impact and 10 percentile of the scenarios on the right represent the positive impact. Hence, for the evaluation of the results we use the decision rule as shown in Figure 4.

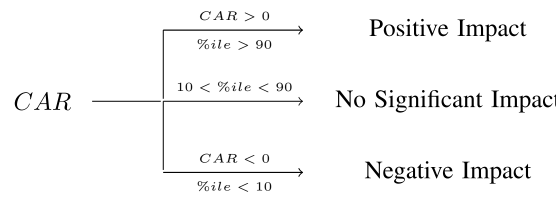

Fig. 4: Decision Rule.

IV. Results

The complete results for our study are shown in Table III in Appendix A. According to the results of our analysis we observe a significant negative impact in the case of *International Netherlands Group* and *EA sports*. Whereas, a delayed negative effect is noticeable in the case of *Bank of America*, *Storebrand* and *Nordea Bank*. In most cases we do not see a negative effect on the victim stock prices.

In cases where the announcements state that the availability of the infrastructure under attack did not affect the customers, no significant impact was noticed. For example, in the case of *Visa* and *MasterCard* the infrastructure under attack was their *website* but the customers were still able to use their cards for payment purposes. Whereas in the case of *International Netherlands Group*, customers had troubles using the payment services. Similarly, in the case of *EA Sports*, gamers were not able to log onto their on-line gaming accounts.

In the case of *Ziggo*, the customers did face troubles due to the unavailability of internet services but as the firm is a part of a bigger conglomerate *Liberty Global*, we were unable to spot any significant impact on the stock prices.

V. Conclusion

As a conclusion, we can say that there is a noticeable negative impact on the stock prices of the victim firm whenever the attack causes interruptions to the services provided by the firm to its customers. This drop is consistent with the results of the previous studies [7, 9]. However, it is not possible to comment on the intensity of the impact because it is firm dependent.

References

[1] *Worldwide Infrastructure Security Report, Arbor Networks*. 2015.

[2] *2015 Cost of Cyber Crime Study: Global, Ponemon Institute*. 2015.

[3] J. J. Santanna and A. Sperotto. "Characterizing and mitigating the DDoS-as-a-Service phenomenon". *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (2014).

[4] R. Anderson, C. Barton, R. Bohm, R. Clayton, M. J. G. Van Eeten, M. Levi, T. Moore, and S. Savage. "Measuring the Cost of Cybercrime". *Workshop on Economics of Information Security* (2012).

[5] G. Spanos and L. Angelis. “The impact of information security events to the stock market : A systematic literature review”. *Computers & Security* 58 (2016), pp. 216–229.
[6] M. Sauter. *The Coming Swarm*. Bloomsbury, 2014.
[7] A. Hovav and J. D’Arcy. “Impact of Denial-of-Service attack announcements on the market value of firms”. *Risk Management And Insurance Review* 6.2 (2003), pp. 97–121.
[8] K. Campbell, L. A. Gordon, M. P. Loeb, and L. Zhou. “The Economic Cost of Publicly Announced Information Ssecurity Breaches : Empirical Evidence from the Stock Market”. *Journal of Computer Security* 11 (2003), pp. 431–448.
[9] A. Garg, J. Curtis, and H. Halper. “Quantifying the financial impact of IT security breaches”. *Information Management & Computer Security* 11.2 (2003), pp. 74–83.
[10] H. Cavusoglu, B. Mishra, and S. Raghunathan. “The Effect of Internet Security Breach Announcements on Market Value: Capital Market Reactions for Breached Firms and Internet Security Developers.” *International Journal of Electronic Commerce* 9.1 (2004), pp. 69–104.
[11] K. Kannan, J. Rees, and S. Sridhar. “Market Reactions to Information Security Breach Announcements: An Empirical Analysis”. *International Journal of Electronic Commerce* 12.1 (2007), pp. 69–91.
[12] L. A. Gordon, M. P. Loeb, and L. Zhou. “The impact of information security breaches : Has there been a downward shift in costs?” *Journal of Computer Security* 19 (2011), pp. 33–56.
[13] A. C. Mackinlay. “Event Studies in Economics and Finance.” *American Economic Association* XXXV.March (1997), pp. 13–39.
[14] D. Santos. “Technology Investment Announcements on the Market Value of the Firm” (1993).
[15] E.F. Fama and K.R. French. “Common risk factors in the returns of stocks and bonds.” *Journal of Financial Economics* 33 (1993), pp. 3–56.
[16] M. C. Arcuri and M. Brogi. “The effect of information security breaches on stock returns: Is the cyber crime a threat to firms?” *European Financial Management Meeting, Rome* (2014).
[17] B. Efron. “Bootstrap methods: another look at the jackknife”. *Breakthroughs in Statistics* (1992), pp. 569–593.

APPENDIX

A: Complete Results.

TABLE III: Results of analysis.

Company	CAR	CAR **Percentile**	**Impact**	**Event Period**
MasterCard	-0.015882584	26.9273	None	[-1,0]
	-0.027930361	19.52314	None	[-1,1]
	-0.025912927	27.83942	None	[-1,3]
	0.107126511	97.48828	Positive	[-1,5]
	0.135604103	97.36842	Positive	[-1,10]
Visa	-0.028139803	12.72802	None	[-1,0]
	-0.040441177	9.26076	Negative	[-1,1]
	-0.047573044	11.8319	None	[-1,3]
	0.140838043	99.09936	Positive	[-1,5]
	0.112939429	94.97662	Positive	[-1,10]
Bank of America	-0.024699949	19.20136	None	[-1,0]
	-0.024230469	24.77702	None	[-1,1]
	-0.031326586	24.99882	None	[-1,3]
	-0.092847266	3.46072	Negative	[-1,5]
	-0.128977999	2.344	Negative	[-1,10]
Vodafone	0.000824461	51.7293	None	[-1,0]
	0.00794087	65.27714	None	[-1,1]
	0.004882324	57.58806	None	[-1,3]
	-0.012009277	35.3259	None	[-1,5]
	-0.011377693	39.66936	None	[-1,10]
Apple	-0.027029116	11.10264	None	[-1,0]
	-0.023728852	18.3817	None	[-1,1]
	-0.005504079	42.55964	None	[-1,3]
	-0.005196594	44.34158	None	[-1,5]
	0.001828533	51.35376	None	[-1,10]
AT&T	0.00547585	73.01768	None	[-1,0]
	0.014332099	89.90238	None	[-1,1]
	0.024144556	94.53076	Positive	[-1,3]
	0.014879076	80.10654	None	[-1,5]
	0.027903421	88.6526	None	[-1,10]
Wells Fargo	0.002251211	57.74708	None	[-1,0]
	0.002846928	58.18658	None	[-1,1]
	0.006975269	64.68026	None	[-1,3]
	0.010258418	67.66082	None	[-1,5]
	0.006787068	60.10972	None	[-1,10]
JP Morgan Chase	-0.007305775	30.4058	None	[-1,0]
	0.013550503	77.18096	None	[-1,1]
	0.031340549	90.29374	Positive	[-1,3]
	0.053073337	96.23408	Positive	[-1,5]
	0.09046202	98.84216	Positive	[-1,10]
TD Canada Trust	-0.001108209	43.57652	None	[-1,0]
	-0.009229913	14.02556	None	[-1,1]
	-0.005118312	32.22566	None	[-1,3]
	-0.013999826	13.95322	None	[-1,5]
	0.023281975	91.56936	Positive	[-1,10]
American Express	-0.00041386	51.144	None	[-1,0]
	-0.003047091	43.91128	None	[-1,1]
	0.006055721	63.35356	None	[-1,3]
	0.025735512	86.15674	None	[-1,5]
	0.050253429	94.5455	Positive	[-1,10]

TABLE III continued.

Company	CAR	CAR Percentile	Impact	Event Period
International Netherlands Group	-0.053961291	2.95846	Negative	[-1,0]
	-0.06072401	4.1384	Negative	[-1,1]
	-0.020229264	34.1261	None	[-1,3]
	-0.029848597	30.17358	None	[-1,5]
	-0.081706673	12.26994	None	[-1,10]
LinkedIn	0.016841037	74.30582	None	[-1,0]
	-0.002526331	46.45178	None	[-1,1]
	-0.017375856	34.262	None	[-1,3]
	-0.026284125	30.81402	None	[-1,5]
	-0.045621561	26.63628	None	[-1,10]
Microsoft	-0.017162556	18.47456	None	[-1,0]
	-0.024200351	16.51522	None	[-1,1]
	-0.034090835	15.74556	None	[-1,3]
	-0.015471464	36.68258	None	[-1,5]
	0.034940648	76.79054	None	[-1,10]
Royal Bank of Scotland	0.007847170	62.39716	None	[-1,0]
	-0.007792594	44.4221	None	[-1,1]
	-0.014817017	40.55122	None	[-1,3]
	0.048606528	79.92352	None	[-1,5]
	0.026742735	65.6532	None	[-1,10]
JP Morgan Chase	0.004977842	64.09092	None	[-1,0]
	0.014513902	80.37984	None	[-1,1]
	0.000234979	49.82888	None	[-1,3]
	-0.014250438	29.04242	None	[-1,5]
	-0.031128703	18.06696	None	[-1,10]
Bank of America	-0.000184061	46.84568	None	[-1,0]
	0.016315624	80.3436	None	[-1,1]
	0.017620533	76.0839	None	[-1,3]
	0.004226565	55.21462	None	[-1,5]
	0.025992899	75.85016	None	[-1,10]
Facebook	-0.007029030	29.70018	None	[-1,0]
	-0.009490565	28.69322	None	[-1,1]
	0.024868377	73.9342	None	[-1,3]
	0.047184864	86.43622	None	[-1,5]
	0.092061897	95.16446	Positive	[-1,10]
Activision Blizzard	0.001928050	54.8177	None	[-1,0]
	0.001096061	52.14442	None	[-1,1]
	-0.016714484	24.34886	None	[-1,3]
	-0.006333017	41.35782	None	[-1,5]
	-0.062767985	4.28474	Negative	[-1,10]
Danske Bank	-0.000274242	47.75408	None	[-1,0]
	-0.016656729	24.76632	None	[-1,1]
	-0.014954993	31.98618	None	[-1,3]
	0.008732713	58.03892	None	[-1,5]
	-0.007350568	44.4036	None	[-1,10]
Storebrand	-0.004439445	35.08586	None	[-1,0]
	-0.018229923	15.0597	None	[-1,1]
	-0.063078035	0.4896	Negative	[-1,3]
	-0.061395155	1.39984	Negative	[-1,5]
	-0.049772166	7.76122	Negative	[-1,10]
Gjensidige Forsikr	0.000963002	49.70118	None	[-1,0]
	0.003381149	54.0087	None	[-1,1]
	-0.010505422	37.04708	None	[-1,3]
	-0.040286066	15.8641	None	[-1,5]
	-0.028966577	29.2466	None	[-1,10]
Sony Corporation	0.002407147	60.15424	None	[-1,0]
	0.004563586	62.29666	None	[-1,1]
	0.001822970	58.2152	None	[-1,3]
	-0.021498560	37.79418	None	[-1,5]
	0.014746326	63.87318	None	[-1,10]

TABLE III continued.

Company	CAR	CAR Percentile	Impact	Event Period
Amazon	0.021753872	88.64916	None	[-1,0]
	0.016990920	78.1646	None	[-1,1]
	-0.036447006	11.17068	None	[-1,3]
	-0.043888322	11.2798	None	[-1,5]
	-0.038297272	21.30828	None	[-1,10]
Activision Blizzard	-0.000709556	48.81262	None	[-1,0]
	-0.007735669	39.30916	None	[-1,1]
	0.004492289	56.1743	None	[-1,3]
	-0.002983879	48.68772	None	[-1,5]
	0.087616411	92.7746	Positive	[-1,10]
Sony Corporation	-0.003403517	44.67244	None	[-1,0]
	-0.010883831	36.797	None	[-1,1]
	-0.000200726	50.39402	None	[-1,3]
	0.026361475	68.49948	None	[-1,5]
	0.026080234	64.358	None	[-1,10]
Rackspace	0.014832688	88.2169	None	[-1,0]
	0.025240246	94.41064	Positive	[-1,1]
	0.043310538	97.7079	Positive	[-1,3]
	0.040679243	94.7607	Positive	[-1,5]
	0.040587064	89.53928	None	[-1,10]
Microsoft	-0.018099374	21.19232	None	[-1,0]
	-0.012956852	32.89316	None	[-1,1]
	0.019714934	71.0867	None	[-1,3]
	0.028748607	74.6767	None	[-1,5]
	-0.021794832	37.10918	None	[-1,10]
Sony Corporation	0.017723392	92.3236	Positive	[-1,0]
	0.026038429	94.92672	Positive	[-1,1]
	0.029414053	92.04924	Positive	[-1,3]
	0.04572172	96.4814	Positive	[-1,5]
	0.037697846	87.84194	None	[-1,10]
Alibaba Group	0.003252883	55.78888	None	[-1,0]
	0.006038200	58.02368	None	[-1,1]
	0.027994135	73.14122	None	[-1,3]
	0.028993768	71.19542	None	[-1,5]
	0.064338831	82.87406	None	[-1,10]
Nordea Bank	-0.010079453	26.95334	None	[-1,0]
	0.002073589	55.11578	None	[-1,1]
	-0.030816091	12.2077	None	[-1,3]
	-0.061577132	2.58652	Negative	[-1,5]
	-0.174724652	0.0002	Negative	[-1,10]
Facebook	0.012003977	73.88932	None	[-1,0]
	-0.007382446	39.45172	None	[-1,1]
	0.034738393	85.06418	None	[-1,3]
	0.030894154	78.7436	None	[-1,5]
	0.028141425	71.76988	None	[-1,10]
Amazon	-0.001261847	48.43654	None	[-1,0]
	-0.007662918	39.32008	None	[-1,1]
	-0.014995234	34.24676	None	[-1,3]
	-0.003671321	48.09398	None	[-1,5]
	0.002219653	53.17424	None	[-1,10]
EA Sports	-0.026102614	10.94388	None	[-1,0]
	-0.044632962	5.67572	Negative	[-1,1]
	-0.052965749	7.55248	Negative	[-1,3]
	-0.020028623	30.5396	None	[-1,5]
	-0.034627666	26.39366	None	[-1,10]
Liberty Global	0.009412519	73.84972	None	[-1,0]
	0.037493964	94.77486	Positive	[-1,1]
	0.099809937	99.5675	Positive	[-1,3]
	0.101846496	99.21738	Positive	[-1,5]
	0.106292715	98.23724	Positive	[-1,10]
Overstock.com	0.000637514	52.07072	None	[-1,0]
	-0.018705128	30.38584	None	[-1,1]
	-0.023468622	31.49814	None	[-1,3]
	-0.003278425	49.49494	None	[-1,5]
	0.010503096	58.08244	None	[-1,10]