Software vulnerability disclosure and security investment

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Abstract

Around the debate on software vulnerability disclosure, existing works have mostly explored how disclosure gives an incentive to software vendors to better secure their software. The role of third parties such as business users, security firms or downstream software vendors is rarely taken account, while in fact these actors are increasingly involved in improving the security of a software. In this paper, we argue that vulnerability disclosure may act as a signal that revises the perceived security quality of the affected software and we examine how it affects the level of security effort exerted by different actors.

Using data from 2009 to 2018 on a public vulnerability database, we show that after the disclosure of a critical vulnerability, the vulnerability research activity on the software that is subject to the disclosure significantly increases compared to the control group of unaffected software. In particular, vulnerability disclosure has a greater impact on actors who perceive the disclosure as an opportunity to find new security flaw and to financially benefit from it (such as the security firms and individual researchers) than on those who suffer the security risks (such as users and downstream vendors).

Keywords: information security economics, software vulnerability disclosure, vulnerability discovery, software security

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1 Introduction

In January 2018, Intel revealed that millions of their computer processors were exposed to a critical vulnerability named Spectre and Meltdown.[1] Instead of going public right after its discovery, Intel had exclusively informed some of its main customers and kept the information confidential for more than half a year.[2] The secrecy kept by Intel can be explained by the increasing security risk it would have been exposed to if the vulnerability information became public before they find a solution to secure the flaw (Schneier, 2000). However, it also prevented other firms and users to timely assess their own risk and to react.

In line with Intel's defense, the public disclosure of a vulnerability can be harmful to a system's security because it increases the probability that the disclosed information is exploited by a malevolent actor. Empirical estimates support this idea, showing how the frequency of attacks increases when the vulnerability is disclosed to public (Arora, Nandkumar, and Telang, 2006). On the other side, many studies, both theoretical and empirical, find that vulnerability disclosure encourages software vendors to deliver patches more quickly and to provide a better software quality over time (Nizovtsev and Thursby, 2007; Cavusoglu, Cavusoglu, and Raghunathan, 2007; Arora, Telang, and Xu, 2008; Arora, Krishnan, Telang, and Yang, 2010). All of these studies consider that the disclosure of a vulnerability allows the attackers to exploit the disclosed information and in turn affects the users and the software vendors' behavior. Besides, a vulnerability disclosure may also impact the stakeholders' behavior without being specifically related to the disclosed vulnerability information. It may act as a signal, to third parties like consumers, investors, or security experts, that the actual security level of the affected software is lower than what it was considered until now. For instance, Telang and Wattal (2007) show that public vulnerability announcements lead to significant loss in the affected software vendor's market value. In our paper, we consider precisely this 'signaling effect' and study whether the disclosure of a specific vulnerability on a software gives an incentive to improve its

[1] `https://meltdownattack.com`

[2] https://www.wsj.com/articles/intel-warned-chinese-companies-of-chip-flaws-before-u-s-government

overall security.

Specifically, we examine empirically how the public disclosure of a critical vulnerability with heavy media coverage affects the discovery of new vulnerabilities in the software that is subject to the disclosure. We study the case of three markets – by market, we mean a group of software that belong to the same type and which present strong substitutability – at the heart of Internet security and which are well-known to standard users and thus generate significant attention from general media as well as from the security community, namely the web browser, the desktop operation system and the mobile operation system markets. For each market, we identify a vulnerability that has received a particularly large media coverage and has generated a peak in web search volumes. Then, using data collected from a well-known public vulnerability database on software vulnerabilities – SecurityFocus BugTraq – reported from January 2009 to December 2018, we examine the impact of the disclosure event on the number of vulnerabilities reported by each type of actors over time. We use a difference-in-difference specification in order to measure the change in the level of security effort exerted on the software affected by the disclosure compared to other unaffected software.

Theoretically, the answer to our question is not straightforward. First, regarding the effect on users, the vulnerability disclosure may reduce the perceived security quality of a software. If users are passive agents that do not contribute to the security level of the software, the disclosure of a vulnerability may just reduce the user demand. However if they can also choose to invest in security, they could be affected by the disclosure in a different way, depending on the available alternatives, the switching costs, and their investment capability in software security. The larger a business is – i.e., the larger and complex its information system is –, the less flexible it would be to switch from one software to another even though it realizes that the software it uses has a poor security quality. Companies who have large switching costs may prefer to actively collaborate with the software vendor and other third parties (security firms, individual security experts, public organizations, etc.) to improve the security of the software rather than waiting for the vendor to provide a better security. Secondly, the disclosure of a critical vulnerability may

also act as an event that revises the belief – i.e., the subjective probability – to find new vulnerabilities. Thus for actors that look for new opportunities to contribute to software security – such as security firms or individual researchers –, vulnerability disclosure may give an incentive to exert more effort in discovering new vulnerabilities. However if the disclosed information is public and shared with everyone, the increased probability to compete with others can also deter them to exert an additional effort. All in all, the overall effect of vulnerability disclosure on the effort exerted by different actors to improve the affected software's security is uncertain.

Our analysis shows strong evidence that after the disclosure of a critical vulnerability, the vulnerability research activity on the software affected by the disclosure significantly increases compared to the control group of unaffected software. Interestingly, third parties, in particular security firms and individual researchers, are more affected by the disclosure than the software vendor itself. The impact on third parties is all the more significant as we find that they contribute more than the software vendor to the discovery of new security flaws in general. Our findings suggest that one should not ignore the incentives and the potential contribution of third parties when studying software security.

The rest of the paper is structured as follows. In the next section, we review the relevant literature. Section 3 presents the identification strategy and the data. We present the estimation results in Section 4 and Section 5 concludes.

2 Related work

Who should invest in security and how to encourage the right actor in the right way is a question at the heart of information security economics. Various topics are handled in this literature, from modeling attack and defense (Varian, 2004; Bier, Oliveros, and Samuelson, 2007; Bohme and Moore, 2010), liability policies (Kim, Chen, and Mukhopadhyay, 2011; August and Tunca, 2011; Lam, 2016), risk sharing and coordination between vendor and users (August and Tunca, 2006; Cavusoglu, Cavusoglu, and Zhang, 2008; Kim, Chen, and Mukhopadhyay, 2009), to product differentiation (August, Niculescu, and Shin, 2014; Dey, Lahiri, and Zhang, 2014). In particular, some papers participate to the debate around

whether promoting software vulnerability disclosure is socially desirable (Cavusoglu et al., 2007; Arora et al., 2008; Choi, Fershtman, and Gandal, 2010; Nizovtsev and Thursby, 2007). Their main finding is that, when vendors do not sufficiently internalize user loses, vulnerability disclosure provides an incentive for vendors to secure their product more quickly.[3]

Our paper tackles two aspects lacking in this literature. First, prior works mostly consider that users are passive agents, which mainly undertake damage control activities (patch installations, work-arounds) rather than actively engaging in preventive actions. However, a considerable part of users, especially business users – i.e., companies that use the software, including downstream and upstream software vendors and service providers – contribute actively and significantly to global cybersecurity. They often manage their own security research and incident response team, pay security firms to secure their systems, collaborate with public CERTs and academic researchers, crowdsource individuals through vulnerability reward programs. In fact, businesses with large scale information systems necessarily have "a lot at stake", hence they have not only the ability but also the incentives to actively find and fix software vulnerabilities. In our paper, users actively invest in software security by discovering and reporting vulnerabilities to the software vendor.

To our knowledge, only one paper considers the active involvement of users in security (Nizovtsev and Thursby, 2007). They consider the case of open source software where users can actively participate in finding and fixing vulnerabilities and show that the positive effect of vulnerability disclosure becomes greater when users are able to fix the software by themselves. Our paper is in line with the idea of Nizovtsev and Thursby (2007) that parties other than the software vendor may actively contribute in software security and we examine it empirically in markets that are not exclusively open source.

Secondly, a dearth of research exists on the role of third parties, while in practice, they are often actively involved in the lifecycle of a software and in improving security. Indeed, a company's information system is formed by multiple software; these software use various frameworks and libraries created and maintained by external organizations, they

[3]Besides, Choi et al. (2010) take also account the probability of an attack in relation with network effects and show that mandatory disclosure is not necessarily welfare improving.

use components, modules and extensions provided by other editors, they communicate with each other and with the outside network through various protocols whose guidelines are maintained by public entities. Thus, the security of a company's system depends on a multitude of actors that in turn are dependent each other. In fact, this complexity already exists for the security of a single software. For example, any organization that has some networked data accessible on the Web (e.g., e-commerce companies, website hosting service providers) is necessarily dependent to the security of web browsers, since a web browser is the main tool used to access to the World Wide Web. The security of a web browser is in turn dependent to a multitude of components, from language like Javascript, runtime environment like Adobe Flash, communication protocol and cryptography library like OpenSSL, plug-ins and web applications, etc. Since developers and users of each components internalize a part of the security risk, each of them may have an incentive to improve web browsers' security. This paper tries to fill the gap in the literature by analyzing not only the behavior of the software vendors but also of other third parties that actively contribute to software security, like downstream and upstream software vendors, security firms and individual researchers, public organizations and competitors.

Several empirical studies examine the impact of vulnerability disclosure on security related activities such as on the attack frequencies (Arora et al., 2006), on software vendors' market value (Telang and Wattal, 2007), and on software vendors' patch release behavior (Arora et al., 2010). We are also interested in whether a vulnerability disclosure gives an incentive to improve the security of the affected software. However our approach differs from them at least in two ways. First, we consider the disclosure of a vulnerability as a signal that updates the perceived security quality of the affected software rather than considering the effect that is directly related to the disclosed information. Secondly, we are interested in the impact of vulnerability disclosure on an activity – vulnerability discovery – that is specifically related to security spending. This is in line with the idea that the expected cost to breach a system, i.e., finding a vulnerability that was unknown before, can be a reasonable measure of the strength of a system (Schechter, 2002). Further, some argues that the market price to find an additional vulnerability may be a practical measure

of the security level of a system (Camp and Wolfram, 2000; Schechter, 2002; Ozment, 2004).

Our work is also related to the recent economic literature on open innovation. A large number of researches document how users have been contributing efficiently to improve products and processes. Besides, open innovation is not only limited to the involvement of user communities; it encompasses all the "inflows and outflows of knowledge" that contribute to innovation (Chesbrough, Vanhaverbeke, and West, 2006). That is, it is most of all about an ecosystem of partners with whom to collaborate. In that sens, this stream of research is in tight relation with the industry platform literature, which focus on strategies that platforms employ to influence and stimulate collaboration on complementary products and services from third parties (Gawer and Cusumano, 2014). One of the main goal of these streams of research is to examine the means and conditions that induce a more efficient participation from external resources. In our paper, we also study how a particular event affects third parties' incentives to exert an additional effort.

Furthermore, many researches insist on the fact that the notion of collaboration within the context of open source project and in business context is different (Boudreau and Lakhani, 2009; Pénin, Hussler, and Burger-Helmchen, 2011). In contrast with this observation, we study cases in which there is a mix between the contribution of user communities and a market mechanism. Indeed, by third parties, we designate both private actors that benefit from the market for software vulnerabilities as well as public actors and user communities. Moreover, the delimitation between private business purposes and the security community's goal is blurred. For instance, private actors like security firms are part of the security community and are even major actors that actively contributes to it. All in all, the effort exerted by an actor to improve software security can be either motivated by direct benefits from improving the security of the software because it is dependent to it, because of some intrinsic motivation to contribute to global security, or because of monetary incentives and other extrinsic motivation (reputation feedback, reciprocity).

3 Data and empirical Strategy

Our goal is to examine how a critical vulnerability disclosure on a software affects the effort exerted by various actors to improve its security. For that, we consider the effort exerted by an actor to discover new security flaws as a measure of its effort to improve the overall security of the software.[4] We study three markets, which attract significant media attention from end users and thus for which we are able to identify a vulnerability disclosure that raised a particular media coverage compared to others: the web browser, the mobile OS and the desktop OS markets.

In order to study the causal relationship between a vulnerability disclosure and the effort of each actor that contributes actively to the security of the software, we use a difference-in-difference specification. That is, we compare the difference in the number of vulnerabilities reported by each actor, before and after the extensive media coverage of a security flaw on the targeted software (the treatment group) and other software (the control group).

The main data set we use comes from Security Focus Bugtraq, which is a public database on software vulnerabilities. From this database, we collected information about all the vulnerabilities that affect any web browsers and operation systems and published from January 2009 to December 2018.[5] The raw data set provides the disclosure date of the vulnerability, which software it affects and who discovered it. We categorize the discoverers of the vulnerabilities into 6 types of actors: the software vendor, users (including companies that use the software or provide a service related to the affected vulnerability, as well as downstream and upstream vendors), security firms, individual researchers who do not precise their affiliation to a company or an organization, academics and public organizations, and the competitors of the affected software. The dependent variables for each specifications are built by consolidating this raw data set in several ways (see

[4]The idea that the cost-to-break, i.e., the cost to find new vulnerabilities is an effective metric to measure the security level of a software has been defended by a number of researchers (Camp and Wolfram, 2000; Schechter, 2002; Ozment, 2004).

[5]The reason we limit our study to this period is because a considerable amount of manual checks is needed to build our data set, especially in order to categorize the actors that have identified each vulnerabilities. We consider that a period of 10 years is large enough to have a robust result.

Subsection 3.3). The treatment is identified using Google Trends data. More precisely, we identify a particular vulnerability disclosure that has generated a spike in media coverage compared to all other vulnerability disclosures in a market (i.e., in web browsers, mobile OS or desktop OS).[6] We then examine how this shock affects the number of vulnerabilities that are discovered for each software belonging to the market.

We detail the econometric specification in the next subsection, then Subsection 3.2 presents the raw data set. Subsection 3.3 describes how we build our dependent variable for the three different specifications we use, then follows Subsection 3.4 where we discuss the identification of our treatment variable. Lastly, we verify the parallel trend assumption and detail the descriptive statistics in Subsection 3.5.

3.1 Empirical specifications

We use a difference-in-difference specification to study how a vulnerability disclosure affects the effort made by an actor to secure the software. This identification strategy allows us in particular to overcome the reverse causality issue between the number of vulnerabilities and the media coverage intensity that we would have had if we simply used the intensity of a vulnerability media coverage as our regressor.

Specifically, the baseline specification we use is as following:

$$y_{it} = \beta_0 + \beta_1 A_i \cdot P_t + FE_i + FE_t + \gamma X_{it} + \epsilon_{it}, \tag{1}$$

Where, y_{it}, our dependent variable, is the total number of vulnerabilities affecting software i, reported at period t (monthly date). In this first specification, the effort of the different actors are taken altogether and we first focus on how the disclosure affects the global security investment level. A_i (referring to "Affected software") is a dummy which indicates whether software i is the software targeted by the vulnerability disclosure, i.e., whether it belongs to the treatment group ($A_i = 1$) or to the control group ($A_i = 0$).[7]

[6] For the web browser market, the data set is composed of vulnerabilities that affect only web browsers, and for operation system market only vulnerabilities that affect operation systems.

[7] In our data set, the treatment group is the software that suffers from the disclosure and all other software in the same market – unaffected by the disclosed vulnerability – belongs to the control group.

P_t (referring to "treatment Period") is a dummy which is equal to one for the period we consider as "affected" by the critical vulnerability disclosure event, and to zero outside this period. We use 4 alternative specifications for this treatment period: the first 6 months following the vulnerability disclosure ($post6m$), the first year ($post12m$), the two first years ($post24m$), and the whole period after the vulnerability disclosure ($post$).[8] FE_i and FE_t are software and time fixed effects.[9] X_{it} is a vector of control variables at the software level. It includes the $SoftwareAge$ and a dummy which indicates whether the vendor provides support for the software at period t ($EndofLife$). Lastly, ϵ_{it} is the error term. Our explanatory variable of interest is the interaction term $A_i \cdot P_t$, which represents the difference in the effect of the vulnerability disclosure – our treatment – between the treatment group and the control group. We expect that the sign of the coefficient β_1 is positive, i.e., a critical vulnerability disclosure would increase the global effort made in securing the software that suffers from the vulnerability disclosure.

Next, we estimate the following equation:

$$\begin{aligned} y_{ijt} =& \beta_0 + \beta_1 A_i \cdot P_t + \beta_2 A_i \cdot P_t \cdot ThirdParty_j + \beta_3 A_i \cdot ThirdParty_j \\ &+ \beta_4 P_t \cdot ThirdParty_j + \beta_5 ThirdParty_j + FE_i + FE_t + \gamma X_{it} + \epsilon_{ijt}, \end{aligned} \tag{2}$$

where y_{ijt} is the number of vulnerabilities affecting software i, discovered by type of actors j at period t. $ThirdParty_j$ is a dummy which is equal to 0 if the identifier of the vulnerabilities is the software vendor and equal to 1 if it is a third party. The interaction between our treatment variable $A_i \cdot P_t$ and the $ThirdParty_j$ dummy allows us to measure the difference between the impact of the vulnerability disclosure on a third party and on a software vendor (the software vendor being the base value).

Lastly, we use the following specification to study the effect of the vulnerability

[8] We consider that periods of more than 6 months are appropriate because the discovery of new vulnerabilities on a software (which differs for instance to discovering a simple bug on a functionality) does not happens more frequently.

[9] Thus the effect of A_i and P_t are included in the fixed effects

disclosure on each actor separately:

$$\begin{aligned} y_{ijt} =& \beta_0 + \beta_1 A_i \cdot P_t \\ &+ \sum_{K_j \in Identifier\_Type} \beta_2^{K_j} A_i \cdot P_t \cdot K_j + \beta_3^{K_j} A_i \cdot K_j + \beta_4^{K_j} P_t \cdot K_j + \beta_5^{K_j} K_j \\ &+ FE_i + FE_t + \gamma X_{it} + \epsilon_{ijt}, \end{aligned} \tag{3}$$

where $Identifier\_Type = \{Users_j, Sec\_firms_j, Individuals_j, Public\_org_j, Competitors_j\}$ and $K_j \in Identifier\_Type$ is a dummy equal to one if j belongs to the identifier type K. In this specification, the coefficients of interest are the five different $\beta_2^{K_j}$, which reflect the difference in the effect of a vulnerability disclosure on each actors' behavior, while the base value is the software vendor's behavior.

3.2 Raw data set

The raw data set consists in all the vulnerabilities reported from January 2009 to December 2018, associated to one or multiple web browsers or operation systems. The data is collected from Security Focus Bugtraq, which is a well-known public database on vulnerabilities. We use this database because it is the unique public database that provides information about who discovered – i.e., who first reported – a given vulnerability. An example of the raw information on Security Focus Bugtraq is presented in Figure 9 in Appendix.

All the vulnerabilities in our data set have a patch at the date they are disclosed to public.[10] For vulnerabilities that affect more than one product, we have duplicated the observations in order to take the vulnerability into account for each software. Table 1 presents the number of observations we have in the raw data set for each market we consider. Software that do not present sufficient number of disclosed vulnerabilities during the observed period of time, i.e., that have less than one vulnerability discovered each month, are ignored. For instance, mobile OS such as RIM Blackberry, Nokia mobile or Windows mobile are not considered in our data set.[11]

[10] We exclude from our data set vulnerabilities that cannot be fixed with a patch. Within the scope we study, only 2 vulnerabilities belong to this case.

[11] This is why for mobile OS, only Apple iOS and Google Android are considered. Besides, in our regressions, we consider the operation systems as a whole and not the mobile OS separately.

Table 1: Number of observations in the raw data set

Type of software	Total number of vulnerabilities	Number of considered software	List of considered software
Web browser	2 651	6	Apple Safari, Google Chrome, Microsoft Internet Explorer or Edge, Mozilla Firefox, Mozilla Seamonkey, and Opera.
OS	12 539	16	
of which:			
Desktop OS	8 864		Apple MacOS, Debian Linux, Microsoft Windows, Oracle Linux, Red Hat Linux, SUSE Linux, Ubuntu Linux
Mobile OS	1 143		Apple iOS, Google Android
Other Unix like OS	1 625		FreeBSD, GNU, Oracle Solaris
Server OS	297		CentOS
Router/Switch OS	610		Cisco IOS, Juniper Junos

Figure 8 (in Appendix) shows the evolution of the total number of vulnerabilities affecting web browsers and operation systems during the studied period. We observe that there is a slight increase in the number of vulnerabilities over time. Note that our specifications include a time fixed effect.

3.3 Dependent variable

Our dependent variable for the first specification (see Subsection 3.1 for the econometric specifications) is the total number of vulnerabilities discovered in each software, each month, while for the second and third specifications, it is the number of vulnerabilities discovered in each software each month by each type of actor.

In the raw data set, the discovery of each vulnerability is credited either to an individual, an organization, or a group of individuals and organizations. For each vulnerability, we code the type of actor the discoverers belong to.[12] When a vulnerability is credited to more than one contributor, we replicate the observation as many times as the number of contributors and we attribute to each observation a weight of one over the number of contributors. Then the raw data at vulnerability level is aggregated at a monthly

[12]As mentioned before, we categorize the vulnerability discoverers into 6 types of actors. Table 6.1 in Appendix describes how each actor may value the externality caused by the security of a software and thus would be affected by the disclosure of a critical vulnerability.

level in 3 different manners so as to be used in the 3 different specifications presented in Subsection 3.1. For the first data set, we count the number of vulnerabilities affecting each software each month without considering who are the actors that have contributed. In the second data set, we define a dummy variable which indicates whether the identifier of the vulnerability is the software vendor or a third party ($ThirdParty$ dummy). Then we count the number of vulnerabilities in each software each month either by a third party or the software vendor. In the third data set, we count the number of vulnerabilities in each software, each month for each type of actor. An example of how we have built our dependent variable is given in Table 6 in Appendix.

3.4 Treatment variables

Our goal is to measure the impact of a vulnerability disclosure on vulnerability discovery activity. In the three markets we study, an average of 5 to 14 vulnerabilities are reported each month for each software, all severity level taken together (see Table 7 for summary statistics). Measuring the effect of all of these vulnerability disclosures separately is not possible; we thus focus on the effect of a disclosure that is sufficiently serious and critical to have a significant impact compared to other events. For that, we need to identify a vulnerability that has raised particularly large media attention compared to other vulnerabilities. By considering a vulnerability that has been particularly critical and highly publicized compared to others, we claim that the effects that we identify are due to this disclosure rather than to other events.

In order to identify a vulnerability disclosure that has received a particularly intense media coverage, we use Google Trend (`http://trends.google.fr`), which allows us to visualize the relative evolution of a given search term on Google Search compared to other search terms. We consider that the overall information seeking behavior on a search engine is correlated to the magnitude of the media coverage. Specifically, we checked the search trend on Google for the terms that associate the name of a software and the word "vulnerability". For example, in the case of web browsers, we compare the search trends for the terms "Internet Explorer vulnerability", "Chrome vulnerability", "Safari vulnerability",

"Firefox vulnerability" and "Opera vulnerability" (see Figure 5 in Appendix). Then, for each of the three markets we study, we identify a peak search volume from the graphs obtained from Google Trend, which actually corresponds to the disclosure of a critical vulnerability. For instance, in Figure 5, we observe a peak search volume in mid 2014 for the search term "Internet Explorer vulnerability". This peak corresponds to a critical vulnerability affecting Internet Explorer, disclosed to public in April 26th 2014. This vulnerability was discovered by an independent security firm FireEye who reported it to Microsoft. It is a zero day vulnerability, that is, a vulnerability that is all the more critical because it did not have a security patch at the time it was disclosed. For the second case, the mobile operation systems, the identified critical vulnerability disclosure event corresponds to the disclosure of Android StageFright vulnerability in July 2015. As for the Zero Day in Internet Explorer, this critical and well-known vulnerability was also discovered by an independent security firm. Lastly, for desktop operation systems, the peak search volumes corresponds to the famous WannaCry ransomware attack happened in May 2017. It was the NSA that previously warned Microsoft about the possible theft of EternalBlue, which is the exploit used in WannaCry. Each of these events can be considered as unexpected, except by the software vendor. More details about the three vulnerability disclosure are presented in Figure 9 in Appendix.

These three vulnerability disclosures are our treatments in each market. We consider the software that is targeted by the vulnerability disclosure as the treatment group while other software in the same market belongs to the control group. With regard to the treatment period, we consider that a "treatment" begins at the date of the peak search volumes. Four alternative treatment periods are used, corresponding to a 6 months to 2 year-period after the disclosure.[13]

Besides, in the three cases we study, the software vendor who is targeted by the critical vulnerability disclosure is alerted about the existence of the vulnerability before the public announcement. This means that an increase in the number of vulnerabilities reported on Security Focus at the moment (just before or just after) the vulnerability is disclosed can be

[13]Specifically, we consider the first 6 months after the disclosure, the first year, the first two years, and the whole period after the disclosure as the alternative treatment periods.

due to an action that does not reflect the actual effort put in vulnerability discovery activity. Indeed, the software editor can suddenly become responsive in patching vulnerabilities that were actually reported by third party identifiers before the critical disclosure happens. To overcome this bias, we exclude all the vulnerabilities that are disclosed during a six months period around the disclosure date. Indeed, most organizations apply these days a disclosure policy of 90 days.[14] Excluding the last three months preceding the disclosure and the first three months following it insures that we do not take into account the flaws that would have been reported to the vendor before the discovery of the critical vulnerability and which would have been fixed by the software editor in response to the disclosure.

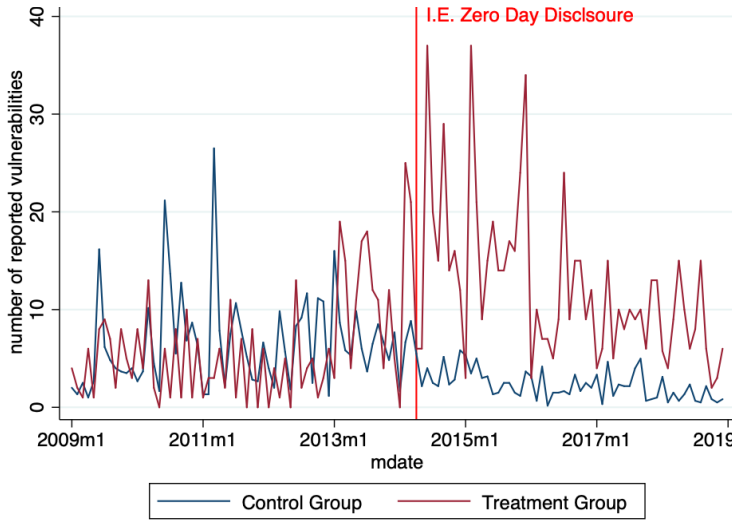
3.5 Descriptive statistics

In this subsection, we provide some descriptive statistics related to the dependent variable and the impact of the treatment. Then we discuss the distribution of the different actors' contribution in our data set.

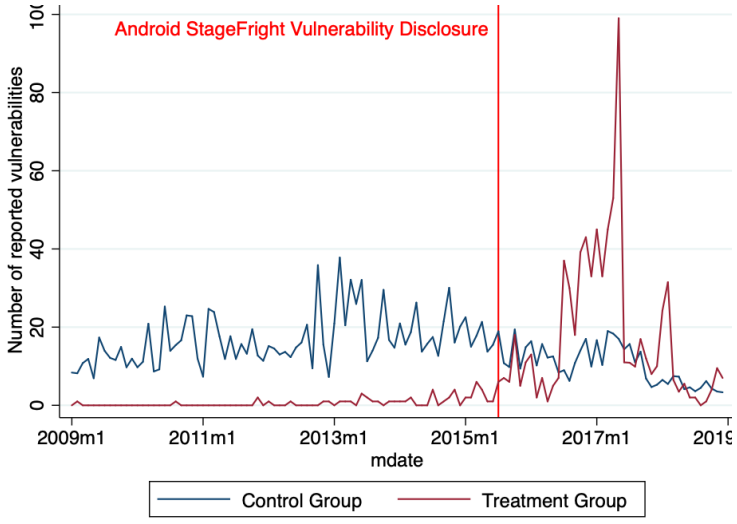
In Figures 1a, 1b, and 1c we first plot the average number of reported vulnerabilities over time, for the treatment group and the control group. In each case, we do not observe any remarkable difference in the evolution of the number of vulnerabilities between the treatment and the control groups, before the critical vulnerability disclosure occurs. Then, for each cases, we visualize a significant increase in the number of vulnerabilities on the treatment group after the year the public announcement of a critical vulnerability occurs. We note that for Figure 1a and Figure 1c, the number of vulnerabilities drastically increases just after the disclosure, while it is less the case for Google Android. There are two possible explanations for this immediate reaction. First, as mentioned in subsection 3.4, the sudden increase in the number of vulnerabilities could reflect the software vendor's behavior that suddenly publishes patches for security flaws that were discovered before, to lessen the negative impact of the announcement of a critical vulnerability. We deal with this potential source of bias by excluding a 6-month period before and after the disclosure date. Secondly, firms that actively participate in finding vulnerabilities and securing the

[14] In the case of web browsers, Jo (2017) estimates the average patching time by a software vendor at 88 days.

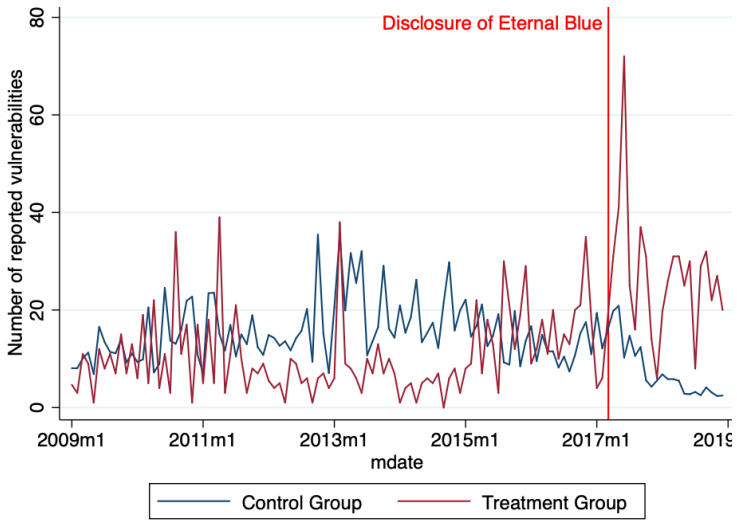
Figure 1: Dependent variable for Specification 1



(a) Internet Explorer Zero Day case



(b) Android StageFright case



(c) Windows WannaCry and EternalBlue case

software could be alerted in advance about the existence of the flaw before its public disclosure (like the case of Intel we mention in our introduction), which then would not distort our result.

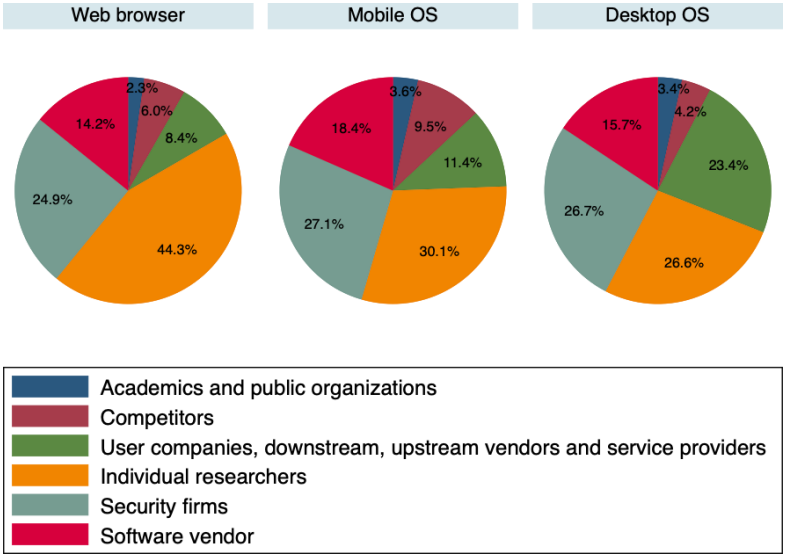


Figure 2: Distribution of vulnerability identifiers

Figure 2 shows the distribution of vulnerability identifiers in the markets we study and Figure 10 (in Appendix) shows the evolution of the distribution over time. We observe that in each market, less than 20 % of the total vulnerabilities are found by the software vendor itself. That is, third parties contribute 4 times more than the software vendor in discovering new vulnerabilities. In particular, individuals without a precise affiliation contribute the most in general. Interestingly, their contribution is more significant in the web browser market. Note that the contribution of individual researchers is much more considerable in open source software than in closed or mixed source ones. Our data set allows us to check this trend but we do not use this information in our estimations as we have a panel data set and we account for software fixed effects. We also observe that security firm also contributes more than software vendors in general. As to business users' contribution, we note that their contribution vary from 8.4% to 23.4% depending on the market. We also observe that the overall contribution of individual researchers decreases over time, while security firms and the software vendor's contribution increase.

4 Results

Table 2 reports the estimation results for our baseline specification (equation 1), for the three cases we study. In each column, we report the results for each alternative treatment periods, from the first 6 months after the vulnerability disclosure ($post6m$) to the whole period after the disclosure ($post$).

Table 2: Effect of a critical vulnerability disclosure on the number of discovered vulnerabilities.

treatment period is:	(1) $post6m$	(2) $post12m$	(3) $post24m$	(4) $post$
	Case of Internet Explorer Zero Day vulnerability disclosure			
$A \cdot P$	0.808*	0.712**	1.057***	1.775***
	(0.481)	(0.357)	(0.273)	(0.220)
Observations	819	819	819	819
Number of software				
Wald χ^2	432.85	433.99	445.66	490.81
AME of $A \cdot P$	4.179*	3.673**	5.372***	8.752***
	(2.510)	(1.867)	(1.449)	(1.271)
	Case of Android Stagefright vulnerability disclosure			
$A \cdot P$	0.747	0.611*	2.194***	3.332***
	(0.493)	(0.369)	(0.270)	(0.265)
Observations	1,872	1,872	1,872	1,872
Number of software				
Wald χ^2	646.61	646.95	720.50	814.01
AME of $A \cdot P$	4.123	3.369*	12.00***	18.23***
	(2.729)	(2.045)	(1.601)	(1.653)
	Case of Windows Eternal Blue vulnerability disclosure			
$A \cdot P$	0.686	0.648*	1.320***	
	(0.476)	(0.348)	(0.283)	
Observations	1,856	1,856	1,856	
Number of software				
Wald χ^2	626.02	627.50	648.96	
AME of $A \cdot P$	3.676	3.464*	7.066***	
	(2.574)	(1.881)	(1.603)	

Note: Negative binomial regressions. Dependent variable is number of reported vulnerabilities. Product fixed effects and time fixed effects are included in all specifications as well as other controls ($SoftwareAge$, $EndofLife$) and a constant. For Eternal Blue case, $post24m = post$. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

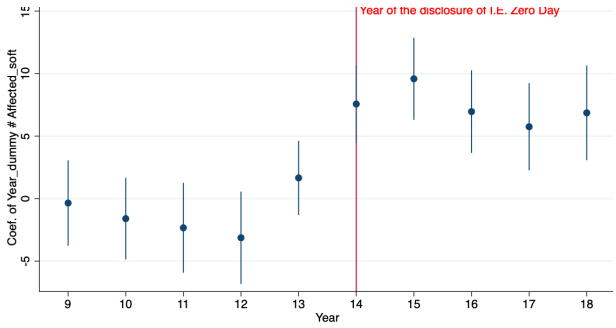
We have count data and given the presence of significant over-dispersion of the dependent variable with standard deviation superior to the mean (see Summary Statistics in Appendix Table 7), we use a negative binomial regression to estimate the equations. To facilitate the exposition, we only report the main regressors of interest, although

all the regressions include the product and time fixed effects as well as other controls ($SoftwareAge$, $EndofLife$) and a constant. For the Eternal Blue case, the last column (4) is empty as our data is limited to the period before 2019 (thus $post24m = post$).

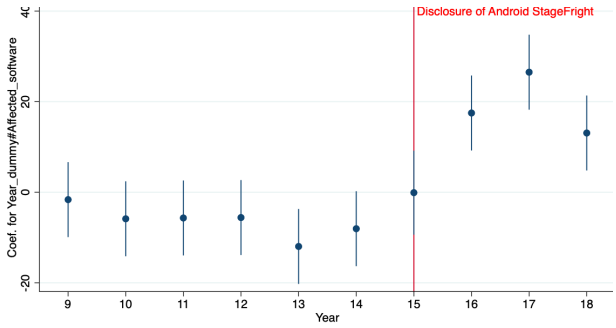
As expected, all the coefficients for $A \cdot P$ are positive for each of the three markets we study. That is, after the disclosure of a critical vulnerability, the total number of vulnerabilities discovered on the software concerned by the disclosure increases. Specifically, 5 more vulnerabilities are discovered in Microsoft Internet Explorer each month during the two years after the disclosure of a critical Zero Day on it compared to the unaffected web browsers. In the same way, the disclosure of Android Stagefright vulnerability disclosure has increased the number of vulnerabilities discovered in Google Android by 12 additional vulnerabilities each month during the first two years following the disclosure, while the number of vulnerabilities found in Microsoft Windows has increased by 7 more vulnerabilities each month after the disclosure of Eternal Blue. We also observe that the effect of the disclosure becomes more significant when we consider a longer period as the treatment period, and that the magnitude of the effect also increases with a longer treatment period. This suggests that the vulnerability disclosure does not have an immediate effect on the behavior of the vulnerability discoverers but rather a gradual effect over time. Two explanations can be advanced. First, discovering new security flaws in a software is not a trivial task; it is not because one puts an effort in vulnerability research that it would systematically find some relevant information to improve software security. Secondly, we count the number of vulnerabilities found in a given period using the date each vulnerability was disclosed. The actual discovery of the vulnerability might have occurred before the date we consider in our estimations, which means that our result may show a lagged effect. Nevertheless, this imprecision does not alter the main result we are interested in.

Additionally, Figure 3a to 3c display the coefficients of the interaction term between the year dummies and the A_i (Affected Software) dummy which identifies whether the observation belongs to the treatment or the control group, with 95% confidence intervals. The plotted estimation includes all the control variables and fixed effects included in

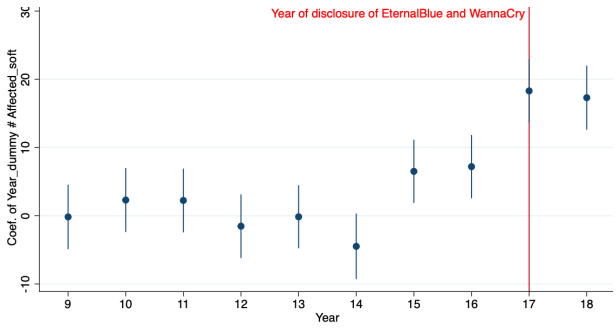
Figure 3: Difference between treatment and control group's outcome, all actors confounded.



(a) Internet Explorer Zero Day case



(b) Android StageFright case



(c) WannaCry and Eternalblue case

Specification 1. Each graph shows that the difference between the treatment and the control groups is not varying significantly over time during the non-treated period. This visual inspection allows us to check the validity of the parallel trend assumption and to visualise the timing of the effect.

Next, Table 3 reports the estimation results using our second specification (equation 2), in which we examine the effort exerted either by the software vendor and other third parties separately. Going from column (1) to (3), we consider a longer period as the treated period. Again, we only report the main regressors of interest in order to facilitate the exposition, although all the regressions include the other interaction terms we specified

Table 3: Effect of a highly publicized vulnerability disclosure on the software vendor vs. third party identifiers' behavior

treatment period is:	(1) $post12m$	(2) $post24m$	(3) $post$
	Case of Internet Explorer Zero-day vulnerability disclosure		
$A \cdot P$	-0.556	-1.051**	-0.619*
	(0.746)	(0.468)	(0.333)
$A \cdot P \cdot ThirdParty$	1.500	1.870***	1.339***
	(0.912)	(0.584)	(0.412)
$ThirdParty$	1.971***	2.034***	2.137***
	(0.0970)	(0.100)	(0.106)
Observations	1,734	1,734	1,734
Wald χ^2	992.48	998.28	1027.34
	Case of Android Stagefright vulnerability disclosure		
$A \cdot P$	0.424	0.627	1.499***
	(0.661)	(0.488)	(0.369)
$A \cdot P \cdot ThirdParty$	-0.0146	0.487	1.124**
	(0.910)	(0.658)	(0.496)
$ThirdParty$	2.297***	2.309***	2.365***
	(0.0641)	(0.0656)	(0.0679)
Observations	3,744	3,744	3,744
Wald χ^2	2028.30	2036.17	2119.79
	Case of Windows Eternal Blue vulnerability disclosure		
$A \cdot P$	0.675	0.121	0.549
	(0.629)	(0.463)	(0.378)
$A \cdot P \cdot ThirdParty$	0.284	1.030	1.351***
	(0.865)	(0.636)	(0.514)
$ThirdParty$	2.304***	2.376***	2.465***
	(0.0648)	(0.0662)	(0.0677)
Observations	3,712	3,712	3,712
Wald χ^2	2016.87	2038.32	2093.08

Note: Dependent variable is the number of reported vulnerabilities. Negative binomial regressions. $A \cdot ThirdParty$, $P \cdot ThidParty$, Product fixed effects and time fixed effects are included in all specifications as well as other controls ($SoftwareAge$, $EndofLife$). For Eternal Blue case, $post24m = post$. Coefficients are average marginal effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

in Specification 2 (the terms $A \cdot ThirdParty$, $P \cdot ThirdParty$), as well as product and time fixed effects, other controls ($SoftwareAge$, $EndofLife$) and a constant.

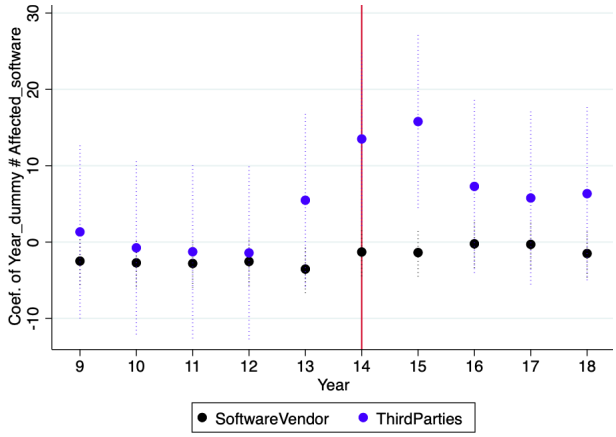
First, all the coefficients for $ThirdParty$ are positive and significant for the three cases we study, meaning that in general, third parties contribute more in finding new security flaws than the software vendor. The positive sign of the coefficient is as expected, as the distribution of each actors' contribution (see Subsection 6.1) already shows that in general less than 25 % of the vulnerabilities are found by the software vendor itself. Regarding the interaction term between $ThirdParty$ and the treatment variable $A \cdot P$, the coefficient is not systematically significant, but it is always positive. That is, overall, the behavior of third parties is more affected by the critical vulnerability disclosure than the software vendor, but the effect is not always significant. Indeed, the effect of the vulnerability disclosure on a given type of actor could be different from another, but as we encompass all the different actors in one category – the "$ThirdParty$" –, the significant positive effect on some type of actors could be mitigated by a less significant or negative effect on others.

In Figure 4a to 4c, we plot again the yearly evolution of the difference in the number of vulnerabilities between the treatment and control group, but we separate the effort of the software vendor (in black dots) from the third parties' effort (in blue dots). The graphs clearly show that in each of the three cases, third parties' contribution increases significantly after the critical vulnerability disclosure occurs, while the change is less significant for the software vendor's contribution.

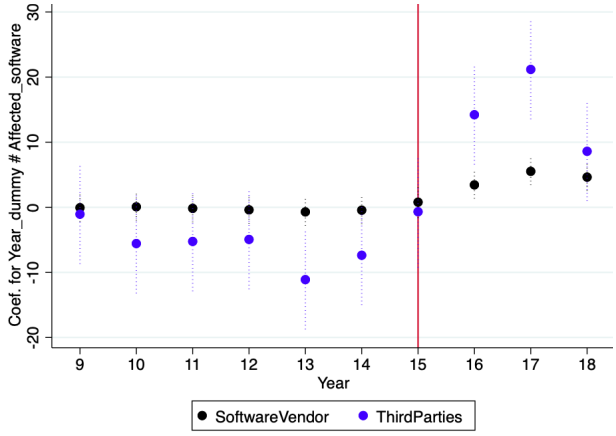
Lastly, Table 4 reports the effect of a critical vulnerability disclosure on each actors' behavior. To facilitate the exposition, we report the results using only one specification for the treatment period ($post24m$). Moreover, we only report the coefficients for our main explanatory variables, namely the treatment variable, the interaction between the treatment variable and the $Identifier\_type$ dummies, and the $Identifier\_type$ dummies. The estimation results using other specifications are reported in Table 8 in Appendix.

With regard to the $Identifier\_type$ dummies, the base line value is the $Software\_vendor$. Estimation results show that actors that contribute the most are the individuals, while academics and public organizations contribute the less. Software vendors contribute less

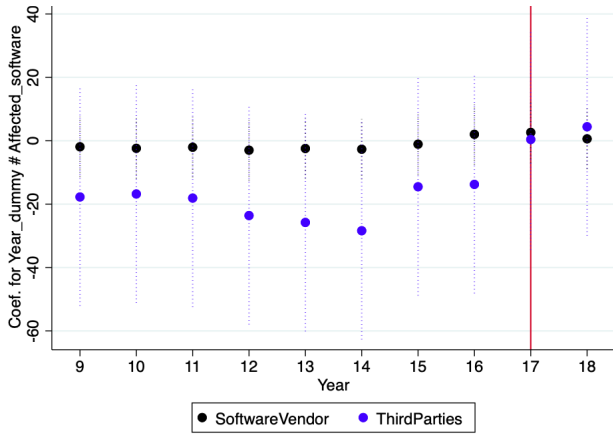
Figure 4: Difference between treatment and control group's outcome, comparison of the software vendor's contribution and third parties' contribution.



(a) Internet Explorer Zero Day case



(b) Android StageFright case



(c) WannaCry and Eternalblue case

Table 4: Effect of a highly publicized vulnerability disclosure on each actors ($post24m$ as the treatment period).

	(1) Web browser case	(2) Mobile OS case	(3) Desktop OS case
$A \cdot P$	-0.475	1.321***	0.515
	(0.350)	(0.364)	(0.371)
$A \cdot P \cdot Public\_org$	0.455	1.042	2.232***
	(0.960)	(0.775)	(0.663)
$A \cdot P \cdot Competitors$	0.916*	-1.789	-15.74
	(0.556)	(28,494)	(2,417)
$A \cdot P \cdot Users$	0.264	1.179**	1.665***
	(0.664)	(0.549)	(0.522)
$A \cdot P \cdot Individuals$	0.826*	1.126**	1.017*
	(0.472)	(0.512)	(0.524)
$A \cdot P \cdot Sec\_firms$	1.805***	0.969*	0.956*
	(0.492)	(0.512)	(0.516)
$Public\_org$	-1.256***	-1.644***	-1.603***
	(0.160)	(0.0829)	(0.0814)
$Competitors$	-0.0505	-0.991***	-0.831***
	(0.127)	(0.0751)	(0.0724)
$Users$	-1.300***	0.518***	0.655***
	(0.163)	(0.0665)	(0.0646)
$Individuals$	1.815***	1.552***	1.635***
	(0.114)	(0.0651)	(0.0632)
Sec_firms	-0.0633	-0.276***	-0.244***
	(0.129)	(0.0695)	(0.0678)
Observations	5,202	11,232	11,136

Note: Dependent variable is the number of reported vulnerabilities. Negative binomial regressions. A, P, $A \cdot K$ and $P \cdot K$ with $K \in Identifier\_type$, product fixed effects and time fixed effects, $SoftwareAge$, $EndofLife$ and a constant are included in all the regressions, but are not reported (see Appendix for more detailed results). $P = post24m$. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

than individual researchers and users but they contribute more than their competitors or the security firms. Note that the coefficient for $Users$ dummy is negative for the web browser case, meaning that contrary to the case of operation systems, the contribution of the users is lower than the software vendor's. This could be explained by the fact that there might be a greater number of companies contributing actively to IT security and which considers that operation systems' security is more important than the security of web browsers. As to the interaction terms between the treatment variable $A \cdot P$ and the identifier's dummy, we observe that most of the coefficients are positive except for the term $A \cdot P \cdot Competitors$. That is, our estimation results suggest that third parties are more sensible to vulnerability disclosure than the software vendor, except the competing software

vendors. Overall, users are the most affected by the vulnerability disclosure, but they are more affected in the case of operation systems than in web browser. On the contrary, security firms react more to vulnerability disclosure in web browsers than in operation systems. While security firms contribute less than software vendors in general to the discovery of new security flaws, their effort is more positively affected by the vulnerability disclosure. Besides, it is interesting to note that the actors that contribute the most are still the individuals that do not specify their affiliation and that they are also affected positively by the vulnerability disclosure.

In sum, the increasing number of vulnerabilities after the disclosure of a critical vulnerability is likely to be largely produced by actors that want to seize the opportunity to find new vulnerabilities, such as the security firms and the individual researchers. The increase in the contribution of companies that are dependent to the security of the affected software – those that we designate as "Users" – after the vulnerability disclosure is also significant and greater than the change in the software vendor's effort to find new security flaws.

5 Interpretation and conclusion

By studying the impact of three renowned vulnerability disclosure on three different types of software, we analyze how the vulnerability discovery activity on a software is impacted by the disclosure of a critical vulnerability.

First, our results show that after the disclosure of a critical vulnerability, the number of vulnerabilities that are found in the software affected by the disclosure increases significantly compared to other software. Moreover, the effect becomes greater and more significant over time. Secondly, we find that third parties are more affected by vulnerability disclosure than the software vendor. Users and individual researchers are not only contributing more than the software vendor in general but their contribution is also more affected by the disclosure. While security firms are contributing less than the software vendor in general, the number of vulnerabilities they find increases after the disclosure of a critical vulnerability. These results are all the more important as (1) existing works on software

security focus much more on the behavior of software vendors in providing security than on the contribution of other third parties, while (2) we show that third parties' overall contribution in software security is considerable, and (3) their contribution is significantly affected by externalities like the disclosure of a critical vulnerability. Overall, our results suggest that is is important to take account the incentives of third parties to invest in security to better understand the economic mechanisms behind software security.

With regard to the larger impact of a vulnerability disclosure on users than on software vendors, it may be explained by the fact that the vulnerability disclosure acts more significantly as a negative signal to users than to the software vendor. Indeed, the software vendor may be more aware of its actual security quality than others. As to the effect on individuals and security firms, vulnerability disclosure is likely to be perceived as an opportunity to find new security flaws and to benefit from it: security firms would benefit from selling new security solutions, individuals would have more opportunity to gain reputation and peer recognition.

This work is still at its preliminary stage and presents a number of limitations, that present opportunities for future research. First, in a future version of the work, in order to obtain more robust results, I intend to examine the correlation between some particular security investment events and the contribution of third parties. Indeed, one concern regarding the result we obtain is that third parties' contribution could actually be affected by the launch of particular vulnerability research programs sponsored by the software vendor itself or a specific group of users. Secondly, our findings rely on three specific cases on three markets that present some similarities each other. The study of an additional case may strengthen the reliability of our results. Lastly, it might be possible to go further in the empirical analysis by building some proxies for the users' switching cost, which would allow to study whether vulnerability disclosure affects the users in different magnitude according to their switching cost.

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6 Appendix

6.1 Categorization of the actors

The public announcement of a vulnerability may affect each type of actors for different reasons and in different degrees. Depending on how a given actor values the externality caused by a vulnerability disclosure (or more generally by the security of a software), we can categorize them as following:

- Competitors: by competitors we designate software vendors that play in the same market. Their behavior can be affected by the disclosure in several ways. First, it may have a negative effect on the affected software reputation (i.e. the competing product). This can be an incentive for a competitor to put more effort in finding new flaws in its adversary's product. At the same time, investing in a competitor's product security can be costly and may not be so profitable. Secondly, vulnerability disclosure on one product in the market can deteriorate the overall reputation of the market and thus have a negative effect on the overall demand. Considering this effect, vulnerability disclosure may give an incentive to firms to provide an effort to secure competitors' product as much as theirs. More importantly, products within the same market often share common vulnerabilities. Thus the effort made by a vendor to improve its own product's security may have some spillover on the security of competing products whether it is intentional or not. Overall, it is difficult to predict whether a vulnerability disclosure on a software would have a positive or negative effect on a competitor's effort to improve the security of the software affected by the disclosure.

- Users, downstream and upstream software vendors and service providers: they are dependent to the security of the affected software in various degrees and thus internalize a part of the risk due to vulnerability disclosure. If these actors have the possibility to choose between switching to another product or spending some effort to secure the vulnerable software, their behavior would depend on how high the switching cost is compared to the security investment cost.

- Security firms: these firms provide security solution and services to vendors and users. We include here firms that sell all types of security solutions, from anti-virus software to incident response services, as well as consulting services such as security assessment or penetration testing. The profits of a security firm comes from selling security solutions to its clients whether the client is the software vendor or the users, and finding a new vulnerability increases the value of its services. The disclosure of a new vulnerability can work as a signal that updates the probability to find additional vulnerabilities in the affected software. Thus it can be an incentive to security firms to look more thoroughly at the security of the affected software. Additionally, a security firm which has signed a contract with the software users or has sold a security product to them internalizes a part of the user damage cost. At the same time, as the disclosed information is shared with all the other third parties, competition can also reduce the effort they may exert.

- Academic researchers, public CERTs, and public organizations:[15] we group in this category actors for which the main goal is to improve global security rather than

[15] Private CERTs are accounted as a private company

making their own profit. They may internalize a part of the loss due to a vulnerability disclosure on a software, but this might be insignificant compared to the end users.

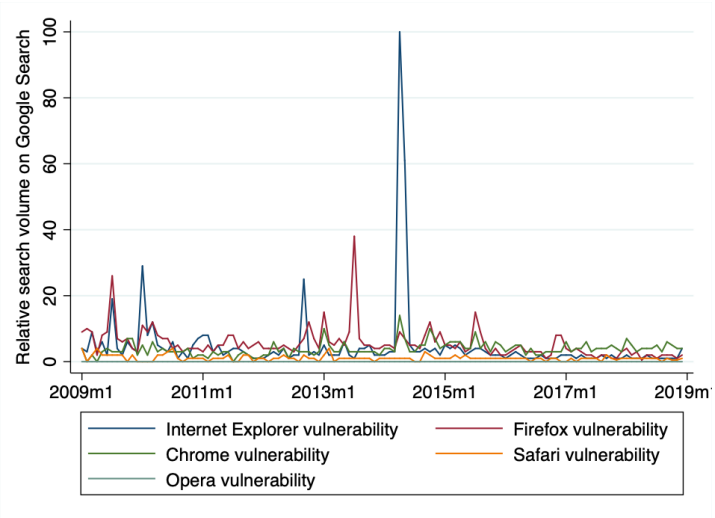
- Individuals: in our dataset, the discovery of numerous vulnerabilities are credited to an individual or a group of individuals without an affiliation. Even though they can actually be affiliated to an organization, we consider that when the affiliation is not specified, the discovery of the vulnerability is voluntarily credited to the individual itself. Here, we can relate the motivation of an individual to find and fix security flaws to the intrinsic and extrinsic motives attributed to open source phenomenon, which has been widely dealt in the literature. A vulnerability disclosure can signal the existence of additional undiscovered vulnerabilities and give an incentive to individuals that look for an opportunity to signal their skills to the community.

This categorization suggests that the public announcement of a vulnerability may affect each type of actors for different reasons and in different degrees.

6.2 The three critical vulnerability disclosures

- Treatment for the case of web browsers: Microsoft Internet Explorer CVE-2014-1776 Zero-Day disclosed in April 2009

Figure 5: Google Search trend for web browser vulnerabilities from 2009 to 2018



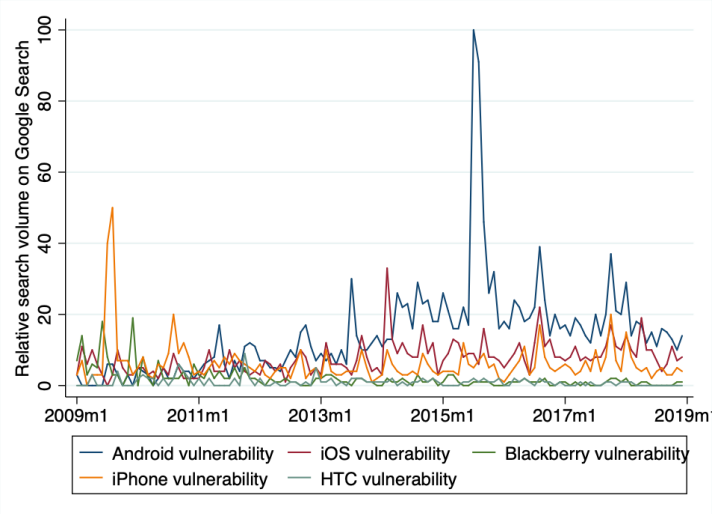
In Figure 5 we observe a peak search volume in mid 2014 for the search term "Internet Explorer vulnerability". This corresponds to a vulnerability that was announced in April 26th 2014 by Microsoft and the security firm FireEye. It is a zero day vulnerability – i.e. a vulnerability that did not have a security patch at the time it was disclosed – which allows an attacker to take full control over the system after a user views a specific web page in its web browser. Its severity scores are evaluated at the highest level of criticality and it affects all existing versions of Microsoft Internet Explorer.[16] The vulnerability was exploited in several targeted attacks. The exact

[16]These scores are called Common Vulnerability Scoring System (CVSS) and prioritize the vulnerabilities according to the threats they represent. Scores are calculated based on a formula that depends on several metrics that approximate the ease of exploit and the impact of exploit. The scores range from 0 to 10, with 10 being the most severe. While the average severity score for web browser vulnerabilities is around 5, this vulnerability presents a score of 10 for every criteria. *Source: the National Vulnerability Database*

date the vulnerability was discovered and reported to Microsoft is not known, but a patch was published on the 1st May, after the public disclosure. The flaw was so widespread that Microsoft has released patches for Windows versions for which support was already ended.[17]

- Treatment for the case of mobile OS: Google Android Stagefright vulnerability disclosed in July 2015

Figure 6: Google Search trend for mobile OS vulnerabilities



The peak search volume we visualize in Figure 6 corresponds to the disclosure of Android StageFright vulnerability in July 2015. Indeed, the security firm Zimperium announced on July 27th that it had discovered a serious vulnerability in the core of Google Android operation system, which is a flaw related to the way Android handled media, allowing a remote code execution without users opening a malicious file. News headlines announced that nearly a billion of Android devices could potentially be taken over without their users even knowing it.[18] The vulnerability was previously reported to Google in April 2015 and details of an exploit was disclosed at the BlackHat conference in August 2015. Google's security team released a patch for the initial bug within weeks, but it inspired a wave of new attacks on the way Android processes audio and video files. The first copycat bugs were reported just days after the first patch, with more serious exploits arriving months later.[19]

- Treatment for the case of desktop OS: Microsoft Windows Eternal blue and the famous *Wannacry* malware

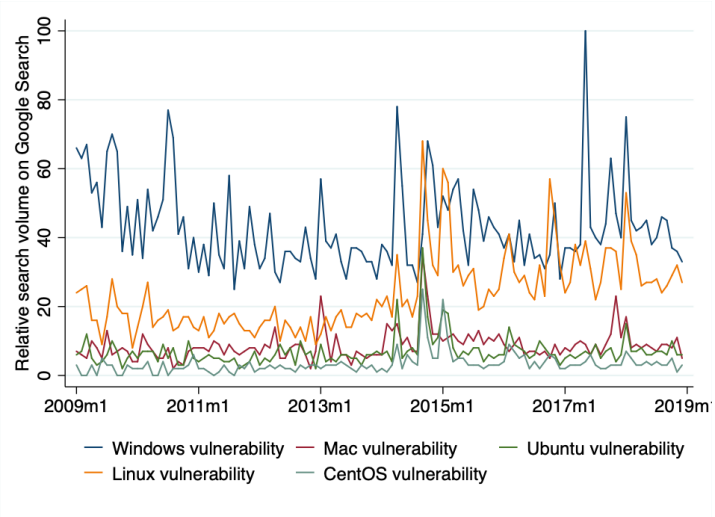
  Figure 7 plots the relative search volumes for terms that are the most popular in Google search related to operation systems' vulnerability. Note that we have also included CentOS and we include the term Ubuntu while Linux is already included

[17] *Source:* https://nvd.nist.gov/vuln/detail/CVE-2014-1776, https://blogs.technet.microsoft.com/srd/2014/04/26/more-details-about-security-advisory-2963983-ie-0day/, https://www.fireeye.com/blog/threat-research/2014/04/new-zero-day-exploit-targeting-internet-explore
html

[18] source https://www.theguardian.com/technology/2015/jul/28/stagefright-android-vulnerability-heartb
http://blog.zimperium.com/experts-found-a-unicorn-in-the-heart-of-android/

[19] https://www.theverge.com/2016/9/6/12816386/android-nougat-stagefright-security-update-mediaserver

Figure 7: Google Search trend for Desktop and Server OS vulnerabilities



in another search term. Search terms related to other operation systems are not included in the graph because they do not display sufficient search volumes. The peak search volumes occurs in mid 2017, which corresponds to the famous WannaCry ransomware attack happened in May 2017. The WannaCry attack uses an exploit that is originally created by the U.S. National Security Agency (NSA) named *EternalBlue*, which exploits the Microsoft Server Message Block, a network file sharing protocol that allows applications on a computer to read and to write to files within the same network.[20] The exploit was leaked by a hacker group named Shadow Brokers in April 14th 2017 and was used in WannaCry ransomware attack on May 12th 2017. The exploit was also used to carry out the NotPetya cyberattack on late June 2017. Previously, the NSA warned Microsoft after learning about EternalBlue's possible theft, allowing the company to prepare a software patch issued in March 2017, after cancelling all security patches in February 2017.[21] Microsoft released a patch event for Windows XP which support ended in 2014.

[20]The vulnerability is denoted by entry CVE-2017-0144 in the Common Vulnerabilities and Exposures (CVE) catalog.

[21]source: Wikipedia

6.3 Other tables and figures

Figure 8: Evolution of the total number of vulnerabilities

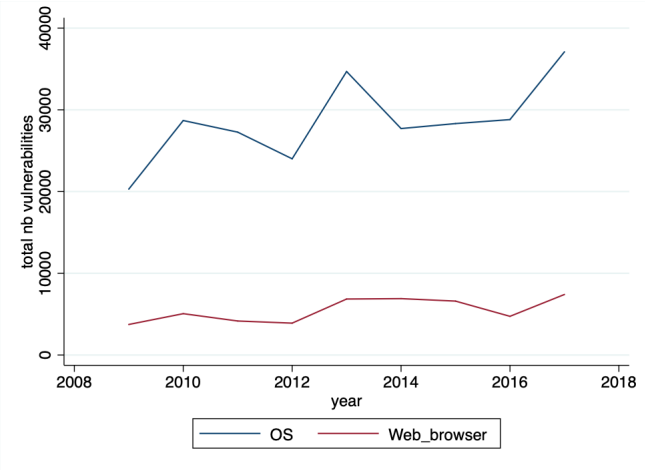


Figure 9: An example of the raw data we collect from Security Focus Bugtraq

info | discussion | exploit | solution | references

Microsoft Windows Kernel 'Win32k.sys' CVE-2016-7255 Local Privilege Escalation Vulnerability

Bugtraq ID:	94064
Class:	Unknown
CVE:	CVE-2016-7255
Remote:	No
Local:	Yes
Published:	Nov 08 2016 12:00AM
Updated:	Sep 25 2017 08:00PM
Credit:	Neel Mehta and Billy Leonard of Googleâ??s Threat Analysis Group Feike Hacquebord, Peter Pi and Brooks Li of Trend Micro
Vulnerable:	Microsoft Windows Vista x64 Edition Service Pack 2 0 Microsoft Windows Vista SP2 Microsoft Windows Server 2016 for x64-based Systems 0 Microsoft Windows Server 2012 R2 0 Microsoft Windows Server 2012 0 Microsoft Windows Server 2008 R2 for x64-based Systems SP1 Microsoft Windows Server 2008 R2 for Itanium-based Systems SP1 Microsoft Windows Server 2008 for x64-based Systems SP2 Microsoft Windows Server 2008 for Itanium-based Systems SP2 Microsoft Windows Server 2008 for 32-bit Systems SP2 Microsoft Windows RT 8.1 Microsoft Windows 8.1 for x64-based Systems 0 Microsoft Windows 8.1 for 32-bit Systems 0 Microsoft Windows 7 for x64-based Systems SP1 Microsoft Windows 7 for 32-bit Systems SP1 Microsoft Windows 10 Version 1607 for x64-based Systems 0 Microsoft Windows 10 Version 1607 for 32-bit Systems 0 Microsoft Windows 10 version 1511 for x64-based Systems 0 Microsoft Windows 10 version 1511 for 32-bit Systems 0 Microsoft Windows 10 for x64-based Systems 0 Microsoft Windows 10 for 32-bit Systems 0

Table 5: Description of the variables

Variable	Description
y_{it}	The number of vulnerabilities on software i discovered at period t
y_{ijt}	The number of vulnerabilities on software i discovered by type of actor j at period t
A_i	A dummy which indicates whether software i is the software targeted by the vulnerability disclosure (= 1 if it belongs to the treatment group)
$Post6m$	A dummy which is equal to one if the vulnerability disclosure took place less than 6 months ago
$Post12m$	A dummy which is equal to one if the vulnerability disclosure took place less than 1 year ago
$Post24m$	A dummy which is equal to one if the vulnerability disclosure took place less than 2 years ago
$Post$	A dummy which is equal to one for if the vulnerability is disclosed
$SoftwareAge$	Number of months since the software was launched (Versions are not taken account)
$EndofLife$	A dummy which indicates whether the vendor provides support for the software at period t
$mdate$	Monthly date (used for time fixed effects)
$id\_software$	ID for each software (used for product fixed effects)

Figure 10: Evolution of the distribution

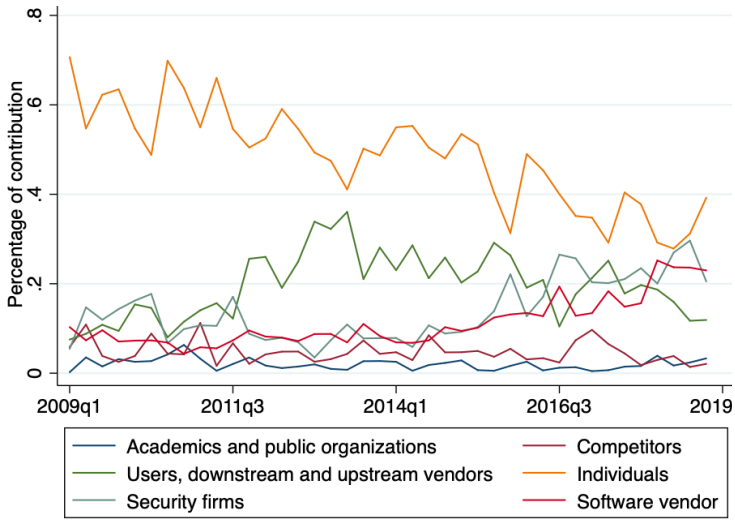


Table 6: Example illustrating how we have built the three data sets

Exemple of raw data set

id	software	Disclosed date	Credit	Explanation
49732	Android	12/4/2019	the software vendor and Individual α	Two types of actors have contributed in finding this vulnerability. Thus we consider that each of the two actors (the software vendor and the individual researchers) have discovered $\frac{1}{2}$ of the vulnerability. $\frac{1}{2}$ vulnerability is attributed to the type of actor "Individual researchers" and the other $\frac{1}{2}$ is attributed to the software vendor.
49900	Android	27/4/2019	Individual β and a security firm	
49999	Android	01/5/2019	Individual γ	
50206	Android	01/5/2019	Downstream vendor, Individual α and the software vendor	
58326	Android	29/5/2019	Public organization	

Aggregated data set for Specification 1

y_{it}	$software$	monthly date	Explanation
2	Android	2019m4	A total of 2 vulnerabilities were found in April 2019 (id 49732 and id 49900)
3	Android	2019m5	A total of 3 vulnerabilities were found in May 2019

Aggregated data set for Specification 2

y_{ijt}	$software$	$mdate$	$ThirdParty$	Explanation
0.5	Android	2019m4	0	In April 2019, the software vendor discovered one vulnerability (Id 49732) with an individual so it has found $\frac{1}{2}$ vulnerability
1.5	Android	2019m4	1	
0.33	Android	2019m5	0	
2.67	Android	2019m5	1	

Aggregated data set for Specification 3

y_{ijt}	$software$	$mdate$	$Identifier\_Type$	Explanation
0.5	Android	2019m4	Software vendor	
1	Android	2019m4	Individuals	In April 2019, "Individual researchers" have participated in the discovery of two vulnerabilities (of Ids 49732 and 49900) and for each vulnerability they discovered it with another type of actors. In sum, they discovered $\frac{1}{2} + \frac{1}{2}$ vulnerabilities.
0.5	Android	2019m4	Security firms	
0.33	Android	2019m5	Software vendor	
1.33	Android	2019m5	Individuals	
0.33	Android	2019m5	Users	
1	Android	2019m5	Public Organizations	

Table 7: Summary statistics

		Web browser					Mobile OS					Desktop OS				
	Variable	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
1st	Y_{it}	819	5.17	7.4	0	67	1872	14.07	17.7	0	112	1856	13.95	17.68	0	112
specification	A_i	819	0.14	0.35	0	1	1872	0.06	0.24	0	0	1856	0.06	0.24	0	1
	$post6m$	819	0.05	0.22	0	1	1872	0.05	0.22	0	1	1856	0.05	0.22	0	1
	$post12m$	819	0.1	0.3	0	1	1872	0.1	0.3	0	1	1856	0.1	0.3	0	1
	$post24m$	819	0.21	0.4	0	1	1872	0.21	0.4	0	1	1856	0.17	0.38	0	1
	$post$	819	0.49	0.5	0	1	1872	0.34	0.47	0	1	1856	0.17	0.38	0	1
	$id\_software$	819	4	2	1	7	1872	8.5	4.61	1	16	1856	8.5	4.61	1	16
	$mdate$	819	2014m2	35	2009m1	2018m12	1872	2013m12	35	2009m1	2018m12	1856	2013m11	35	2009m1	2018m12
	$SoftwareAge$	819	14.62	5.16	3	25	1872	15.56	8.34	0	35	1856	15.49	8.33	0	35
	$EndofLife$	819	0	0	0	0	1872	0	0.05	0	1	1856	0	0.05	0	1
2nd	Y_{ijt}	1734	2.62	5.26	0	59	3744	6.95	13.47	0	111	3712	6.89	13.45	0	111
specification	A_i	1734	0.19	0.39	0	1	3744	0.06	0.24	0	1	3712	0.06	0.24	0	1
	$post6m$	1734	0.05	0.21	0	1	3744	0.05	0.22	0	1	3712	0.05	0.22	0	1
	$post12m$	1734	0.1	0.3	0	1	3744	0.1	0.3	0	1	3712	0.1	0.3	0	1
	$post24m$	1734	0.21	0.41	0	1	3744	0.21	0.4	0	1	3712	0.17	0.38	0	1
	$post$	1734	0.52	0.5	0	1	3744	0.34	0.47	0	1	3712	0.17	0.38	0	1
	$ThirdParty$	1734	0.5	0.5	0	1	3744	0.5	0.5	0	1	3712	0.5	0.5	0	1
	$id\_software$	1734	4	2	1	7	3744	8.5	4.61	1	16	3712	8.5	4.61	1	16
	$mdate$	1734	2014m2	35	2009m1	2018m12	3744	2013m12	35	2009m1	2018m12	3712	2013m11	35	2009m1	2018m12
	$SoftwareAge$	1734	13.89	5.85	0	25	3744	15.56	8.34	0	35	3712	15.49	8.32	0	35
	$EndofLife$	1734	0	0	0	0	3744	0	0.05	0	1	3712	0	0.05	0	1
3rd	Y_{ijt}	5202	0.87	2.49	0	34	11232	2.32	5.73	0	61	11136	2.23	5.73	0	61
specification	A_i	5202	0.19	0.39	0	1	11232	0.06	0.24	0	1	11136	0.06	0.24	0	1
	$post6m$	5202	0.05	0.21	0	1	11232	0.05	0.22	0	1	11136	0.05	0.22	0	1
	$post12m$	5202	0.1	0.3	0	1	11232	0.1	0.3	0	1	11136	0.1	0.3	0	1
	$post24m$	5202	0.21	0.41	0	1	11232	0.21	0.4	0	1	11136	0.17	0.38	0	1
	$post$	5202	0.52	0.5	0	1	11232	0.34	0.47	0	1	11136	0.17	0.38	0	1
	$public\_org$	5202	0.17	0.37	0	1	11232	0.17	0.37	0	1	11136	0.17	0.37	0	1
	$competitors$	5202	0.17	0.37	0	1	11232	0.17	0.37	0	1	11136	0.17	0.37	0	1
	$users$	5202	0.17	0.37	0	1	11232	0.17	0.37	0	1	11136	0.17	0.37	0	1
	$individuals$	5202	0.17	0.37	0	1	11232	0.17	0.37	0	1	11136	0.17	0.37	0	1
	sec_firms	5202	0.17	0.37	0	1	11232	0.17	0.37	0	1	11136	0.17	0.37	0	1
	$id\_software$	5202	4	2	1	7	11232	8.5	4.61	1	16	11136	8.5	4.61	1	16
	$mdate$	5202	2014m2	35	2009m1	2018m12	11232	2013m12	35	2009m1	2018m12	11136	2013m11	34	2009m1	2018m12
	$SoftwareAge$	5202	13.89	5.85	0	25	11232	15.56	8.34	0	35	11136	15.49	8.32	0	35
	$EndofLife$	5202	0	0	0	0	11232	0	0.05	0	1	11136	0	0.05	0	1

Table 8: Effect of a critical vulnerability disclosure on each actors (Other treatment periods)

	Case 1			Case 2			Case 3		
Treatment Period is:	$post6m$	$post12m$	$post24m$	$post6m$	$post12m$	$post24m$	$post6m$	$post12m$	$post24m$
$Public\_org$	-1.467***	-1.367***	-1.256***	-1.812***	-1.794***	-1.644***	-1.758***	-1.684***	-1.603***
	(0.152)	(0.155)	(0.160)	(0.0785)	(0.0803)	(0.0829)	(0.0789)	(0.0804)	(0.0814)
$Competitors$	-0.319***	-0.205*	-0.0505	-1.034***	-1.009***	-0.991***	-1.011***	-0.923***	-0.831***
	(0.119)	(0.122)	(0.127)	(0.0697)	(0.0713)	(0.0751)	(0.0702)	(0.0714)	(0.0724)
$Users$	-1.409***	-1.293***	-1.300***	0.434***	0.450***	0.518***	0.448***	0.546***	0.655***
	(0.150)	(0.153)	(0.163)	(0.0623)	(0.0638)	(0.0665)	(0.0624)	(0.0635)	(0.0646)
$Individuals$	1.658***	1.718***	1.815***	1.458***	1.469***	1.552***	1.471***	1.555***	1.635***
	(0.105)	(0.108)	(0.114)	(0.0610)	(0.0626)	(0.0651)	(0.0608)	(0.0619)	(0.0632)
Sec_firms	-0.240**	-0.156	-0.0633	-0.282***	-0.289***	-0.276***	-0.384***	-0.325***	-0.244***
	(0.119)	(0.123)	(0.129)	(0.0643)	(0.0661)	(0.0695)	(0.0653)	(0.0667)	(0.0678)
$P \cdot A$	-0.518	-0.947*	-0.475	0.402	0.602	1.321***	0.591	-0.0118	0.515
	(0.793)	(0.491)	(0.350)	(0.658)	(0.483)	(0.364)	(0.617)	(0.454)	(0.371)
$Public\_org \cdot P \cdot A$	1.293	1.039	0.455	-20.17	0.0871	1.042	0.0663	0.699	2.232***
	(1.524)	(1.296)	(0.960)	(26,854)	(1.083)	(0.775)	(1.282)	(0.891)	(0.663)
$Competitors \cdot P \cdot$ A	-0.292	1.086	0.916*	-0.667	-0.486	-1.789	-15.47	-14.99	-15.74
	(1.215)	(0.756)	(0.556)	(27,412)	(12,213)	(28,494)	(2,577)	(2,314)	(2,417)
$Users \cdot P \cdot A$	-21.03	1.169	0.264	-1.721	-0.408	1.179**	0.712	2.051***	1.665***
	(39,847)	(1.023)	(0.664)	(1.150)	(0.736)	(0.549)	(0.866)	(0.639)	(0.522)
$Individuals \cdot P \cdot A$	0.452	1.169*	0.826*	0.670	0.953	1.126**	0.0696	0.616	1.017*
	(1.068)	(0.668)	(0.472)	(0.925)	(0.671)	(0.512)	(0.874)	(0.646)	(0.524)
$Sec\_firms \cdot P \cdot A$	3.808***	2.760***	1.805**	-0.701	-0.105	0.969*	-0.449	0.280	0.956*
	(1.250)	(0.705)	(0.492)	(0.942)	(0.674)	(0.512)	(0.862)	(0.635)	(0.516)
Observations	5,202	5,202	5,202	11,232	11,232	11,232	11,136	11,136	11,136

Note: Negative binomial regressions. Product fixed effects and time fixed effects are included in all specifications as well as other controls ($SoftwareAge$, $EndofLife$). Coefficients are average marginal effects. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1