Effects of Vulnerability Publications on Stock Returns

JOHN M. SULLIVAN

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Dartmouth College

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ABSTRACT

Recently, there have been many news stories detailing how computer vulnerabilities impact companies and their stock returns. Previous researchers analyzed these media reports and used event studies to test how these news releases about vulnerabilities affected stock returns. Their results were varied and may have been distorted by how they selected articles for their samples. Unlike this previous research, this study utilizes the National Vulnerability Database (NVD). The NVD has records of computer vulnerabilities since 1988, has more vulnerability samples than previous studies, and can be connected to public stocks. This study also uses an event study method to test if abnormal stock returns occur, but in this case focuses on the publication of vulnerabilities in the NVD. The results show that returns are a statistically significant -0.63% on average at 40 days after the announcement. A portfolio strategy is also applied that goes long in the stocks of companies with less vulnerabilities than the past average and goes short in those with more vulnerabilities. This study shows that this strategy could have earned a significant annual alpha (excess returns) of 13.45% per annum since 2002. These results suggest that vulnerability announcements have a gradual negative impact on stock returns.

Acknowledgements: I would like to thank Professor Zitzewitz for the time that he spent with me during his office hours on this paper throughout the term. I would like to thank Professor Cybenko, who advised my Engineering Honors Thesis. This paper is based on some of the ideas from my Honors Thesis. I would also like to thank my parents for their consistent support during my education.

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I. Introduction

The National Vulnerability Database (NVD), established by the National Institute of Standards and Technology (NIST), contains descriptions of 98,442 software vulnerabilities published since 1988. Event studies have been conducted that examine the effect of a media announcement on a public company's stock returns. These event studies involved choosing a selection of news articles (generally less than 200) and assessing whether abnormal returns for the stock occurred on their date of publication. A study of this type has not yet been done using data from the NVD. This study addresses the varied results of past event studies, and then examines the potential for earning excess returns by trading stocks based on data from the NVD.

There have been many recent and noteworthy instances of when a company's stock price has fallen following a vulnerability disclosure. After Equifax disclosed that their customers' data had been compromised because of an unpatched vulnerability, the company's stock price fell from $142.72 to $92.98 (-34.85%) between September 7 and September 15, 2017 [Siegel Bernard, Hsu, Perlroth, and Lieber (2017)]. When Intel announced in January 2018 that its computer chips had a security issue that could affect many electronic devices, its "shares were down nearly 5 percent" [Balakrishnan (2018)]. Thus, reports of these vulnerabilities in the news directly impacted the stock prices and market values of the affected companies. It is also interesting to note that reports of the vulnerabilities associated with these events can be found in the NVD [Equifax - CVE-2017-5638 (Apache Struts), Intel - CVE-2017-5754 (Meltdown) and CVE-2017-5753 (Spectre)].

Without consulting any research, it is difficult to predict what effect computer vulnerabilities will have on stock prices. Telang and Wattal (2007) considered the effect of vulnerabilities on stock prices as consisting of two cost factors:

$$\begin{pmatrix} \textit{Cost of software} \\ \textit{vulnerability} \end{pmatrix} = \begin{pmatrix} \textit{Cost of patching the} \\ \textit{vulnerability} \end{pmatrix} + \begin{pmatrix} \textit{Cost of future} \\ \textit{lost sales} \end{pmatrix} \tag{1}$$

However, despite these two costs, it is also possible that vulnerabilities might occur at a time when a firm is performing above expectations. For example, if Apple releases a great new product, although there may be some initial flaws and vulnerabilities associated with it, if the product sales beat expectations then Apple's stock may still rise. Sullivan (2018) finds that an increase in the number of vulnerabilities may be found around the time of software updates or product releases.

Without studying updates specifically, a goal of this research is to use the NVD to test whether an increase in the number of vulnerabilities has a positive or negative impact on stock returns.

Unlike prior research, which focuses mainly on a small set of events in the news, this study takes advantage of the large dataset contained in the NVD to construct an unbiased sample. With the valuable data from the NVD, this paper addresses two hypotheses:

Hypothesis 1: *When all vulnerabilities in the NVD during a specific time period are considered, the impact of a vulnerability publication on the stock returns of the affected company is negative.*

This first hypothesis is tested in section IV on the NVD using the same approach as prior research using media announcements. Based on the first hypothesis, if stock prices do not immediately correct in response to these announcements, it would be possible to earn long-term returns as the market adjusts.

Hypothesis 2: *If it takes time to incorporate security flaws into stock prices, then it is possible to earn excess returns using a portfolio strategy that goes long in the stock of secure companies and goes short in the stocks of other companies.*

This second hypothesis is tested in section V by making hypothetical portfolios of stocks from companies in the NVD based on their relative number of vulnerabilities at a given time. The excess returns resulting from this strategy are tested using the Fama and French (1993) and Carhart (1997) models.

II. Background and Literature Review

In general, previous event studies focused on media reports of vulnerabilities. For this reason, these prior studies generally consisted of small samples sizes (less than 200, observations with only a few companies). These other studies are limited because they selected what articles to include, which may have biased their results in a certain direction.

Telang and Wattal (2007) gathered a sample of news articles from sources such as *The Wall Street Journal* and *The New York Times*. They searched for specific terms, such as “vulnerability.” From their search, they compiled a sample of 147 vulnerability announcements for 18 companies. The authors then used the text from the associated articles to classify the vulnerability (for example, identifying it as “severe”).

In their main regression, Telang and Wattal found that the Day 0 Cumulative Abnormal Returns (CAR) were generally negative and statistically significant. They also found that the CAR was negative for a period after Day 0. Their study is definitely limited because they manually selected the vulnerability announcements for their sample. Further, Telang and Wattal (2007) studied only a small selection of 147 vulnerabilities, of which Microsoft “accounts for more than 40 percent.”

Goel and Shawky (2009) used public news sources, including the Lexis Nexis database, and they constructed a sample of 168 vulnerability announcements. They looked at the Abnormal Returns (AR) and CARs around the publication date. They generally found statistically negative ARs and CARs in the one or two days prior to the announcement of vulnerabilities. Goel and Shawky (2009) attributed a “negative impact of about 1% of the market value of the firm” to the announcement of these vulnerabilities.

Hovav and D’Arcy (2005) considered the impact of viruses specifically on the affected companies’ stock returns. Using the Lexis Nexis database, the authors searched for articles containing the word “virus.” They selected a sample of 92 virus announcements between 1988 and 2002, of which Microsoft accounted for a large part of the sample. The authors categorized these announcements based on the type of virus and analyzed the results for Microsoft separately. After testing the ARs and CARs like the other studies, Hovav and D’Arcy (2005) found a negative market reaction only 50% of the time that was “not statistically significant over extended periods.”

III. Data

The data in this study is current as of December 31, 2017. At the time of this study, this was the most recent date available to download returns from the Wharton Research Data Services (WRDS). Unless otherwise stated, this study utilizes all of the vulnerability data from the NVD, for which statistics are shown in Table I. For this paper, main tables are included in the main part and additional papers are in section A. Results are examined with data from before 2002 and without it, since the return profile for stocks in this period was impacted by the dot-com bubble. As shown in Table I, this dataset consists of nearly 100,000 vulnerability observations with an increasing number each year (2017 having the most to date).

Table I

Vulnerability Frequencies by Year

Year	Frequency	Year	Frequency
1988	2	2004	2,451
1989	3	2005	4,932
1990	11	2006	6,608
1991	15	2007	6,516
1992	13	2008	5,632
1993	13	2009	5,732
1994	25	2010	4,639
1995	25	2011	4,150
1996	75	2012	5,288
1997	252	2013	5,187
1998	246	2014	7,937
1999	894	2015	6,487
2000	1,020	2016	6,447
2001	1,677	2017	14,642
2002	2,156	2018	3,840
2003	1,527	Total	98,442

Each vulnerability in the NVD has a unique Common Vulnerabilities and Exposures (CVE) identification code [CVE (2018)]. When a vulnerability is added to the directory of CVE codes, an analyst for the NVD verifies the vulnerability and updates its data points, which are used in this study [NVD (2018)]. A sample NVD entry is shown in Figure 11. Anyone can submit a vulnerability to be reviewed, but most are reported by the affected companies or cybersecurity firms [CVE (2018)].

For each of these vulnerabilities, there are variety of data points (see Figure 12 for an example). The features used in this study include:

1. **CVSS Score** - Measure of a vulnerability severity (1-10 scale, where > 7 is severe).
2. **Affected Vendors** - Vendors affected by the vulnerability (used to connect data from the NVD to stock returns).
3. **References** - Other websites that contain reports of the same vulnerability (these might include the news reports, which were used in previous studies).

The features not used in this study include:

1. **Products** - The specific product that a vulnerability affects (e.g. Windows 10).

2. **Description** - Although the descriptions contain useful information when processed, these features are outside the scope of this study [see Sullivan (2018)].

A. Reference Data

Prior studies used news articles that may have been recorded in the Reference Section in the NVD for a vulnerability. In this study, these references are analyzed under the premise that a vulnerability with many references is thoroughly reported and may exhibit a distinct pattern. As shown in Figure 1 and Table II, the number of references for a vulnerability appears normally distributed with a 4.78 mean and 5.12 standard deviation. In this study, vulnerabilities that have enough references to be in the 90^{th} percentile (9) are designated as *High Reference* vulnerabilities and are analyzed separately. The results found using other cutoffs above the mean are similar.

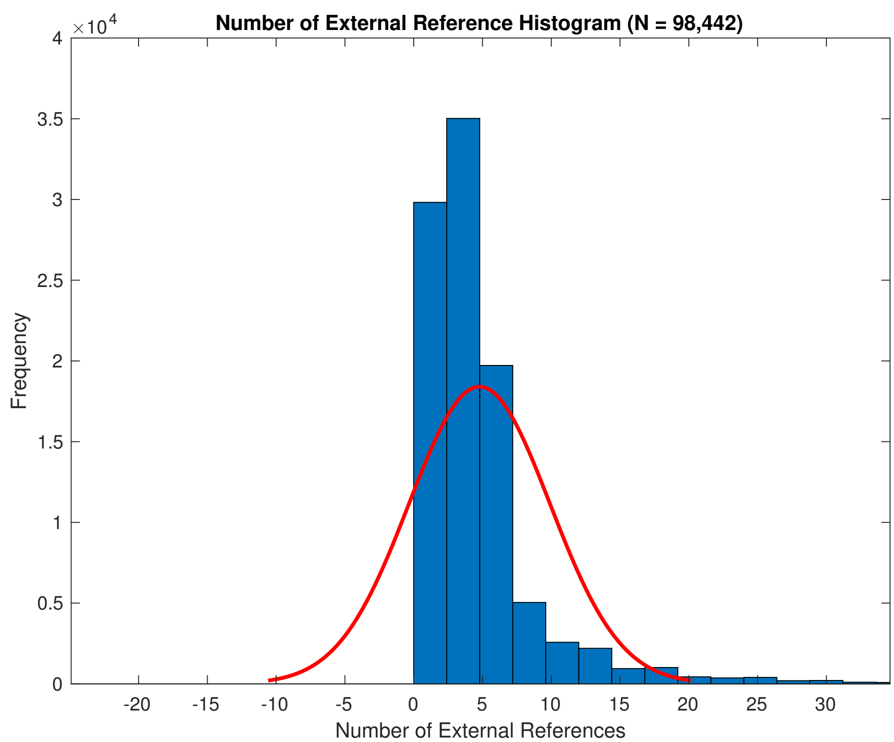


Figure 1. Histogram of Number of External Vulnerability References

Table II

External References Summary Statistics

(a) Mean & SD

Mean	SD
4.7802	5.1205

(b) Percentiles

10%	25%	50%	75%	90%
1	2	3	5	9

B. Company Selection

This study uses a selection criterion by which companies may have been included in the sample ex ante (without any foreknowledge of their results). This approach differs from prior studies in section II, which selected companies and news events ex post (after they had made a vulnerability announcement). For the tests in this paper, companies are only selected into the sample if they have *more than 100 vulnerabilities* over the designated time period. As is shown in the Table III, this approach will limit the sample to certain companies but it will also reduce any selection bias.

In previous studies (Telang and Wattal (2007) and Hovav and D'Arcy (2005)), Microsoft represented a majority of the sample. In the NVD, Microsoft represents the affected company for 5,610 out of 98,884 total reported vulnerabilities (5.67%) and also for 5,610 out of 36,405 vulnerabilities for companies with more than 100 of them (15.41%). Although Microsoft has the most vulnerabilities in this sample, using it together with other companies reduces the bias that Microsoft might introduce into the results.

Some of these companies in the NVD do not deal primarily with computers and software. Table VI shows description classifiers for the selection of companies from the NVD in Table III. In Table III, an asterisk is placed next to the NAIC code for which its NAIC description contains either the word "software" or "computer," and these companies are used as a *Special Company* subsample later. It is understandable that the stock prices of these firms might be most affected by the vulnerabilities listed in the NVD.

C. Return Data

For the companies listed in Table III, daily stock returns are taken from the Center for Research in Security Prices (CRSP) for both the event studies and portfolio strategy. The data from the

Table III

Vulnerability Frequencies by Company

Company	Frequency	Ticker	Exchange	NAIC	Stock Start	Stock End	NVD Start	NVD End
Microsoft	5610	MSFT	NASDAQ	* 511210	Mar-86	Dec-17	Jan-95	Mar-18
Oracle	4957	ORCL	NYSE	* 511210	Mar-86	Dec-17	Jul-97	Jan-18
Apple	4088	AAPL	NASDAQ	334220	Dec-80	Dec-17	Jun-96	Mar-18
IBM	3854	IBM	NYSE	* 541512	Dec-25	Dec-17	Mar-92	Mar-18
Cisco	3385	CSCO	NASDAQ	* 334118	Feb-90	Dec-17	Dec-92	Apr-18
Google	3362	GOOGL	NASDAQ	519190	Aug-04	Dec-17	Aug-02	Apr-18
Adobe	2533	ADBE	NASDAQ	* 511210	Aug-86	Dec-17	Aug-96	Feb-18
Red Hat	1701	RHT	NYSE	* 511210	Aug-99	Dec-17	Dec-94	Mar-18
HP	1607	HPQ	NYSE	* 334111	Mar-61	Dec-17	Dec-90	Mar-18
Novell	1536	NOVL	NYSE	* 511210	Jan-85	Apr-11	Sep-93	Mar-18
Symantec	474	SYMC	NASDAQ	* 511210	Jun-89	Dec-17	May-97	Feb-18
SAP	422	SAP	NYSE	* 511210	Jun-01	Dec-17	Jun-00	Mar-18
Dell EMC	411	DVMT	NYSE	* 334118	Jun-88	Oct-13	Nov-01	Mar-18
VMware	315	VMW	NYSE	* 541512	Aug-07	Dec-17	Jun-99	Mar-18
Juniper	259	JNPR	NYSE	* 334118	Jun-99	Dec-17	Aug-01	Feb-18
SGI	252	SGI	NASDAQ	* 334111	Oct-86	Nov-05	Oct-90	Aug-15
McAfee	251	MCAF	NASDAQ		Dec-99	Sep-02	Dec-99	Oct-17
CA	223	CA	NASDAQ	* 511210	Dec-81	Dec-17	Mar-96	Apr-18
RealNetworks	204	RNWK	NASDAQ	* 541511	Nov-97	Dec-17	Jan-98	May-17
Citrix	201	CTXS	NASDAQ	* 511210	Dec-95	Dec-17	Mar-00	Mar-18
Fortinet	143	FTNT	NASDAQ	* 511210	Nov-09	Dec-17	Jun-05	Feb-18
F5	142	FFIV	NASDAQ	* 541511	Jun-99	Dec-17	Nov-99	Mar-18
Nvidia	130	NVDA	NASDAQ	334413	Jan-99	Dec-17	Oct-06	Mar-18
Santa Cruz Operations	127	SCOC	NASDAQ		May-93	Oct-03	Dec-92	Apr-18
Macromedia	114	MACR	NASDAQ	* 511210	Dec-93	Dec-05	Mar-97	Oct-10
Intel	104	INTC	NASDAQ	334413	Dec-72	Dec-17	May-99	Mar-18
Nam Tai Property	84	NTP	NYSE	333318	Mar-88	Dec-17	Aug-04	Mar-18
Pivotal	83	PVTL	NYSE		Aug-99	Feb-04	Jan-15	Mar-18
Caldera	82	CALD	NASDAQ	* 511210	Mar-00	Dec-07	Oct-96	May-14
Checkpoint	78	CHKP	NYSE	* 511210	Jun-96	Dec-17	May-98	Nov-14
Avaya	76	AV	NYSE	334210	Oct-00	Oct-07	Aug-01	Feb-18
Netgear	75	NTGR	NASDAQ	334210	Jul-03	Dec-17	Jul-01	May-17
TIBCO	70	TIBX	NASDAQ	* 511210	Jul-99	Dec-14	Jun-06	Dec-17
Yahoo	66	YHOO	NASDAQ	* 541512	Apr-96	Jun-17	Oct-99	Jul-17
Xerox	62	XRX	NYSE	423420	Jul-61	Dec-17	Oct-99	Sep-17
NetIQ	62	NTIQ	NASDAQ	* 511210	Jul-99	Jun-06	Apr-05	Mar-18
AOL	57	AOL	NYSE	512110	Mar-92	Dec-17	Feb-98	Sep-16
Qualcomm	56	QCOM	NASDAQ	334220	Dec-91	Dec-17	Jul-98	Mar-18
Rockwell Automation	54	ROK	NYSE	335312	Dec-96	Dec-17	Feb-09	Jan-18
Palo Alto Networks	52	PANW	NYSE	* 511210	Jul-12	Dec-17	Aug-13	Jan-18
Total	37,362							

The * NAIC codes indicate that they meet the special company criteria.

CRSP is obtained through WRDS. Standard returns from the factors for the Fama-French and Carhart models are also taken from WRDS. Using these returns, results are generally considered both including and excluding data from before 2002 to account for the effects of the dot-com bubble.

D. Data Preparation

The following steps are taken to process the data from the NVD:

1. **Download XML file** - From the NVD website, the main XML file is downloaded.
2. **Process using XQuery** - The XML file is restructured so that the relevant data is accessible.
3. **Load table into Matlab** - With the XML file reformatted, a table can be transferred to Matlab for further analysis.
4. **Construct date table** - For each date (rows), a company is marked for the number of vulnerabilities that are published (see Figure 13).

The date table that is produced is used for both the event study and portfolio strategy analysis.

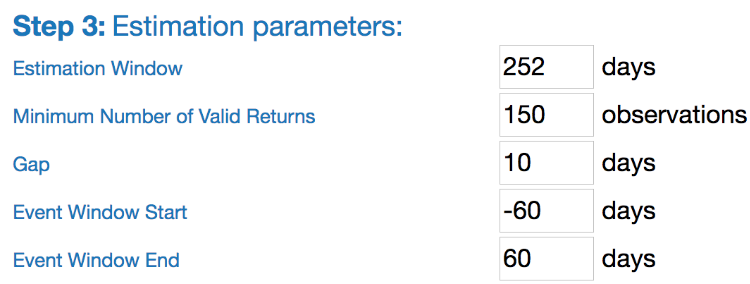
IV. Event Study

To test Hypothesis 1, the date that a vulnerability is reported is focused on (the event date) and the abnormal returns are examined around this date (the event window). The Efficient Market Hypothesis states that "security prices reflect all publicly available information" [Fama (1991)]. If information provided by vulnerability publications affects stock prices, it will be possible to observe "the incremental effect of the information announcement" using an event study [Konchitchki and O'Leary (2011)]. For Hypothesis 1 to be proven correct, it would have to be true that vulnerability information is reflected at some point in the stock price during the event window, even if not immediately apparent.

A. Methodology

This study uses the Event Study Tool provided by WRDS. From the date table that is created and described in section III, the number of vulnerabilities that each company has on a given day is extracted. Once uploaded to WRDS, multiple settings must be chosen for the event study (these are summarized in Figure 2):

1. **Estimation Window** - In making a model for what the returns should be during the event period, a trading year (252 days) of returns is used.
2. **Minimum Number of Valid Returns** - For this time period, 150 observations must be available for the estimate to be calculated.
3. **Gap** - There is a 10-day gap separating the estimation window from the event window.
4. **Event Window** - In this study, the start date is chosen two days prior to the vulnerability publication, consistent with the study by Goel and Shawky (2009).


Step 3: Estimation parameters:

Estimation Window	252	days
Minimum Number of Valid Returns	150	observations
Gap	10	days
Event Window Start	-60	days
Event Window End	60	days

Figure 2. WRDS Event Study Settings

Both the Fama-French and Carhart models are constructed using the estimation window. These models are used to predict what returns would be during the event window if the event had not happened. This analysis is performed both including and excluding data from before 2002.
From the event study results, two measures and their statistical significance are analyzed [these explanations are based on those by Goel and Shawky (2009)]:

1. **Abnormal Returns (AR)** - These are found by taking the difference between the actual return and the return predicted by the Fama-French or Carhart models during a time interval [Fama and French (1993) and Carhart (1997)]:

$$AR = R - E(R) = R - [R_f + \alpha + \beta_1(R_m - R_f) + \beta_2(SMB) + \beta_3(HML)] \tag{2}$$

Fama-French Model

$$AR = R - E(R) = R - [R_f + \alpha + \beta_1(R_m - R_f) + \beta_2(SMB) + \beta_3(HML) + \beta_4(MOM)] \tag{3}$$

Carhart Model

2. **Mean Average Return (MAR)** - This is calculated by taking the average AR for a time period:

$$\overline{AR_t} = \frac{1}{N_t} \sum_{i=1}^{i=N_t} AR_t; t = (-2, -1 \ldots 59, 60) \tag{4}$$

3. **Cumulative Abnormal Returns (CAR)** - These are found by aggregating the abnormal returns to show how they change over time:

$$CAR_{-2,t} = \sum_{i=-2}^{i=t} \overline{AR_t}; t = (-2, -1 \ldots 59, 60) \tag{5}$$

The following statistics calculate how likely it is that the previous measures are not zero and are statistically significant:

1. **MAR T-Stat** - This measure considers the change in volatility that the event may have caused, but assumes that cross-sectional abnormal returns are independent [WRDS (2018)].
2. **Patell Z for MAR** - A common event study measure that standardizes abnormal returns based on the volatility of abnormal returns during the estimation window [WRDS (2018) and Patell (1976)].
3. **CAR T-Stat** - This measure is based on the standard deviation that is provided by WRDS and the calculation by Telang and Wattal (2007):

$$t = \frac{CAR}{\sqrt{S^2_{CAR}}} \tag{6}$$

B. Results

As one of the subsamples from section III, computer and software focused companies are studied separately. As shown in Figure 3, abnormal returns are consistently negative prior to Day 45 for these *Special Companies* and flat after. From Table IV, the CAR is -0.63% at Day 40 and -0.73% at Day 60. In Table IV, it is shown that the mean abnormal returns are not statistically significant for any date range, including on Day 0 (vulnerability publication date). However, when these abnormal returns are cumulated (Cum. Avg. Ret.), the results are statistically significant and become increasingly so over time (even at the 5% level).

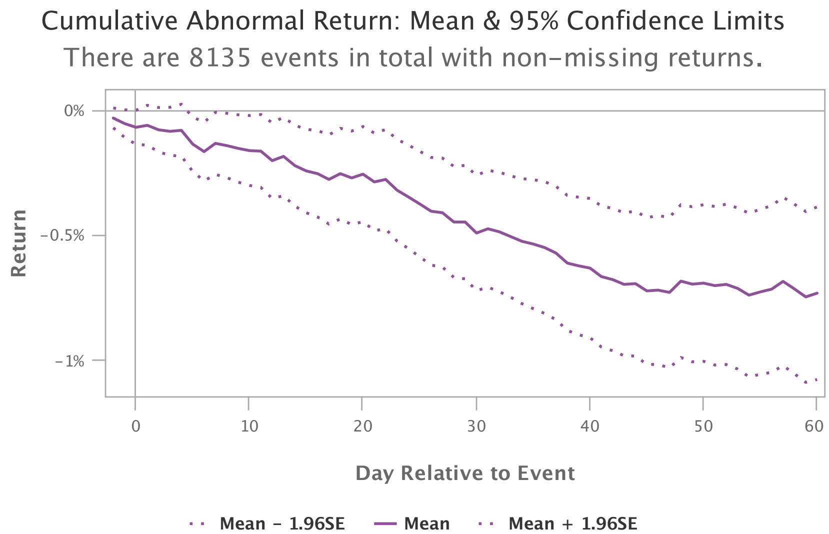


Figure 3. Full Sample, Carhart Model, Special Company Vulnerabilities

Table IV
Abnormal Returns Around NVD Vulnerability Publication

	Special Companies (N = 8,135)			
	$R_{-2,0}$	$R_{-2,+20}$	$R_{-2,+40}$	$R_{-2,+60}$
Panel A: Full Sample, Fama-French Model				
Mean Ab. Ret.	-0.00010	0.00014	-0.00015	0.00023
	(-0.48)	(0.66)	(-0.72)	(1.13)
Patell Z for MAR	-0.57	0.10	-0.62	0.27
Cum. Avg. Ret.	-0.0007*	-0.0019*	-0.0049***	-0.0056***
	(-1.86)	(-1.95)	(-3.40)	(-3.18)
CAR Std. Dev.	0.0004	0.0010	0.0014	0.0018
CAR 95% CI Upper	0.0000	-0.0007	-0.0035	-0.0039
CAR 95% CI Lower	-0.0014	-0.0045	-0.0091	-0.0108
Panel B: Full Sample, Carhart Model				
Mean Ab. Ret.	-0.00015	0.00014	-0.00010	0.00013
	(-0.73)	(0.68)	(-0.49)	(0.64)
Patell Z for MAR	-0.76	0.05	-0.51	-0.08
Cum. Avg. Ret.	-0.0007**	-0.0026***	-0.0063***	-0.0073***
	(-1.97)	(-2.66)	(-4.52)	(-4.24)
CAR Std. Dev.	0.0004	0.0010	0.0014	0.0017
CAR 95% CI Upper	0.0000	0.0000	-0.0021	-0.0022
CAR 95% CI Lower	-0.0014	-0.0038	-0.0076	-0.0090

t statistics in parentheses. Patell Z Source: Patell (1976)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

From inspection of Figure 3 and Table IV, it appears that vulnerability information is incorporated as negative abnormal stock returns in the first 45 days after the NVD publication date. In Table IV, after 40 days the CAR does not change much from about -0.7% nor does it become more statistically significant. At 40 days, the 95% confidence interval is also completely below zero for both models.

In section A, this event study is tested on different samples from the NVD for robustness. Generally, the trend is the same as that for the *Special Companies* just discussed, even when all vulnerabilities or only severe vulnerabilities are analyzed. These same results are consistent whether data from before 2002 is included or not. Although the *High Reference* vulnerabilities (see section III) show negative returns on average, the trend here is not statistically significant like it is for the other subsamples. Across these tests, the Carhart model shows CARs that are consistently negative over time, suggesting that momentum might be an important factor for the expected return models.

In Figure 4, the event window is extended to include a larger time period than before. From this figure, it appears that abnormal returns might start trending downward 15 to 20 days before the vulnerability is published in the NVD. This trend indicates that vulnerability information may be incorporated into stock returns even before it is published in the NVD.

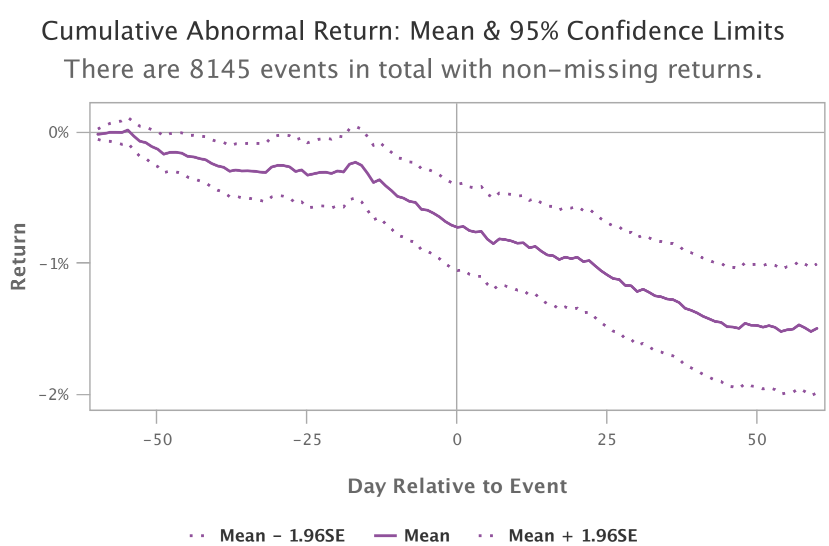


Figure 4. Full Sample, Carhart Model, Special Company Vulnerabilities (Larger Event Window)

V. Portfolio Strategy

As is shown in the section IV, it appears that vulnerability information gradually results in falling stock returns. Long-term costs associated with these vulnerabilities may include "the cost of producing and distributing a patch" and "the cost of lost sales" [Telang and Wattal (2007)]. Companies with more vulnerabilities at a given time than normal would have to spend more capital addressing these concerns than companies with fewer vulnerabilities. If a firm has more negative events than normal, it makes sense that each negative event will combine to contribute to lower stock returns. Based on this premise, Hypothesis 2 is tested by determining whether a strategy that longs low vulnerability stocks and shorts high vulnerability stocks will have excess returns compared to the stock market performance as a whole.

A. *Methodology*

In this section, the tests and results are discussed for data from the sample since 2002. Inflated returns for some companies and the closing of others during the dot-com bubble would distort the excess return measures with data that is not relevant if the strategy was used today. However, Table XIV shows that results would be similar if this data was included (a long portfolio of low vulnerability companies still earns excess returns over the full sample).

In order to test the long-short strategy, two hypothetical portfolios are constructed based on the number of vulnerabilities that a company has relative to its past trading year's average. Companies that, on average, have more vulnerabilities during the past 45-day period than the past trading year average are considered vulnerable, while those with less over the same time period are considered secure. A 45-day period is used because this timeframe is when stock returns appear to have reached their low in section IV (vulnerability information has likely been incorporated by this time). For IBM, this moving average ratio idea is shown in Figure 5 and Figure 6. If the ratio in Figure 6 is above the dotted line, the stock is longed; otherwise it is shorted.

In addition to the vulnerability criterion, there are other criteria that a public company must fulfill in order to be included in either the long or short portfolio.

1. It matches the vulnerability ratio criteria for the portfolio.
2. There have been 252 trading days of vulnerability data to construct the trailing averages

without distortion.

3. There have been more than 100 vulnerabilities recorded. As explained in section III, this rule means it would be possible to select the sample in real time.
4. It has an active stock ticker to measure return data.

Within either the long or short portfolio, the returns for all stocks that meet the criteria to be included are averaged to find the daily returns for that portfolio. If no companies are available on a particular date for either the long or short portfolio based on the above criteria, the market return is used instead.

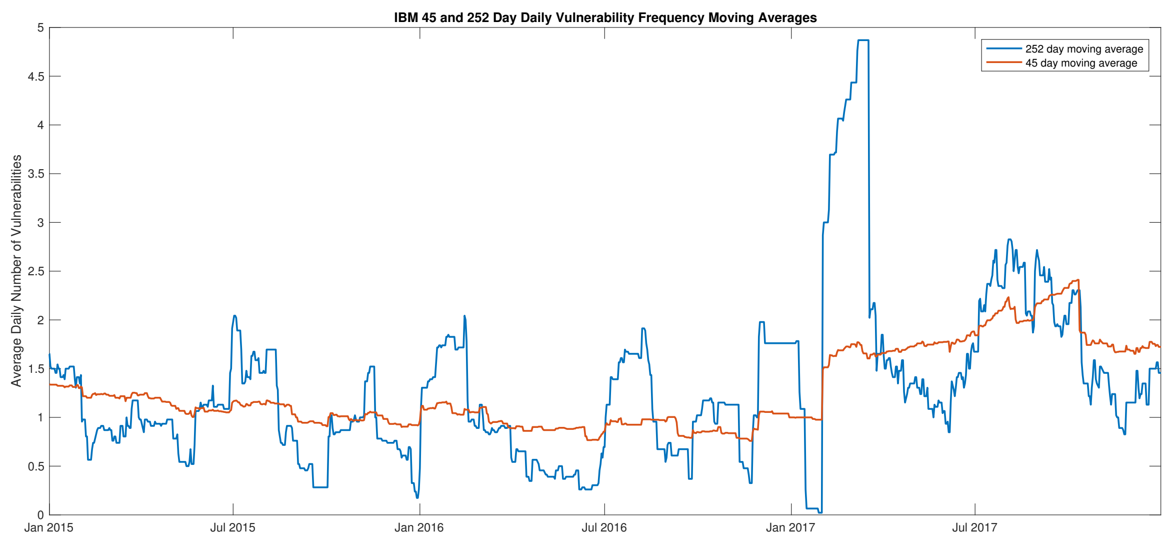


Figure 5. IBM 45 and 252 Day Daily Vulnerability Frequency Moving Averages.

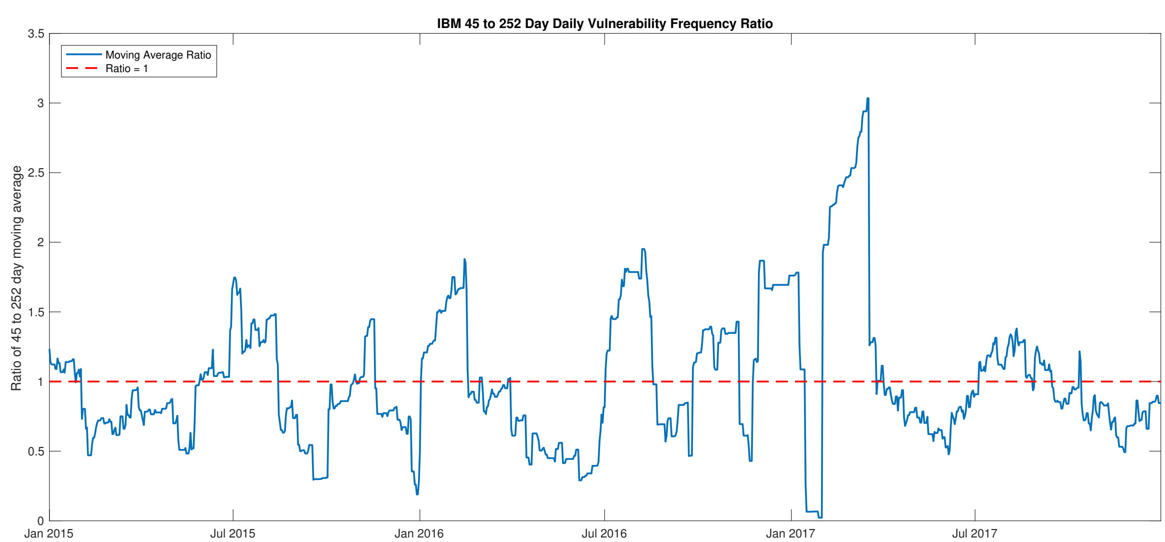


Figure 6. IBM 45 to 252 Day Daily Vulnerability Frequency Ratio.

In order to measure excess returns from this trading strategy, the returns for these portfolios are regressed on the Fama-French and Carhart factor returns. Before running these regressions, the risk-free rate of return is subtracted, consistent with how the factors for these models are constructed. In order to isolate the returns attributable to this strategy, the difference between the long and short portfolio returns is taken. In this study, consistent with long-short portfolio strategies, the risk-free rate is not subtracted from the returns for this final portfolio.

The annual returns in excess of those predicted by the Fama-French or Carhart models or annual alpha is found by using the regression intercept (daily alpha) with the following calculation [Agnes (2016)]:

$$\alpha_{annual} = (1 + \alpha_{daily})^{252} - 1 \tag{7}$$

B. Results

As shown in Table V, a strategy that was long in past high vulnerability ratio companies and short in low ones produced an annualized alpha of 13.45%. Going long in all of the stocks that match criteria (2) through (4) in this sample yields a high annual alpha of about 6%. Going long in the stocks of companies that have a low vulnerability ratio produces an annual alpha of about 9%, while shorting stocks of companies with a high ratio produces an annual alpha of about 4%. This alpha constant is statistically significant at the 5% level for longing the stocks of low vulnerability companies. Although the alpha constant is not significant for the short strategy, it is significant for the long-short strategy at the 5% level.

The coefficients for the Fama-French and Carhart regressions for the overall sample suggest certain characteristics about these companies. With a *mktrf* coefficient of about 1, these companies have similar volatility to the market. As expected for technology companies, the near zero *smb* coefficient indicates that these are larger companies and the negative *hml* coefficient indicates that they are high growth.

These findings are robust for different subsamples. The same results occur when all vulnerabilities (including those that are not severe) are considered in Table XI, with a slightly lower alpha from the long-short strategy of 12%. When isolating *High Reference* vulnerabilities in Table XII, the alpha constant of about 10% is only statistically significant for going long in the stocks of com-

Table V

Portfolio Trading Strategy I

Fama-French and Carhart Regressions, Severe Vulnerabilities Since 2002

Regressions (1) and (2) are for all companies, regardless of their vulnerability ratio. (3) and (4) are for companies with a vulnerability ratio less than 1 - the long strategy (see subsection V.A). (4) and (5) are for companies with a vulnerability ratio greater than 1 - the short strategy. (5) and (6) are found by taking the returns for the long strategy and subtracting those for the short strategy.

	(1) all_rf	(2) all_rf	(3) lt1_rf	(4) lt1_rf	(5) gt1_rf	(6) gt1_rf	(7) l_s	(8) l_s
mktrf	1.041***	1.034***	1.053***	1.049***	1.028***	1.023***	0.0242	0.0261
	(88.72)	(86.18)	(67.67)	(65.90)	(58.35)	(56.72)	(1.11)	(1.17)
smb	0.0478**	0.0530**	0.0689**	0.0715**	0.0146	0.0187	0.0543	0.0528
	(2.11)	(2.33)	(2.29)	(2.37)	(0.43)	(0.55)	(1.29)	(1.25)
hml	-0.295***	-0.323***	-0.258***	-0.272***	-0.321***	-0.343***	0.0638	0.0717
	(-13.51)	(-13.30)	(-8.89)	(-8.44)	(-9.79)	(-9.41)	(1.57)	(1.59)
umd		-0.0415***		-0.0210		-0.0330		0.0119
		(-2.59)		(-0.99)		(-1.37)		(0.40)
_cons	0.000225*	0.000229*	0.000332**	0.000334**	-0.000169	-0.000166	0.000502**	0.000501**
	(1.81)	(1.84)	(2.01)	(2.02)	(-0.91)	(-0.89)	(2.17)	(2.16)
Ann. α	5.83%	5.94%	8.72%	8.78%	-4.17%	-4.10%	13.48%	13.45%
N	3776	3776	3776	3776	3776	3776	3776	3776
R^2	0.698	0.699	0.577	0.577	0.497	0.497	0.002	0.002

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

panies with a low vulnerability ratio at the 5% level. For only the *Special Companies* in Table XIII, the alpha constant for the long-short strategy of about 11% is only statistically significant at the 5% level.

VI. Discussion

Using data from the NVD, these results suggest that vulnerabilities are incorporated into stock prices over a longer period than previous studies suggested. The authors discussed in section II all used media reports, whether from news articles or from the Lexis Nexis database to test how these announcements affected stock prices. Their results were varied. Telang and Wattal (2007) and Goel and Shawky (2009) found negative event returns, whereas Hovav and D'Arcy (2005) found no significant result overall. In subsection IV.B, it takes about 45 days for the full negative CARs to be presented.

As stated in section III, the reference data for the NVD entries contains links to other sites that refer to the vulnerability, such as press releases that may have been used in other studies. Using the reference data in section IV, the *High Reference* vulnerabilities did not exhibit the same strong negative returns as the entire sample or other subsamples. It is possible that vulnerabilities that may have more of an impact on stock prices are not consistently reported by the media. This finding is consistent with the varied results found using media reports for event studies in section II.

There are some concerns with implementing a trading strategy based on the NVD. First, since such a strategy would require daily portfolio rebalancing, it is possible that transaction costs may take away from the potential excess returns. Second, it seems that some of the downward abnormal return effect due to the vulnerabilities is incorporated before the vulnerability is published (see subsection IV.B). If this information is being incorporated into the stock price before it is reported in the NVD, it is possible that an investor using this strategy may not realize the full potential of the possible excess returns.

VII. Conclusion

Both of the original hypotheses have been tested:

Hypothesis 1: *When all vulnerabilities in the NVD during a specific time period are considered, the impact of a vulnerability publication on the stock returns of the affected company is negative.*

The event study shows a statistically significant negative CAR of -0.63% at Day 40 after a vulnerability publication, which then flattens out after Day 45. The results for this event study show that information from the vulnerability publication is reflected in the market price of the stock within about 45 days.

Hypothesis 2: *If it takes time to incorporate security flaws into stock prices, then it is possible to earn excess returns using a portfolio strategy that goes long in the stock of secure companies and goes short in the stocks of other companies.*

It is possible to construct a long-short strategy using the trailing 45 and 252 daily vulnerability moving averages and trading based on whether a company has more or less vulnerabilities than in the past. The alpha constant from the Carhart regression for only severe vulnerabilities shows that such a strategy would have yielded 13.45% in annual excess returns from 2002 through 2017. Vulnerabilities may not be reflected immediately in prices, but generally and in aggregate, they are reflected in the long-term. It should be possible to earn positive excess returns using a long-term automated trading strategy based on data from the NVD. Ideally, corrective market forces are benefiting consumers and shareholders by forcing companies to address vulnerabilities in response to their stock prices falling.

A. Future Directions

There are many possible research opportunities using the vast dataset from the NVD. The NVD contains information for many private companies and it is possible that some of the vulnerability reports may have an impact on their valuations. Campbell, Gordon, Loeb, and Zhou (2003) found that security vulnerabilities only result in significantly negative results if there is loss of confidential information. Hovav and D'Arcy (2003) found that Denial-of-Service attacks affect the value of "Internet-specific" companies. The NVD also contains score metrics for how a vulnerability affects a company's confidentiality (as Campbell researched) and accessibility (as Hovav researched). It would be interesting to update the findings from these articles using a larger dataset, such as the NVD.

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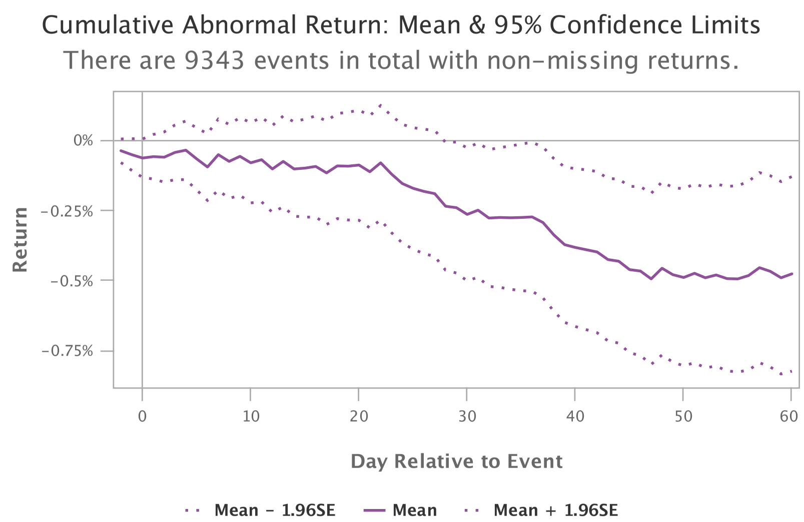
Appendix A. Additional Figures and Tables

Table VI

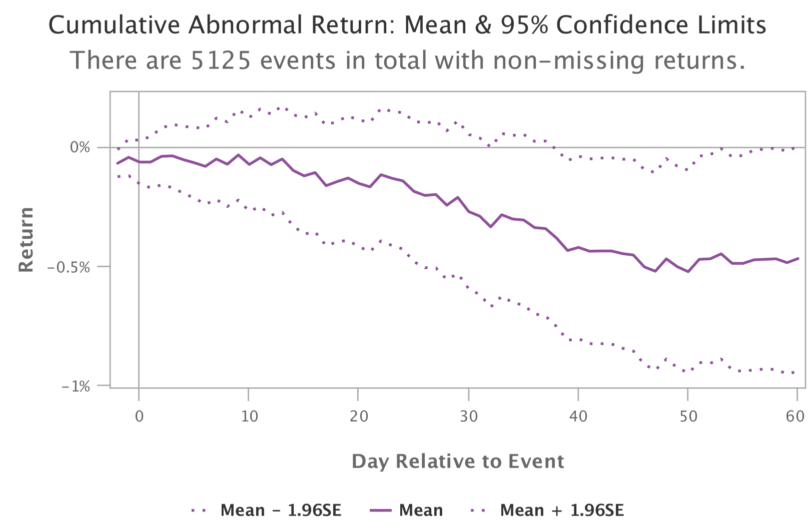
NAIC Codes and Descriptions

NAIC Code	Description
333318	Other Commercial and Service Industry Machinery Manufacturing - Adding machines manufacturing
* 334111	Electronic Computer Manufacturing - Analog computers manufacturing
* 334118	Computer Terminal and Other Computer Peripheral Equipment Manufacturing - ATMs (automatic teller machines) manufacturing
334210	Telephone Apparatus Manufacturing - Carrier equipment (i.e., analog, digital), telephone, manufacturing
334220	Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing - Airborne radio communications equipment manufacturing
334413	Semiconductor and Related Device Manufacturing - Diodes, solid-state (e.g., germanium, silicon), manufacturing
335312	Motor and Generator Manufacturing - Armature rewinding on a factory basis
423420	Office Equipment Merchant Wholesalers - Accounting machines merchant wholesalers
* 511210	Software Publishers - Applications development and publishing, except on a custom basis
512110	Motion Picture and Video Production - Animated cartoon production
519190	All Other Information Services - Clipping services, news
* 541511	Custom Computer Programming Services - Applications software programming services, custom computer
* 541512	Computer Systems Design Services - CAD (computer-aided design) systems integration design services

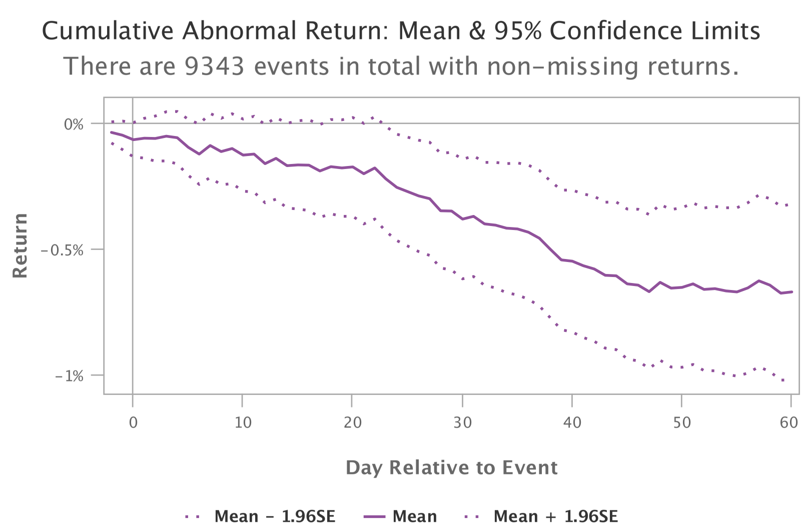
* Indicates description contains the word “software” or “computer”



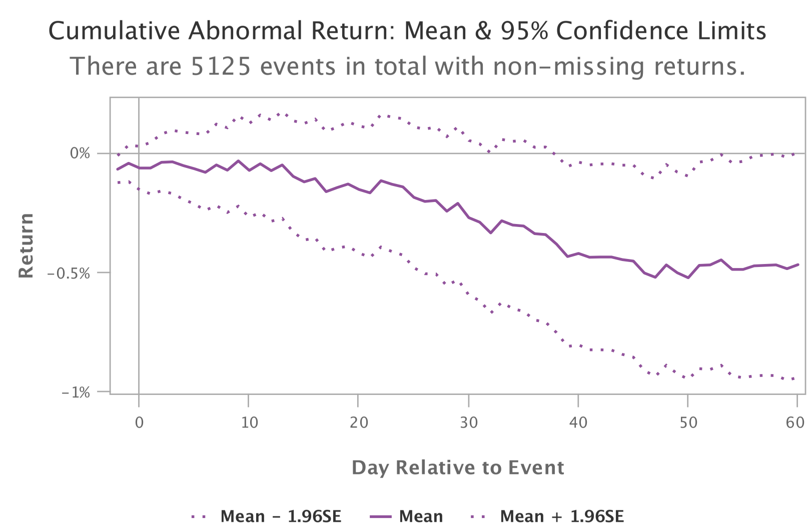
(a) Fama-French Model, All Vulnerabilities



(b) Fama-French Model, Severe Vulnerabilities



(c) Carhart Model, All Vulnerabilities



(d) Carhart Model, Severe Vulnerabilities

Figure 7. Full Sample Event Studies 1 (including before 2002)

Table VII

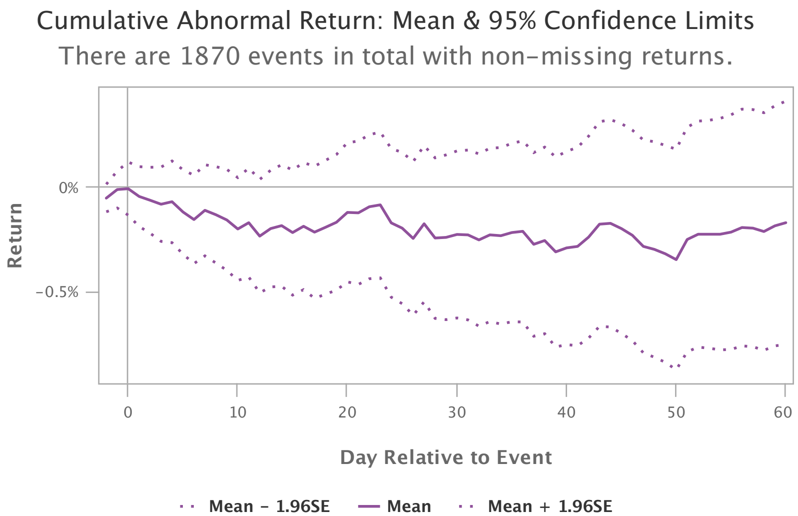
Abnormal Stock Returns Around Vulnerability Publication in NVD, Full Sample I

	All Vulnerabilities (N = 9,343)				Only Severe Vulnerabilities (N = 5,125)			
	$R_{-2,0}$	$R_{-2,+20}$	$R_{-2,+40}$	$R_{-2,+60}$	$R_{-2,0}$	$R_{-2,+20}$	$R_{-2,+40}$	$R_{-2,+60}$
Panel A: Full Sample, Fama-French Model								
Mean Ab. Ret.	-0.00013	0.00003	-0.00011	0.00014	-0.00019	-0.00023	0.00013	0.00014
	(-0.61)	(0.15)	(-0.52)	(0.69)	(-0.70)	(-0.82)	(0.44)	(0.52)
Patell Z for MAR	-0.69	0.09	-0.78	-0.03	-1.11	-0.84	0.30	-0.42
Cum. Avg. Ret.	-0.0007**	-0.0009	-0.0038***	-0.0048***	-0.0006	-0.0015	-0.0042**	-0.0047*
	(-1.97)	(-0.88)	(-2.65)	(-2.72)	(-1.39)	(-1.14)	(-2.15)	(-1.95)
CAR Std. Dev.	0.0003	0.0010	0.0015	0.0018	0.0005	0.0014	0.0020	0.0024
CAR 95% CI Upper	0.0000	0.0011	-0.0010	-0.0013	0.0003	0.0011	-0.0004	0.0000
CAR 95% CI Lower	-0.0013	-0.0029	-0.0067	-0.0082	-0.0015	-0.0042	-0.0081	-0.0094
Panel B: Full Sample, Carhart Model								
Mean Ab. Ret.	-0.00018	0.00004	-0.00006	0.00005	-0.00020	-0.00021	0.00017	0.00006
	(-0.85)	(0.19)	(-0.28)	(0.25)	(-0.71)	(-0.78)	(0.59)	(0.23)
Patell Z for MAR	-0.90	0.07	-0.62	-0.34	-1.16	-0.75	0.29	-0.54
Cum. Avg. Ret.	-0.0007**	-0.0017*	-0.0055***	-0.0067***	0.0006	-0.0024*	-0.0057***	-0.0064***
	(-2.00)	(-1.76)	(-3.83)	(-3.74)	(1.28)	(-1.76)	(-2.93)	(-2.64)
CAR Std. Dev.	0.0003	0.0010	0.0014	0.0018	0.0005	0.0014	0.0019	0.0024
CAR 95% CI Upper	0.0000	0.0002	-0.0027	-0.0032	0.0003	0.0003	-0.0019	-0.0016
CAR 95% CI Lower	-0.0013	-0.0037	-0.0083	-0.0102	-0.0015	-0.0050	-0.0095	-0.0111

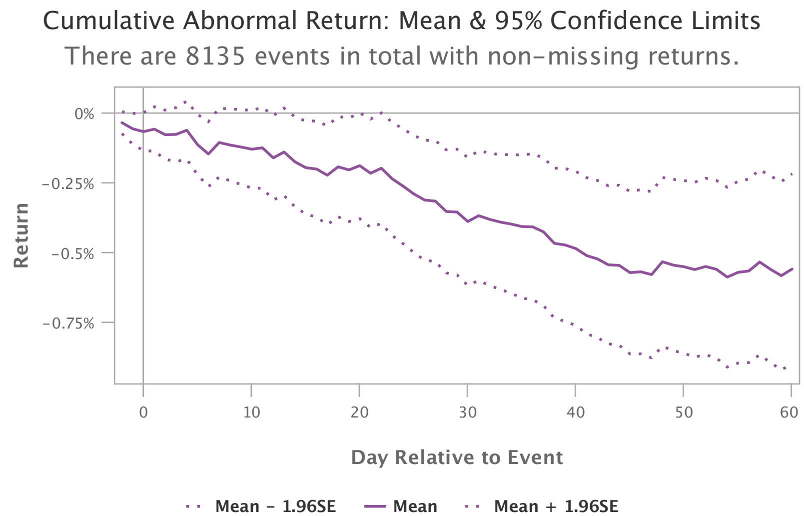
t statistics in parentheses

Patell Z Source: Patell (1976)

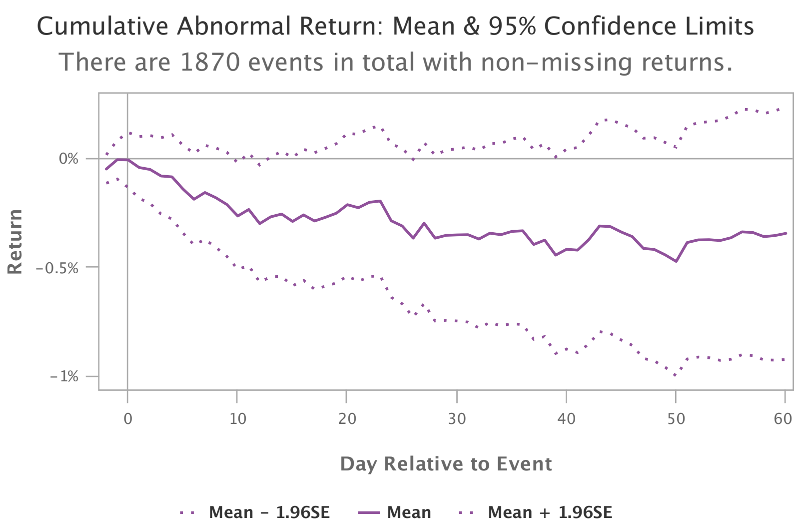
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$



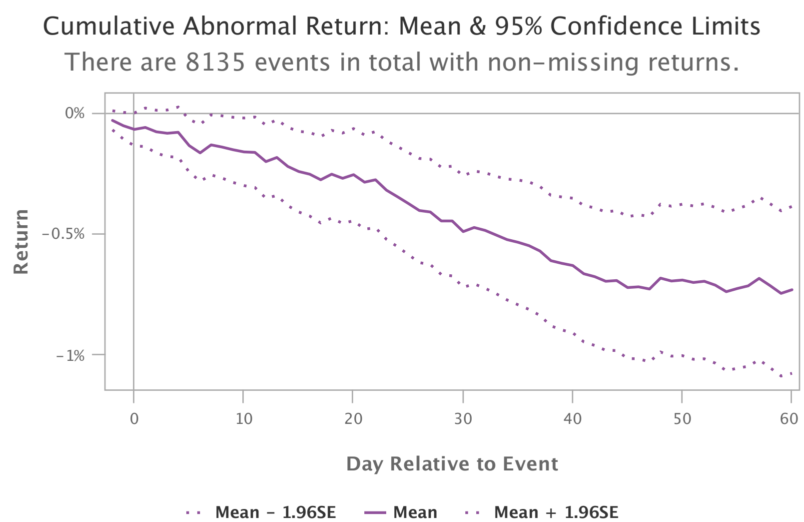
(a) Fama-French Model, High Reference Vulnerabilities



(b) Fama-French Model, Special Company Vulnerabilities



(c) Carhart Model, High Reference Vulnerabilities



(d) Carhart Model, Special Company Vulnerabilities

Figure 8. Full Sample Event Studies 2 (including before 2002)

Table VIII

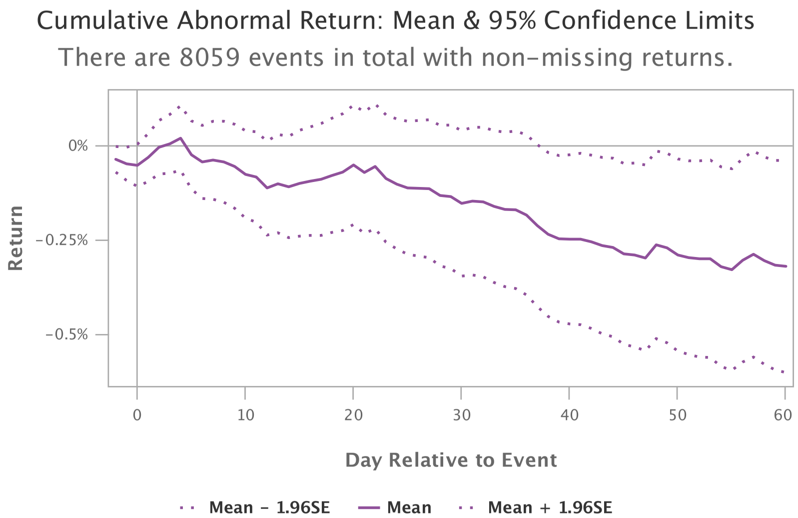
Abnormal Stock Returns Around Vulnerability Publication in NVD, Full Sample II

	High Reference (N = 1,870)				Special Companies (N = 8,135)			
	$R_{-2,0}$	$R_{-2,+20}$	$R_{-2,+40}$	$R_{-2,+60}$	$R_{-2,0}$	$R_{-2,+20}$	$R_{-2,+40}$	$R_{-2,+60}$
Panel A: Full Sample, Fama-French Model								
Mean Ab. Ret.	0.00004	0.00047	0.00019	0.00015	-0.00010	0.00014	-0.00015	0.00023
	(0.10)	(1.22)	(0.52)	(0.39)	(-0.48)	(0.66)	(-0.72)	(1.13)
Patell Z for MAR	0.21	1.39	0.73	0.85	-0.57	0.10	-0.62	0.27
Cum. Avg. Ret.	-0.0001	-0.0012	-0.0029	-0.0017	-0.0007*	-0.0019*	-0.0049***	-0.0056***
	(-0.17)	(-0.75)	(-1.25)	(-0.58)	(-1.86)	(-1.95)	(-3.40)	(-3.18)
CAR Std. Dev.	0.0007	0.0017	0.0024	0.0030	0.0004	0.0010	0.0014	0.0018
CAR 95% CI Upper	0.0012	0.0011	0.0004	0.0023	0.0000	-0.0007	-0.0035	-0.0039
CAR 95% CI Lower	-0.0014	-0.0054	-0.0088	-0.0093	-0.0014	-0.0045	-0.0091	-0.0108
Panel B: Full Sample, Carhart Model								
Mean Ab. Ret.	-0.00001	0.00039	0.00027	0.00010	-0.00015	0.00014	-0.00010	0.00013
	(-0.04)	(1.02)	(0.73)	(0.27)	(-0.73)	(0.68)	(-0.49)	(0.64)
Patell Z for MAR	0.15	1.15	0.92	0.68	-0.76	0.05	-0.51	-0.08
Cum. Avg. Ret.	-0.0001	-0.0022	-0.0042*	-0.0035	-0.0007**	-0.0026***	-0.0063***	-0.0073***
	(-0.15)	(-1.26)	(-1.79)	(-1.18)	(-1.97)	(-2.66)	(-4.52)	(-4.24)
CAR Std. Dev.	0.0007	0.0017	0.0024	0.0030	0.0004	0.0010	0.0014	0.0017
CAR 95% CI Upper	0.0012	0.0021	0.0017	0.0041	0.0000	0.0000	-0.0021	-0.0022
CAR 95% CI Lower	-0.0014	-0.0046	-0.0075	-0.0075	-0.0014	-0.0038	-0.0076	-0.0090

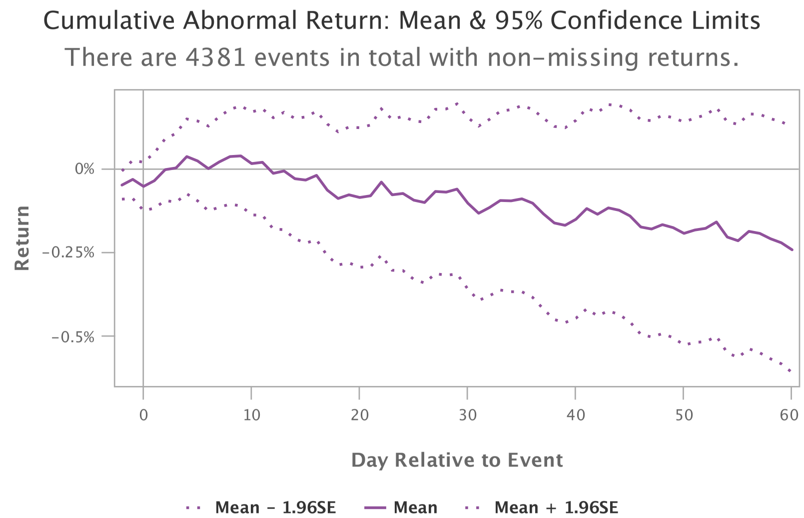
t statistics in parentheses

Patell Z Source: Patell (1976)

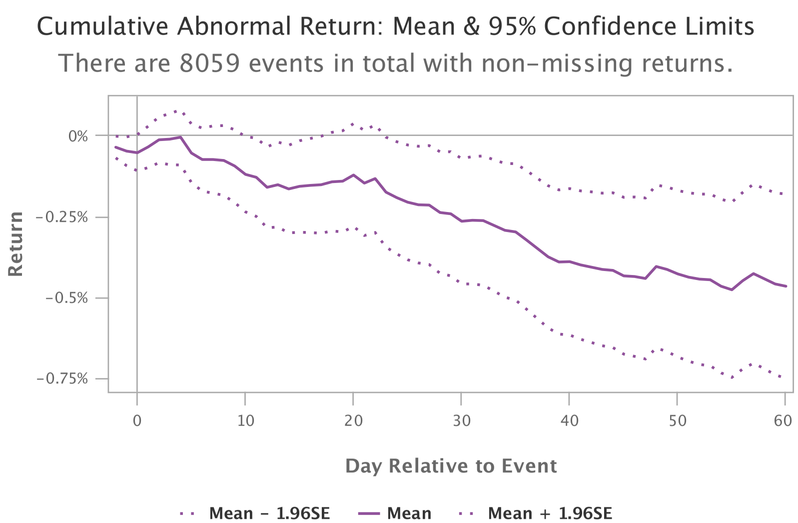
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$



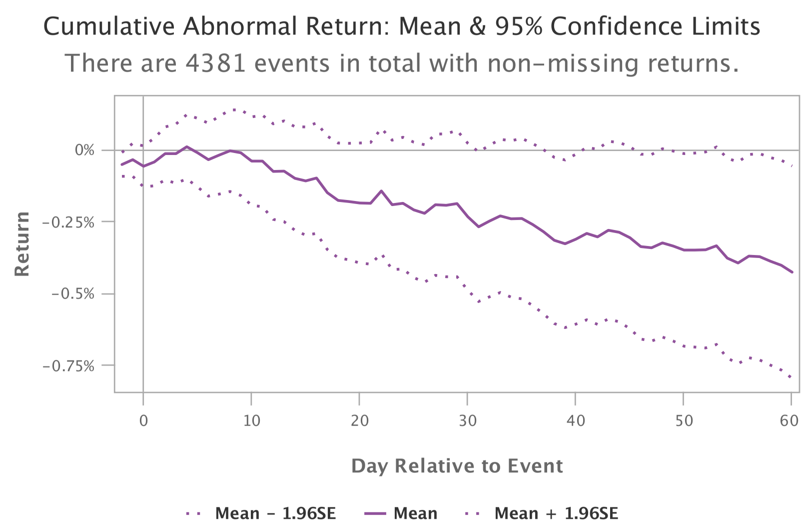
(a) Fama-French Model, All Vulnerabilities



(b) Fama-French Model, Severe Vulnerabilities



(c) Carhart Model, All Vulnerabilities



(d) Carhart Model, Severe Vulnerabilities

Figure 9. Sample Since 2002 Event Studies 1

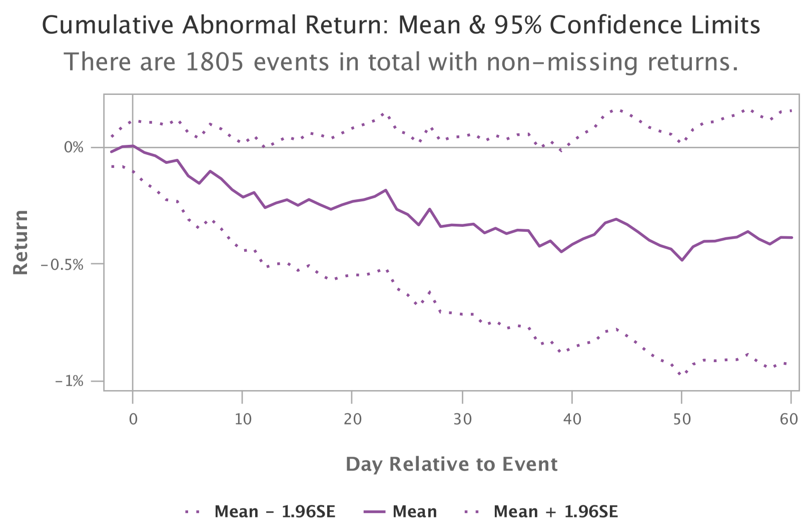
Table IX
Abnormal Stock Returns Around Vulnerability Publication in NVD, Sample Since 2002 I

	All Vulnerabilities (N = 8,059)				Only Severe Vulnerabilities (N = 4,381)			
	$R_{-2,0}$	$R_{-2,+20}$	$R_{-2,+40}$	$R_{-2,+60}$	$R_{-2,0}$	$R_{-2,+20}$	$R_{-2,+40}$	$R_{-2,+60}$
Panel A: Sample Since 2002, Fama-French Model								
Mean Ab. Ret.	-0.00004	0.00019	-0.00002	-0.00003	-0.00021	-0.00008	0.00018	-0.00025
	(-0.22)	(1.05)	(-0.13)	(-0.17)	(-0.91)	(-0.34)	(0.74)	(-1.11)
Patell Z for MAR	-0.52	0.71	-0.23	-0.65	-1.01	-0.27	0.67	-1.33
Cum. Avg. Ret.	-0.0005*	-0.0005	-0.0025**	-0.0032**	-0.0006	-0.0009	-0.0015	-0.0024
	(-1.93)	(-0.65)	(-2.23)	(-2.25)	(-1.45)	(-0.82)	(-1.01)	(-1.31)
CAR Std. Dev.	0.0003	0.0008	0.0011	0.0014	0.0004	0.0011	0.0015	0.0019
CAR 95% CI Upper	0.0000	0.0011	-0.0003	-0.0004	0.0002	0.0012	0.0014	0.0012
CAR 95% CI Lower	-0.0011	-0.0021	-0.0047	-0.0060	-0.0013	-0.0030	-0.0045	-0.0061
Panel B: Sample Since 2002, Carhart Model								
Mean Ab. Ret.	-0.00005	0.00019	0.00000	-0.00007	-0.00023	-0.00005	0.00017	-0.00028
	(-0.27)	(1.07)	(-0.01)	(-0.41)	(-0.99)	(-0.22)	(0.70)	(-1.24)
Patell Z for MAR	-0.59	0.69	-0.09	-0.83	-1.08	-0.17	0.60	-1.35
Cum. Avg. Ret.	-0.0005*	-0.0012	-0.0039***	-0.0047***	-0.0006	-0.0019*	-0.0031**	-0.0043**
	(-1.93)	(-1.50)	(-3.40)	(-3.22)	(-1.61)	(-1.74)	(-2.07)	(-2.26)
CAR Std. Dev.	0.0003	0.0008	0.0012	0.0015	0.0004	0.0011	0.0015	0.0019
CAR 95% CI Upper	0.0000	0.0004	-0.0017	-0.0018	0.0001	0.0002	-0.0002	-0.0006
CAR 95% CI Lower	-0.0011	-0.0028	-0.0062	-0.0075	-0.0013	-0.0040	-0.0061	-0.0080

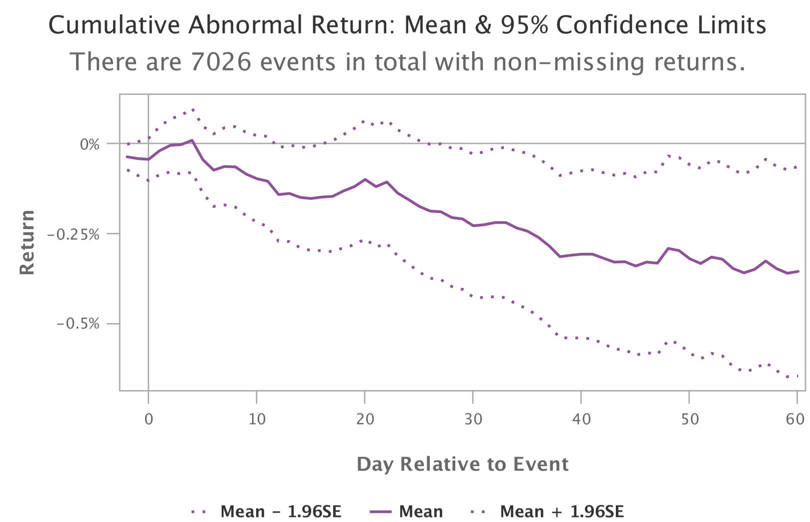
t statistics in parentheses

Patell Z Source: Patell (1976)

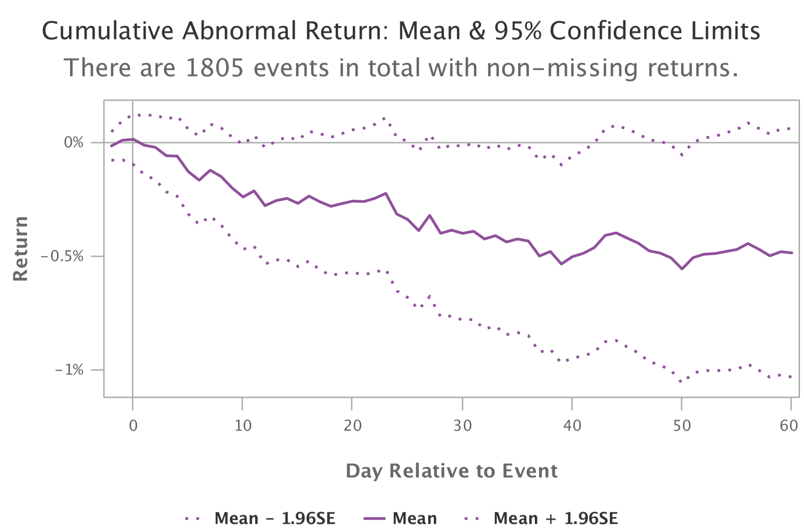
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$



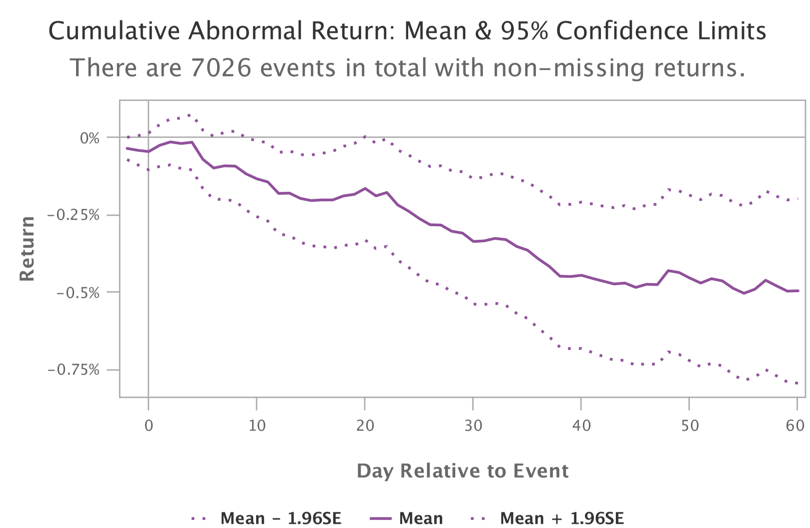
(a) Fama-French Model, High Reference Vulnerabilities



(b) Fama-French Model, Special Company Vulnerabilities



(c) Carhart Model, High Reference Vulnerabilities



(d) Carhart Model, Special Company Vulnerabilities

Figure 10. Sample Since 2002 Event Studies 2

Table X

Abnormal Stock Returns Around Vulnerability Publication in NVD, Sample Since 2002

	High Reference (N = 1,805)				Special Companies (N = 7,026)			
	$R_{-2,0}$	$R_{-2,+20}$	$R_{-2,+40}$	$R_{-2,+60}$	$R_{-2,0}$	$R_{-2,+20}$	$R_{-2,+40}$	$R_{-2,+60}$
Panel A: Sample Since 2002, Fama-French Model								
Mean Ab. Ret.	0.00003	0.00015	0.00032	-0.00001	-0.00002	0.00019	0.00001	0.00003
	(0.09)	(0.41)	(0.86)	(-0.02)	(-0.09)	(1.02)	(0.07)	(0.18)
Patell Z for MAR	0.22	1.09	0.89	0.61	-0.37	0.63	0.01	-0.41
Cum. Avg. Ret.	0.0000	-0.0024	-0.0042*	-0.0039	-0.0005	-0.0010	-0.0031***	-0.0036**
	(0.02)	(-1.47)	(-1.88)	(-1.42)	(-1.61)	(-1.20)	(-2.64)	(-2.41)
CAR Std. Dev.	0.0006	0.0016	0.0022	0.0028	0.0003	0.0008	0.0012	0.0015
CAR 95% CI Upper	0.0011	0.0008	0.0002	0.0015	0.0001	0.0006	-0.0008	-0.0007
CAR 95% CI Lower	-0.0011	-0.0055	-0.0086	-0.0093	-0.0010	-0.0027	-0.0054	-0.0065
Panel B: Sample Since 2002, Carhart Model								
Mean Ab. Ret.	0.00004	0.00011	0.00032	-0.00004	-0.00004	0.00019	0.00002	-0.00002
	(0.12)	(0.29)	(0.85)	(-0.12)	(-0.20)	(1.02)	(0.12)	(-0.09)
Patell Z for MAR	0.25	0.91	0.97	0.44	-0.46	0.60	0.07	-0.62
Cum. Avg. Ret.	0.0001	-0.0026*	-0.0051**	-0.0049*	-0.0005	-0.0017**	-0.0045***	-0.0050***
	(0.20)	(-1.65)	(-2.23)	(-1.74)	(-1.55)	(-1.99)	(-3.73)	(-3.25)
CAR Std. Dev.	0.0006	0.0016	0.0023	0.0028	0.0003	0.0008	0.0012	0.0015
CAR 95% CI Upper	0.0012	0.0005	-0.0006	0.0006	0.0001	0.0000	-0.0021	-0.0020
CAR 95% CI Lower	-0.0010	-0.0057	-0.0095	-0.0104	-0.0011	-0.0033	-0.0068	-0.0080

t statistics in parentheses

Patell Z Source: Patell (1976)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table XI

Portfolio Trading Strategy II

Fama-French and Carhart Regressions, All Vulnerabilities Since 2002

Regressions (1) and (2) are for all companies, regardless of their vulnerability ratio. (3) and (4) are for companies with a vulnerability ratio less than 1 - the long strategy (see subsection V.A). (4) and (5) are for companies with a vulnerability ratio greater than 1 - the short strategy. (5) and (6) are found by taking the returns for the long strategy and subtracting those for the short strategy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	all_rf	all_rf	lt1_rf	lt1_rf	gt1_rf	gt1_rf	l_s	l_s
mktrf	1.063***	1.054***	1.056***	1.053***	1.049***	1.041***	0.00713	0.0118
	(96.82)	(93.95)	(75.75)	(73.79)	(67.44)	(65.43)	(0.37)	(0.60)
smb	0.0739***	0.0809***	0.0875***	0.0900***	0.0808***	0.0869***	0.00672	0.00307
	(3.48)	(3.81)	(3.25)	(3.33)	(2.69)	(2.88)	(0.18)	(0.08)
hml	-0.288***	-0.325***	-0.227***	-0.240***	-0.304***	-0.337***	0.0770**	0.0963**
	(-14.10)	(-14.36)	(-8.75)	(-8.33)	(-10.50)	(-10.46)	(2.16)	(2.43)
umd		-0.0564***		-0.0196		-0.0489**		0.0293
		(-3.77)		(-1.03)		(-2.30)		(1.12)
_cons	0.000210*	0.000216*	0.000360**	0.000361**	-0.000100	-0.0000954	0.000460**	0.000457**
	(1.81)	(1.86)	(2.43)	(2.44)	(-0.61)	(-0.58)	(2.26)	(2.24)
Ann. α	5.43%	5.59%	9.49%	9.52%	-2.49%	-2.38%	12.29%	12.20%
N	3776	3776	3776	3776	3776	3776	3776	3776
R^2	0.735	0.736	0.633	0.633	0.573	0.574	0.002	0.002

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table XII

Portfolio Trading Strategy III

Fama-French and Carhart Regressions, High Reference Vulnerabilities Since 2002

Regressions (1) and (2) are for all companies, regardless of their vulnerability ratio. (3) and (4) are for companies with a vulnerability ratio less than 1 - the long strategy (see subsection V.A). (4) and (5) are for companies with a vulnerability ratio greater than 1 - the short strategy. (5) and (6) are found by taking the returns for the long strategy and subtracting those for the short strategy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	all_rf	all_rf	lt1_rf	lt1_rf	gt1_rf	gt1_rf	l_s	l_s
mktrf	1.045***	1.041***	1.065***	1.061***	1.022***	1.018***	0.0427**	0.0429**
	(84.75)	(82.51)	(71.91)	(70.00)	(62.88)	(61.19)	(2.03)	(1.99)
smb	-0.0288	-0.0258	-0.0144	-0.0113	-0.0550*	-0.0517	0.0406	0.0405
	(-1.21)	(-1.08)	(-0.50)	(-0.39)	(-1.75)	(-1.64)	(1.00)	(0.99)
hml	-0.334***	-0.350***	-0.349***	-0.365***	-0.261***	-0.278***	-0.0881**	-0.0873**
	(-14.56)	(-13.73)	(-12.64)	(-11.92)	(-8.60)	(-8.26)	(-2.25)	(-2.01)
umd		-0.0237		-0.0249		-0.0261		0.00124
		(-1.41)		(-1.23)		(-1.18)		(0.04)
_cons	0.000220*	0.000222*	0.000393**	0.000396**	0.000164	0.000167	0.000229	0.000229
	(1.68)	(1.69)	(2.50)	(2.52)	(0.95)	(0.96)	(1.03)	(1.03)
Ann. α	5.75%	5.75%	10.41%	10.49%	4.22%	4.30%	5.94%	5.94%
N	3776	3776	3776	3776	3776	3776	3776	3776
R^2	0.673	0.674	0.598	0.598	0.534	0.534	0.002	0.002

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table XIII

Portfolio Portfolio Trading Strategy IV

Fama-French and Carhart Regressions, Special Company Vulnerabilities Since 2002

Regressions (1) and (2) are for all companies, regardless of their vulnerability ratio. (3) and (4) are for companies with a vulnerability ratio less than 1 - the long strategy (see subsection V.A). (4) and (5) are for companies with a vulnerability ratio greater than 1 - the short strategy. (5) and (6) are found by taking the returns for the long strategy and subtracting those for the short strategy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	all_rf	all_rf	lt1_rf	lt1_rf	gt1_rf	gt1_rf	l_s	l_s
mktrf	1.065***	1.052***	1.056***	1.049***	1.048***	1.038***	0.00800	0.0113
	(96.89)	(93.88)	(75.07)	(72.90)	(63.09)	(61.09)	(0.40)	(0.56)
smb	0.0812***	0.0909***	0.100***	0.105***	0.112***	0.120***	-0.0118	-0.0143
	(3.82)	(4.28)	(3.68)	(3.87)	(3.48)	(3.72)	(-0.31)	(-0.37)
hml	-0.275***	-0.326***	-0.212***	-0.240***	-0.289***	-0.332***	0.0776**	0.0913**
	(-13.42)	(-14.38)	(-8.08)	(-8.27)	(-9.35)	(-9.66)	(2.09)	(2.22)
umd		-0.0776***		-0.0438**		-0.0645***		0.0208
		(-5.19)		(-2.28)		(-2.85)		(0.76)
_cons	0.0000716	0.0000792	0.000204	0.000208	-0.000215	-0.000208	0.000419**	0.000417**
	(0.61)	(0.68)	(1.37)	(1.39)	(-1.22)	(-1.18)	(1.98)	(1.97)
Ann. α	1.82%	2.02%	5.27%	5.38%	-5.27%	-5.38%	11.13%	11.08%
N	3776	3776	3776	3776	3776	3776	3776	3776
R^2	0.736	0.738	0.631	0.631	0.543	0.544	0.002	0.002

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table XIV

Portfolio Portfolio Trading Strategy V

Fama-French and Carhart Regressions, Special Company Vulnerabilities All Data (Including Before 2002)

Regressions (1) and (2) are for all companies, regardless of their vulnerability ratio. (3) and (4) are for companies with a vulnerability ratio less than 1 - the long strategy (see subsection V.A). (4) and (5) are for companies with a vulnerability ratio greater than 1 - the short strategy. (5) and (6) are found by taking the returns for the long strategy and subtracting those for the short strategy.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	all_rf	all_rf	lt1_rf	lt1_rf	gt1_rf	gt1_rf	l_s	l_s
mktrf	1.044***	1.019***	1.022***	1.011***	1.029***	1.004***	-0.00685	0.00692
	(99.66)	(94.61)	(85.97)	(82.30)	(84.81)	(80.37)	(-0.42)	(0.41)
smb	0.0838***	0.0920***	0.135***	0.138***	0.00219	0.0103	0.132***	0.128***
	(4.18)	(4.61)	(5.91)	(6.07)	(0.09)	(0.44)	(4.24)	(4.10)
hml	-0.283***	-0.347***	-0.196***	-0.224***	-0.256***	-0.319***	0.0593*	0.0947***
	(-14.54)	(-16.86)	(-8.89)	(-9.55)	(-11.34)	(-13.35)	(1.96)	(2.94)
umd		-0.132***		-0.0575***		-0.130***		0.0729***
		(-9.07)		(-3.46)		(-7.71)		(3.20)
_cons	0.000142	0.000190*	0.000215	0.000236*	-0.0000164	0.0000314	0.000232	0.000205
	(1.22)	(1.65)	(1.63)	(1.79)	(-0.12)	(0.23)	(1.28)	(1.13)
Ann. α	3.64%	4.90%	5.57%	6.13%	-0.41%	0.79%	6.02%	5.30%
N	6804	6804	6804	6804	6804	6804	6804	6804
R^2	0.604	0.609	0.529	0.530	0.523	0.527	0.003	0.004

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix B. Sample NVD Entries

Figure 11 shows the Heartbleed vulnerability on the NVD website.

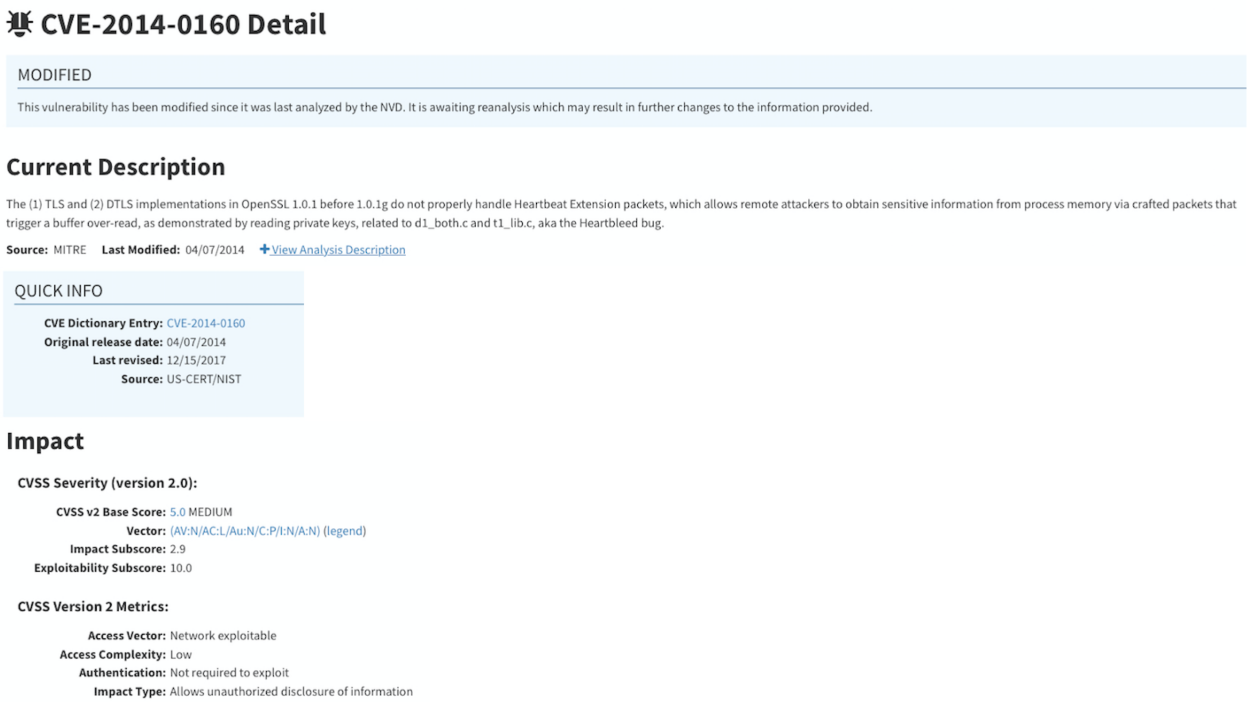


Figure 11. NVD Website Entry

The top entry in Figure 12 is the same as the entry shown on the website in Figure 11. This table shows the format of the dataset that was used for the analysis in this research.

name	date	day	month	year	CVSS_base_score	CVSS_impact_subscore	CVSS_exploit_subscore	access_vector
CVE-2014-0160	4/7/14	7	4	2014	5	2.9	10	3
CVE-2014-0162	4/27/14	27	4	2014	6	6.4	6.8	3
CVE-2014-0164	5/5/14	5	5	2014	2.1	2.9	3.9	1
CVE-2014-0165	4/9/14	9	4	2014	4	2.9	8	3
CVE-2014-0166	4/9/14	9	4	2014	6.4	4.9	10	3
CVE-2014-0167	4/15/14	15	4	2014	6	6.4	6.8	3
CVE-2014-0168	10/6/14	6	10	2014	6.8	6.4	8.6	3
CVE-2014-0170	9/30/14	30	9	2014	4.3	2.9	8.6	3
CVE-2014-0171	1/15/15	15	1	2015	5	2.9	10	3
CVE-2014-0172	4/11/14	11	4	2014	6.8	6.4	8.6	3

name	access_complexity	authentication	confidentiality	integrity	availability	vendor	prods	description
CVE-2014-0160	1	1	2	1	1	openssl	openssl	The (1) TLS a
CVE-2014-0162	2	2	2	2	2	openstack	icehouse ima	The Sheepdo
CVE-2014-0164	1	1	2	1	1	redhat	openshift	openshift-or
CVE-2014-0165	1	2	1	2	1	wordpress	wordpress	WordPress b
CVE-2014-0166	1	1	2	2	1	wordpress	wordpress	The wp_valid
CVE-2014-0167	2	2	2	2	2	openstack	compute ice	The Nova EC
CVE-2014-0168	2	1	2	2	2	jolokia	jolokia	Cross-site re
CVE-2014-0170	2	1	2	1	1	jboss redhat	teiid jboss_d	Teiid before
CVE-2014-0171	1	1	2	1	1	redhat	jboss_data_v	XML externa
CVE-2014-0172	2	1	2	2	2	elfutils_proje	elfutils	Integer overf

Figure 12. NVD Datasheet Entry

The following is a selection from the date table that is described in subsection III.C. Each cell is the number of vulnerabilities that a company had on a given date.

date	Oracle	Microsoft	SGI	Dell EMC	IBM	Palo Alto Net	Apple	CA	HP
3/3/03	3	0	1	0	1	0	2	0	2
3/4/03	0	0	0	0	0	0	0	0	0
3/5/03	0	0	0	0	0	0	0	0	0
3/6/03	0	0	0	0	0	0	0	0	0
3/7/03	0	0	1	0	0	0	3	0	1
3/8/03	0	0	0	0	0	0	0	0	0
3/9/03	0	0	0	0	0	0	0	0	0
3/10/03	0	0	0	0	0	0	0	0	0
3/11/03	0	0	0	0	0	0	0	0	0
3/12/03	0	0	0	0	0	0	0	0	0
3/13/03	0	0	0	0	0	0	0	0	0

Figure 13. Date Data Illustration