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Auto-sélection des hackers dans les programmes « crowdsourcés » de chasse aux bogues

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HACKERS' SELF-SELECTION IN CROWDSOURCED BUG BOUNTY PROGRAMS¹

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 **Mots-clés :** hackers, crowdsourcing, concours d'innovation, contrat de travail et performance, auto-sélection des travailleurs, aversion à l'incertitude

1. INTRODUCTION

Five years ago, a 17-year-old teenager in India discovered a serious vulnerability in several airline booking systems that allowed travelers to get free plane tickets. Despite his effort to contact the airline companies and to alert them about the flaw, only one company took him seriously and reacted.² This is less true nowadays: an increasing number of companies seek

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2 Source: <https://medium.com/@kanishksajjani/how-i-could-have-travelled-the-world-for-free-5bbroac46ae5>.

to collaborate with benign vulnerability identifiers—the so-called white-hat hackers—to improve their systems' security. Methodical approaches have been developed to work with independent researchers, such as offering incentives in the form of a “bounty”. Organizations started running *Vulnerability Research Programs* (VRPs)—also commonly called *Bug Bounty Programs*—which give monetary compensation to crowdsourced resources in exchange for information about vulnerabilities. Along with it, web platforms called “Bug bounty platforms” have emerged, hosting and managing these VRPs as a third party (E.g. HackerOne, BugCrowd, Yeswehack).

Launching a VRP has become a typical way to improve software and system security and is becoming accepted as a normal part of the software development lifecycle. However, managing a successful VRP is not an easy task. One of the key challenges companies face is to strike the right balance between attracting enough participants and setting sufficiently high standards for participation in order to limit the proportion of low-value participations.³ Indeed, a VRP aims to benefit from the diversity of participants, so it is important to let a large pool of individuals participate. Yet, each participation induces a cost, as it requires dedicated resources to sort the relevant participations from those which are invalid, and to communicate with participants.⁴

One method applied by bug bounty platforms to reduce the rate of invalid participations is to allow only individuals that have been sufficiently efficient in the past to participate.⁵ Unfortunately, one can also lose potentially valuable participations by applying such restrictive policies (Zhao, Laszka, and Grossklags, 2017). Apart from setting such a *minimum quality standard*, the contest's policies—i.e., the terms and rules of the contest—may shape the outcome of the contest.

The policy of a crowdsourced contest such as VRPs is comparable to an employment contract, as it defines the contractual relationship between the contest owner and participants, especially by specifying the compensation scheme

3 Source: <https://www.hackerone.com/blog/signal-requirements>.

4 Specifically, VRPs in our data set are public, i.e., any hacker on the platform can submit a report. The submitted report has to be examined and evaluated by the VRP to decide whether they accept the report as a relevant one, so it incurs a “triage cost”.

5 For instance, HackerOne allows hackers to submit a report only when they meet a given *Level of valid to invalid submission ratio*.

the contest offers to participants and what it expects in exchange. The relationship between workers' performance and the attributes of an employment contract have been extensively studied by economists. The literature distinguishes at least two types of effects. First, a compensation scheme can affect a worker's performance—for instance, through a pay-for-performance scheme—by producing a certain Level of effort from the worker, which may be referred to as *effort effects*. Secondly, it can have an effect on personal attributes. For example, a number of empirical works show that more productive workers systematically prefer variable-pay to fixed-pay schemes (e.g., Dohmen and Falk, 2011). The possibility that agents with different individual characteristics feel attracted by different pay schemes and therefore self-select into particular forms of contracts may be referred to as *self-selection effects*.

In the same way as an employment contract, the characteristics of a contest's policy may affect both the Level of effort provided by participants and the type of individuals that choose to participate in the contest. In this paper, we focus on the second aspect, that is, how the attributes of a VRP affects the decision of an individual to participate. In particular, we are interested in how the completeness of the contract offered by a VRP affects a hacker's choice to participate. By completeness of the contract, we mean how much information the VRP's policy provides about the compensation scheme and about what it expects as an outcome.

Crowdsourced innovation contests like VRPs present several important specificities that make it difficult to derive the answer to our question directly from the case of a standard employment contract. First, the number of participants—the number of brains that work on a problem—is an important factor that defines the effectiveness of a crowdsourced innovation contest (Terwiesch and Xu, 2008; Boudreau, Lacetera, and Lakhani, 2011). A contest policy should be thus applicable and attractive enough to a wide panel of individuals. At the same time, it has to be specific enough to provide adequate incentives and streamline the search process. Secondly, in VRPs, participants are asked to find new security flaws that were unknown before. That is, they are asked to find an innovative way to penetrate a system rather than to carry out predefined tasks as is the case in other crowdsourcing platforms such as Amazon Mechanical Turk. Certain types of individuals may be more qualified to innovate. Solvers who have extensive knowledge and experience in the problem domain could be most effective. Or, on the contrary, technical and social marginality could be an advantage

to successfully solve the problem (Jeppesen and Lakhani, 2010). All in all, the success of an innovation contest largely depends on sorting and attracting the right kind of solvers. Third, a VRP offers only variable pay: participants are compensated only if their contributions are relevant enough, regardless of the effort they have actually provided. Variable-pay schemes are likely to attract more productive workers than fixed-pay schemes, but they also occasion a sorting effect on other attributes such as the relative self-assessment or risk preference (Dohmen and Falk, 2011) that might alter the effectiveness of a contest.

The purpose of this study is to examine how the completeness of the contract proposed by a VRP affects its effectiveness. As the goal for a bug bounty program is to find as many relevant vulnerabilities as possible (i.e., it is interested in maximizing the sum across all outcomes, as opposed to a one-prize contest in which the goal is to maximize the value of the highest outcome), we examine the effect of contract type both on quantity (the number of participations) and on quality (whether it attracts more skilled and more experienced participants).

Our analysis is based on publicly available data from the web platform HackerOne. We use an unbalanced panel data set on 156 bug bounty programs run from January 2015 to February 2019. VRPs on this platform are free to choose the Level of information they provide about the contractual terms through a written policy. They can provide more or less detail about their compensation scheme, from fully specifying the payouts for each task to having a large degree of discretion about the monetary rewards and the targeted scope. They can also modify their policy over time. We consider that the Level of information provided in the written policy reflects the degree of completeness of the contract the contest offers. We find that the more precise and detailed the policy is, the more participants it attracts. However, it also attracts participants with more heterogeneous performance and it reduces the average quality of participants. In particular, top hackers are not necessarily attracted by VRPs providing more information. On the contrary, leaving more uncertainty about the monetary rewards and the targeted scope generates fewer, more homogeneous participants, but with higher quality on average.

This paper proceeds as follows. Section 2 reviews the relevant literature, Section 3 develops our hypothesis for analysis and Section 4 describes the

data and estimation strategies. Section 5 reports the results, and Section 6 concludes.

2. RELATED LITERATURE

Our paper is closely related to three streams of research. The first one is on the economics of information security. The literature on the economics of information security aims at studying the potential market failures causing information systems insecurity. Various questions are addressed, from modeling the interaction between attackers and defenders (Varian, 2004; Bohme and Moore, 2010), examining the role of different liability and vulnerability information disclosure (Kannan and Telang, 2005; Arora, Caulkins, and Telang, 2006; Kim, Chen, and Mukhopadhyay, 2011; August and Tunca, 2011; Lam, 2016), risk sharing and coordination possibilities between vendors and users (August and Tunca, 2006; Cavusoglu, Cavusoglu, and Zhang, 2008; Kim, Chen, and Mukhopadhyay, 2009). Although there are far more theoretical studies than empirical ones, this literature contributes to a large number of applied areas related to information security like software vulnerability discovery and patching, security investment decisions and market insurance, network security or payment system security. We contribute empirically to this literature, first by studying a marketplace—a market for software vulnerabilities, where hackers sell vulnerability information to software vendors and companies—that has been barely studied for now as it is so new, and secondly by studying how the design of a bug bounty program affects the contribution of the individual researchers.

Among the few papers that focus on Vulnerability Research Programs, Finifter, Akhawe, and Wagner (2013) analyze two programs run by big pioneers in the vulnerability research community (Google and Mozilla) and examine whether running a VRP is economically profitable for a firm. Zhao et al. (2017) develop an analytical framework that compares different policies that aims at reducing the number of invalid reports.⁶ To our knowledge, there are only two empirical studies that analyze data from

6 They suggest that in VRPs, a penalty system for invalid reports is more efficient than applying a minimum quality standard. Their model also shows that an increasing number of participants may decrease both the organization's and the hackers' utilities.

bug bounty platforms.⁷ Zhao, Grossklags, and Liu (2015) compare the currently biggest bug bounty platform HackerOne run by a US-based company to the well-known Chinese bug disclosure platform Wooyun. They compare the trend in the vulnerabilities discovered in the two platforms, the different reward structures VRPs offer, and how offering monetary incentives attracts more participants to a VRP. Maillart, Zhao, Grossklags, and Chuang (2017) also use data from HackerOne and show that the number of participations in a VRP reduce considerably over its duration and that hackers strategically switch to new programs when new programs become available.

Along with these two papers, our paper is one of very few to provide an empirical analysis of bug bounty platforms. Besides the principal characteristics of VRPs already examined by existing papers—such as the effects related to monetary incentives or the decreasing probability of finding new vulnerabilities—, we identify an important mechanism that affects the effectiveness of a VRP. We are the first to focus on how the amount of information provided by a VRP about its contractual terms affects its effectiveness. We assimilate a VRP's policy to an employment contract proposed by a firm to workers and we study how the perception of the uncertainty to obtain a reward affects a worker's choice to participate in the contest. Our data set is also unique, in that it is a recent and large panel data set on VRPs run by diverse types of organizations managed on a single platform. As we have a panel data set, we were able to account for the different fixed effects and reliably identify the effect attributed to a change in a VRP's policy. Moreover, we used both quantitative (the number of participations) and qualitative (the number of top hackers, participants' average quality and variance) information that defines the outcome of a contest.

Our paper is also related to the literature on innovation contests and tournaments. VRPs are a type of contest in which the organizer commits to rewarding the participants according to the rules and terms it defines, and participants spend resources in order to win the compensation. For each new security flaw, only the first person to find it is rewarded. It is thus close to an innovation contest in that the goal of the contest is to find a new idea—an innovative way to penetrate the system and secure it. Economists have studied the optimal design of contests from various angles, mainly about how to allocate the prizes (Moldovanu and Sela, 2001; Archak and

7 See definition and description of a bug bounty platform in Subsection 4.1.

Sundararajan, 2009; Liu, Yang, Adamic, and Chen, 2014) and whether free entry or restricted numbers of participants yield better outcomes (Fullerton and McAfee, 1999; Terwiesch and Xu, 2008; Boudreau et al., 2011).

As Boudreau et al. (2011), we are interested in how the degree of uncertainty faced by participants affects the outcome of the contest.⁸ However, our scope and approach differ in several aspects. First, we study a type of contest increasingly used with the rise of crowdsourcing but barely studied for now. As mentioned earlier, in contests like VRPs, the goal is to maximize the sum of the outcomes, while “traditional” innovation contests like those launched on the well-known web platform InnoCentive aims at selecting one best solution. Secondly, in Boudreau et al. (2011), the degree of uncertainty is measured by the number of problem domains on which a given solution draws. They focus on the fact that participants exert less effort when they face more uncertainty to solve the problem. In our case, the uncertainty comes from the level of information provided by the contest and we are interested in how the preference for uncertainty attracts a given type of participant. Lastly, the results we obtain are different from the findings of Boudreau et al. (2011). In our work, we find that uncertainty attracts more skilled participants, which has a positive effect on the overall outcome, while in their case, it is the number of participants that compensate for the reduced effort of each individual due to problem uncertainty.

Our analysis also draws on results from the rich body of literature on employment contracts. Specifically, in our paper, we are interested in the incentive schemes used by firms to attract specific types of workers, namely the self-selection effect as defined in Salop and Salop (1976) or in Chow (1983). Analytical works show that individuals with higher skills are more likely to choose a performance-based pay schemes than low-skilled workers (e.g., Salop and Salop, 1976; Demski and Feltham, 1978; Lazear, 2000b; Jensen, 2003). The basic idea is that a worker evaluates the match between his self-perceived personal attributes and the perceived attributes of available employment contracts and selects the contract that maximizes his expected utility. This theory is supported by a number of

8 They show empirically that greater rivalry between the participants in a contest reduces the incentive to exert effort, but adding competitors increases the probability of obtaining an extreme value solution and this effect prevails for problems with more uncertainty.

empirical papers. Most of them are laboratory experiments (Chow, 1983; Waller and Chow, 1985; Cadsby, Song, and Tapon, 2007; Eriksson, Teyssier, and Villeval, 2009; Dohmen and Falk, 2011), except from a field experiment by Fehrenbacher, Kaplan, and Pedell (2017) and the studies of Lazear (2000a,b) based on a large data set of an auto glass company's workforce.

The originality of our work also comes from the fact that we investigate the mechanism of a crowdsourcing contest by referring to research applied to a standard employment framework. In particular, our focus is on participants' self selection, while studies on contests are more concerned with the relationship between the design of the contest and the effort exerted by participants.

To our knowledge, Eriksson et al. (2009) is the only paper that studies the self-selection effect in the context of tournaments. In a laboratory experiment, they show that when workers are allowed to choose between performance-based pay and a tournament, there is a considerable reduction in effort variance among contestants in the tournament. They suggest that this is due to the fact that subjects self-select their payment scheme according to the degree of risk aversion. We also rely on their findings and see whether their arguments can be applied to a more general case where the degree of uncertainty perceived by the participants differs according to the level of information the contest provides about the contractual terms.

3. HYPOTHESIS DEVELOPMENT

The literature on tournaments and innovation contests identifies two opposing effects related to how the number of contestant impacts on its efficiency. The first is how the competition between participants affects the amount of effort exerted by each participant. Related to this effect, analytical works (e.g, Fullerton and McAfee, 1999; Moldovanu and Sela, 2001; Terwiesch and Xu, 2008) suggest that having many contributors working on a single issue leads to a lower equilibrium effort for each contributor because they face a greater risk of not being rewarded for the effort they are exerting. Empirical works have also provided evidence of the effort-reducing impact of an increased number of participants (Casas-Arce and Martínez-Jerez, 2009; Garcia and Tor, 2009).

The second effect is on the probability of finding a solution by increasing the number of “brains” working on a subject. Terwiesch and Xu (2008) argue that a larger number of participants is not necessarily inefficient because it brings a more diverse set of solutions, which can outweigh the negative effect from the underinvestment of each individual. Boudreau et al. (2011) empirically show that in the case of problems with high uncertainty, adding additional participants increases the overall contest performance. In fact, this second effect—the positive effect of having a large number of solvers—is particularly applicable to innovation contests, in which the discovery of a solution and thus obtaining a reward presents a high degree of uncertainty.

Regarding how uncertainty affects the decision of an individual to participate, Eriksson et al. (2009) suggest that when participants are free to choose whether to participate or not in a contest, the uncertainty of success divides up the participants before they enter the contest. The idea is that facing uncertainty, some individuals would choose the minimum effort, that is, they drop out of competition, securing the loser’s prize without bearing any cost. In sum, if there is too much uncertainty to win a reward or it is perceived as such by potential participants, the contest may lose some contributors that would have otherwise exerted an effort, however small.

In this paper, we consider that the uncertainty of being rewarded is induced by the contractual uncertainty. In fact, the level of information provided by a VRP, which determines contractual uncertainty, reflects the extent to which the contest owner commits to internalizing the reward uncertainty borne by participants: the more detailed and accurate are the information provided by the contest about the compensation terms and the scope of work, the better participants can optimize their efforts and reduce the uncertainty of being rewarded.

Based on this discussion, we predict the following about the relationship between the degree of completeness of a VRP’s policy and the number of participants.

Hypothesis 1. *A VRP that provides more detailed information about the contractual terms, i.e., less uncertainty about winning a reward, attracts a larger number of participants.*

According to Terwiesch and Xu (2008) and Boudreau et al. (2011), the uncertainty about being rewarded may negatively affect the overall outcome as it reduces the number of participants that work on the problem. However, Eriksson et al. (2009) argue that the degree of uncertainty also limits the type of participants that actually participate in the contest, hence leads to an *ex-ante* selection process. They show that when workers are given the possibility to choose the degree of uncertainty of their payment scheme, they are sorted by their attributes. This results in a pool of participants with less variance in their performance in contracts with more uncertainty like tournaments (contests), compared to those with more certainty like piece-rate payment schemes.

Based on this reasoning, we predict the following:

Hypothesis 2. *More uncertainty about the contractual terms attract participants more homogeneous in their skill and experience.*

Finally, what argue is that when we offer the possibility of choosing whether to participate or not in a contest, subjects who have a higher probability of winning choose to enter the contest, which actually has a positive effect on the overall efficiency of tournaments.

More generally, the main idea suggested by studies on the self-selection effect in employment is that the *ex-ante* sorting effects contribute significantly to output difference between different incentive systems. For instance, Dohmen and Falk (2011) show in a laboratory experiment that the output in all variable-payment schemes (piece rate, tournament, or revenue-sharing schemes) is higher than the results under the fixed-wage regime and that this output difference is mainly attributable to productivity sorting. That is, when facing the alternative between more or less uncertain payments, more productive workers systematically prefer a payment scheme which is linked to their own performance even though it is more risky. Additionally, in payment schemes like tournaments in which compensation depends on relative performance, they show that relative self-assessment plays an important role in sorting into tournaments. Considering that hackers who have participated more often in other VRPs in the past (i.e., who have more experience in the platform) are more likely to have a better relative self-assessment, we hypothesize the following:

Hypothesis 3. *A VRP with more uncertainty about the contractual terms sorts the participants into more skilled and more experienced participants.*

4. DATA AND EMPIRICAL FRAMEWORK

4.1. Data

For the purpose of our analysis, we collected publicly available data from HackerOne. HackerOne is a well-known web platform, created in November 2013, which partners companies that want to run a Vulnerability Research Programs (VRPs) with white-hat hackers who want to participate in such programs. HackerOne is currently the most dominant bug bounty platform on the market. Bug bounty platforms such as HackerOne are different from innovation crowdsourcing platforms such as InnoCentive, as VRPs do not set out to choose one winner that suggests the best solution but rather look for as many valuable contributions as they can get. That is, in VRPs, all relevant submissions are rewarded. VRPs are also different from crowdsourcing platforms such as Amazon Mechanical Turk, in which workers are usually asked to carry out very simple tasks.

In order to launch a VRP, the organizing company first needs to define and publish its policy on the platform. The policy provides information about the rules and the contractual terms of the contest: vulnerability types the VRP is looking for, the scope it is targeting, the reward structure, a vulnerability disclosure agreement, etc. On HackerOne, it falls to each VRP to define its policy and the level of information it provides within this policy. Some VRPs provide minimal description about their expectations, while others develop detailed sections describing the targeted scope of the VRP, the requirements for being eligible for a bounty or the detailed reward structure and amounts. In Figure 3 in the Appendix, we provide an example of a VRP on HackerOne that gives only basic information about the compensation and what it is looking for, while Figure 4 is an example of a VRP providing a greater amount of information about the compensation and about what they expect in exchange. A VRP can also modify its policy after the program has been launched: it can add new details, change the reward conditions, add bonus rewards, etc.

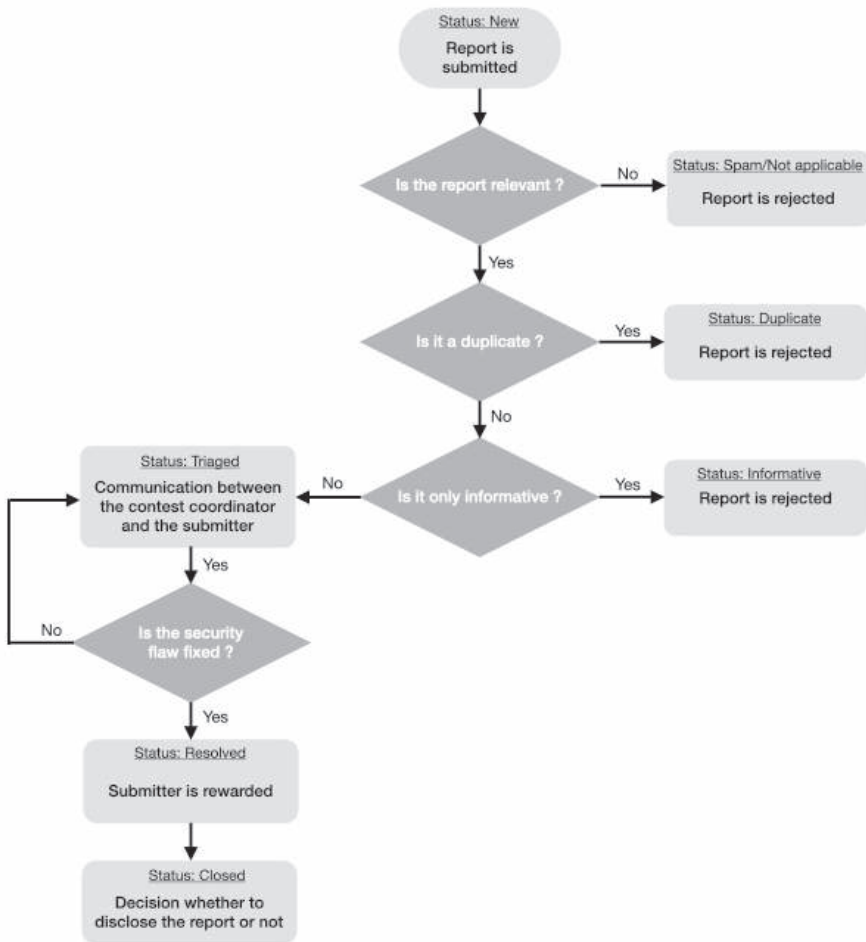
In our study, we only consider VRPs that offer monetary rewards, that are publicly accessible and that do not pre-select their participants. Any hacker that has an account on the platform can participate in these public VRPs. They can browse information about active VRPs in several ways: They can visit the VRP's webpage where the VRP presents its policy, some program statistics (number of closed reports, their average response time, if the VRP disclose it, rewards paid in the past, etc.). They also can look at the title of recent reports and who reported it and the payment amount if the VRP discloses it. Hackers also can classify VRPs according to their launch date, the number of closed reports, or the average amount of reward they offer. However, reward information is not systematically disclosed and this is one of the criteria we use to measure the information level provided by VRPs. Hackers can also look at other hackers' profiles where information about their past performance is available (statistics on the vulnerabilities they have found, Reputation, Signal and Impact score, etc.)

Participating in a contest involves submitting a report about a vulnerability and fixing the reported vulnerability in collaboration with VRP coordinators. The flowchart in Figure 1 provides an overview of how report submissions are processed. The submitted report has to respect the rules and the guidelines defined by the VRP. After a report is submitted, the VRP evaluates whether the submission is relevant and how valuable the submitted report is (i.e., how critical and how important the discovered vulnerability is). If the report is assessed as irrelevant or as a duplicate, then it is rejected.⁹ For reports that are considered as relevant, the VRP validates the submission and starts exchanging with the participant to fix the vulnerability. When the vulnerability is fixed, the report becomes "resolved" and the VRP offers a reward to the participant. Then finally, the submitted report is closed.

The data we collected concerns 156 active VRPs on HackerOne during the period from January 2015 to February 2019. All VRPs in our data set are public (anyone can submit a report) and offer financial compensation. All VRPs in our data set are public (anyone can submit a report) and offer financial compensation. The pie charts in Figure 2 in the Appendix present some information about the VRP owners. More than two thirds of them

9 When a report is rejected, the submitter does not receive any financial reward. Moreover, the signal score is reduced except for reports that are considered informative.

Figure 1. Flowchart of report submission process on HackerOne



are run by US companies. The main industry sectors companies belong to are IT, media and entertainment, hospitality and transportation, and financial services. As VRP policies evolve over time, we were able to build a panel data set. It is an unbalanced panel data set, as all the VRPs were not always active during the period. We collected information about each VRP each month, including the number of valid submissions, the performance indicators of each hacker at the date their submissions were accepted, the number of words used in the policy, whether a VRP presents a dedicated section describing the scope of the contest, and whether it specifies the reward structure. We collected data on how old a program is—i.e., the number of months since its launch—, and whether the program is managed by

HackerOne or by the company itself. We also counted the total number of active VRPs each month on the platform. Additionally, information about the number of employees, the year the company was founded, and the location of its headquarters were collected from Crunchbase, Owler.com and Wikipedia. Indeed, we used the number of employees as a proxy for the size of the company and we categorized the companies into 11 different industries. We also accounted for how old the companies are, whether they are based in the United States and whether they were acquired by another firm during the studied period.

4.2. Empirical specifications

Our objective is to analyze how the level of information given by the contest through its written policy affects the outcome of the contest. As the goal of a VRP is to maximise the sum of the values of all the participations, we consider two complementary measurable aspects that defines the outcome of a VRP: the quantity of participations and the quality of the participants, i.e., how successful and experienced the participants were in the past.

First, to analyze the effect of the level of information on the quantity of participations, we use the following baseline specification:

$$Nb_participation_{it} = \beta_0 + \beta_1 Information_Level_{it} + \beta_2 Prog_Age_{it} + \beta_3 Total_Nb_participation_{i(t-1)} + FE_i + FE_t + \varepsilon_{it},$$

where, $Nb_participation$, our dependent variable, is the number of submissions received by VRP i validated at period t . Our explanatory variable of interest is $Information_Level$, which measures how detailed the policy of VRP i is in period t . Three alternative variables are used as $Information_Level$. The first one is Nb_words , which counts how many words are used in a given VRP's policy in a given period. The second variable is $Reward$, a dummy which identifies whether the VRP provides detailed information about the structure and the amount of the rewards at period t . The third variable we use for $Information_Level$ is the dummy $Scope$, which identifies whether the VRP's policy includes a dedicated section that describes in detail the scope targeted by the contest. Additionally, we use two alternative measures that reflect the $Information_Level$, the first one being $Vocabulary_Diversity$, which measures the vocabulary diversity of the written policy by counting the number of unique words it uses while excluding

all “common words”¹⁰ in English, and the second variable being *Contract_Completeness*, which is an aggregate measure of *Nb_words*, *Reward* and *Scope* equal to $\ln(\text{Nb_words} + 1) + \text{Reward} + \text{Scope}$.

According to Hypothesis 1, we expect to obtain a positive coefficient for β_1 . That is, we expect that the more information a VRP provides about its policy, the less contractual uncertainty participants will perceive, and the more participations it will generate. *Prog_Age* measures how long the VRP ran (in number of months). *Total_Nb_participation* is the total number of valid reports submitted to the contest at $t - 1$. As the *Total_Nb_participation* is observable by any hacker that visits the VRP's webpage, one might expect the decision to participate to be affected by this information.¹¹ We expect the coefficients for *Prog_Age* and *Total_Nb_participation* to be negative because the probability of finding a new vulnerability decreases overtime and also decreases with the number of vulnerabilities that have already been discovered (Maillart et al., 2017).

FE_i and FE_t represent VRPs and time fixed effects respectively. In this specification, as we account for program and time fixed effect, we do not account for variables at the program level that do not vary over time. Lastly, ε_{it} is an error term.

Next, we use the following alternative specification:

$$\text{Nb_participation}_{it} = \beta'_0 + \beta'_1 \text{Information_Level}_{it} + \beta'_2 \text{Prog_Age}_{it} + \beta'_3 \text{Total_Nb_participation}_{i(t-1)} + \beta'_4 \text{Platform_Growth}_t + \beta'_5 \text{Managed_by_HO}_i + \beta'_6 \text{Firm_Size}_i + \beta'_7 \text{Based_in_US}_i + \text{Founded_period_FE}_i + \text{Industry_FE}_i + \varepsilon_{it}$$

In this specification, we include a range of variables specific to VRPs instead of accounting for VRP specific fixed effects. On the platform

10 A list of 422 words that are considered as the most commonly used in English are excluded. For instance, words such as “a”, “each”, “only”, “work” are excluded.

11 We do not account for other information about the contests' statistics in $t - 1$ such as the average quality of participants in the past because this information is not easily computable by participants and we therefore consider that they do not take it into account when deciding whether to participate.

HackerOne, each VRP is run by a distinct company.¹² Thus each VRP is associated to one company. We control for *Prog_Age* and *Total_Nb_participation* in the same way as in Specification 1. *Platform_Growth* measures the number of active VRPs at period t on the platform. It accounts for the time trend. *Managed_by_HO* is a dummy which identifies whether the VRP is fully managed by HackerOne. For the *Firm_Size*, we use the definitions of small, medium-sized and big companies used by the World Bank. Specifically, we classify the companies into 4 categories according to the number of employees they have during the observed period. As the platform is based in the US, contests are subject to US laws so we control for whether the company's headquarters are located in the United States (*Based_in_US*). We also control for the type of industry the company belongs to (*Industry_FE*). Lastly, ε_{it} is an error term. As in Specification 1, we expect β'_1 to be positive according to Hypothesis 1.

It is important to mention that the dependent variable *Nb_participation* is the number of participations that has been evaluated as "valid" participations. In other words, we are not aware of the number of rejected participations. This can be an issue for our specification as the number of relevant participations could also account for some qualitative effects, as valid participations may come from participants with higher Signal scores (i.e., participants who are more likely to submit valid reports. See the following paragraph, which describes the performance indicators we use to measure participant quality). That is, the number of valid participations can be represented as the product of the number of actual participations (rejected participations included) and the probability of each participants submitting a valid report. We perform additional regressions using this definition for the dependent variable, in order to test the robustness of our principal results.

It is also worth noting that in the baseline specifications, we ignore that the number of participations in the period $t - k$ ($k > 0$) can affect the decision of a VRP to modify its policy in period t . In other words, we might ignore the potential simultaneity between the choice of hackers to participate in a VRP (the supply) and the demand of the VRP. Regarding this issue, statistics from show that invalid submissions in HackerOne

¹² Theoretically, a company can run more than one VRP but this is not the case in our data set.

are relatively constant over time.¹³ We could thus consider that ignoring the rejected participations does not have an effect on our estimations. Moreover, according to our data set, VRPs do not change their policy very frequently, which suggests that the “demand effect” is limited: among the 156 VRPs considered in our study, 27,6% of them maintained their choice in providing (or not providing) detailed information about the rewards and 28,2% of them kept their choice in providing (or not) a scope section. On average, VRPs changed their policy 5 times and removed or added detailed information about the rewards and the scope only once during their whole lifetime. Nonetheless, we additionally instrument our main regressor *Information_Level* in order to account for the potential reverse causality. Specifically, we use two variables as our instruments. The first is a dummy which identifies whether the company that owns the VRP (and that finances it) is being *Acquired* by another company at period *t*. The acquisition of the company could cause a change in the VRP’s demand and thus on its policy while it does not directly affect the decision of a hacker to participate in the VRP. We thus consider that the exclusion restriction is satisfied. The second instrument we use is *PSD2*, which accounts for the effect of the second European Directive on Payment Services on cybersecurity investments. This directive came into force in January 2018 and one of its main goals is to improve the security of online and mobile payments and cross-border payment services. The variable *PSD2* identifies whether the core activity of the company that owns the VRP *i* concerns the online or mobile payment sector, whether it is a European company, and whether period *t* is after January 2018. We consider that *PSD2* satisfies the exclusion restriction as it may directly impact the investment decision of a VRP, especially for companies that are regulated (and thus on the choice of the *Information_Level* of a VRP’s policy) but will not impact hackers’ participation.

Next, in order to analyze the effect of the level of information on the quality of participants, three specifications are used.

First, we use Specification 1, with a dependent variable that considers a subgroup of the participations: we use the number of participations by

13 In Zhao et al. (2017), the percentage of valid reports in public VPRs remains relatively stable at around 25% of the total submission during the total observed period of 2 years.

top hackers (*Nb_Top_Hackers*). As suggested in Hypothesis 3, we expect the coefficient for our main explanatory variable *Information_Level* to be negative, i.e., the less information the VRP provides about the contractual terms, the more it attracts “top hackers”, i.e., hackers who are more skilled and experienced.

Secondly, we use a set of dependent variables that reflects the average quality of the participants (*Av_Reputation*, *Av_Signal*, and *Av_Impact*). Indeed, HackerOne provides three different performance indicators that reflect the quality of a hacker over time, which are the *Reputation* score, the *Signal* score and the *Impact* score. These are the indicators we use to build our dependent variables for the quality of the participants. The *Reputation* score is a measure of a hacker's level of experience on the platform. It is an aggregate score of their contribution since the hacker has entered the platform (since it has created an account on HackerOne). It takes account of both the number of valid reports the hacker has submitted and how valuable these contributions are. The *Signal* score is the average relevance of the reports submitted by the hacker. The lower the *Signal* score, the higher the probability that the hacker will submit an invalid report (an invalid report is a report that is considered as not relevant enough or that another participant has already submitted to the VRP). The *Impact* score is a measure of the average severity of the vulnerabilities reported by the hacker. It represents the average value of the relevant reports submitted by the hacker. We compute the mean value of each indicators for participants in each VRP each month to construct our dependent variables *Av_Reputation*, *Av_Signal*, and *Av_Impact*.

The same specification as for *Nb_Participation* (Specification 1) is used to examine the effect of the *Information_Level* on the average quality of the participants. That is:

$$Av_Quality_{it} = \beta''_0 + \beta''_1 Information_Level_{it} + \beta''_2 Prog_Age_{it} + \beta''_3 Total_Nb_participation_{i(t-1)} + FE_i + FE_t + \varepsilon_{it},$$

where we use *Av_Reputation*, *Av_Signal*, and *Av_Impact* as measures of the average quality (*Av_Quality*). Following Hypothesis 3, we expect that β''_1 is negative, i.e., the more detailed a VRP's policy, the lower the participants' average Level of experience and Level of performance.

Lastly, we compute the standard deviation of each quality indicator to define the last series of dependent variables (*Sd_Reputation*, *Sd_Signal*, and *Sd_Impact*). These variables allow us to examine the effect of the level of contractual information provided by a VRP on the variance of participant quality. Again, the same specification is used (Specification 1). As Hypothesis 2 specifies, we expect the coefficient of our main explanatory variable β''_1 to be negative, that is, a less detailed policy attracts participants who are more homogenous in their Levels of both experience and performance.

4.3. Summary statistics

Tables 6 to 10 in the Appendix provide a range of information about the data set we used. Table 6 provides a description of the variables and Table 7 reports the summary statistics. In Table 8, we estimate the mean value of each of our dependent variables (*Nb_Participation*, *Nb_Top_Hackers*, *Av_Reputation*, *Av_Signal*, and *Av_Impact*) according to the total duration of the VRPs and Table 9 presents statistics on the number of times VRPs modified their policies. Lastly, Table 10 reports a correlation matrix for a list of variables.

Our data set is composed of 156 VRPs. A VRP is active for an average of 27 months with a large standard deviation of 17 months. The per-month number of participations varies considerably according to the VRP, with a large proportion of VRP-month pair with 0 participations (25% of the observations are equal to 0). Because of this over-dispersion, we used a Negative Binomial regression for the specifications using the number of participations as the dependent variable.¹⁴

VRPs received an average of 184 valid reports during the total duration of the program and an average of 6.4 valid reports in a month. Overall, for a

¹⁴ Allison and Waterman (2002) shows that the conditional maximum likelihood method for a fixed effects negative binomial regression model presents coefficients that are wrongly statistically significant. We thus use a Negative Binomial regression by including dummy variables for all individuals as they suggest (Also see <https://statisticalhorizons.com/fe-nbreg>). However Wooldridge (1999) recommend using Poisson FE regressions rather than Negative Binomial regressions with fixed effects so we also did some robustness checks using Poisson FE regressions.

given VRP, the number of participations decreased over time. Interestingly, the number of participations is not correlated with the average amount of reward a VRP offered. We also observe that VRPs which ran for a longer period of time had a higher per-month participation rate. On the other hand, it is not because a VRP is run during a longer period of time that participants are more successful on average (See Table 8).

Regarding our main explanatory variables, on average, a VRP's policy was composed of 494 words with large disparity. The average value of *Vocabulary_diversity*—measured by the number of unique “non common” words used in the written policy—was 273. Policies evolved over time, with an average of difference of 654 words between the shortest and the longest version over time. On average, VRPs changed their policy 5 times during their whole lifetime and removed or added a *Reward* or *Scope* section only once during their whole lifetime (See Table 9). From the correlation matrix (See Table 10) we can observe that *Reward* and *Scope* have a positive relation with *Nb_Words*, i.e., a longer policy is more likely to include a reward and a scope section. However, *Reward* and *Scope* are not highly correlated with *Nb_Words*. Lastly, we observe that the number of participations and the average quality of participants are very weakly correlated even though we observe a positive relationship between them.

5. RESULTS

5.1. The effect of the level of information of a VRP's policy on the number of participations

Table 1 reports the regression results for specification 1 and 2 using the number of participations as the dependent variable. We use negative binomial regression with fixed effects by including dummy variables for all individuals.¹⁵ In each pair of columns, we report the results using the three different measures for our main regressor of interest *Information_Level*, namely *Nb_Words*, *Reward*, and *Scope*. The first column of each pair of columns reports the estimation results for Specification 1 and the second

¹⁵ As Wooldridge (1999) has raised some concerns about using Negative Binomial regressions with fixed effects, we also report regression results using Poisson FE in Table 11 in the Appendix.

Table 1. Estimation results for the effect of *Information_Level* on the *Nb_Participation*—Regressions without IVs

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|--------------------------|--------------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| | NB FE | NB | NB FE | NB | NB FE | NB |
| <i>Nb_Words</i> | 0.00263*** (0.000457) | 0.00274*** (0.000395) | | | | |
| <i>Reward</i> | | | 1.620*** (0.552) | 0.887** (0.347) | | |
| <i>Scope</i> | | | | | 2.203*** (0.509) | 0.822** (0.349) |
| <i>Prog_Age</i> | -0.139*** (0.0508) | 0.0469*** (0.0120) | -0.187*** (0.0505) | 0.0429*** (0.0120) | -0.154*** (0.0512) | 0.0463*** (0.0120) |
| <i>Platform_Growth</i> | | -0.0443*** (0.0123) | | -0.0154 (0.0114) | | -0.0187 (0.0118) |
| <i>Firm_Size</i> | | 1.843*** (0.202) | | 1.853*** (0.201) | | 1.896*** (0.201) |
| <i>Managed_byHO</i> | | -0.197 (0.404) | | 0.0589 (0.405) | | -0.114 (0.405) |
| <i>Created_in_90s</i> | | 7.265*** (1.353) | | 6.431*** (1.312) | | 6.116*** (1.382) |
| <i>Created_in2000to2007</i> | | 3.835*** (0.916) | | 3.915*** (0.969) | | 3.431*** (1.072) |
| <i>Created_in2008to2010</i> | | 1.661** (0.754) | | 1.146 (0.792) | | 0.766 (0.877) |
| <i>Created_after_2011</i> | | 1.611** (0.788) | | 1.132 (0.825) | | 0.786 (0.912) |
| <i>Based_in_US</i> | | 2.228*** (0.425) | | 2.724*** (0.418) | | 2.665*** (0.421) |
| VRP FE | ✓ | | ✓ | | ✓ | |
| Time FE | ✓ | | ✓ | | ✓ | |
| Industry dummies | | ✓ | | ✓ | | ✓ |
| Observations | 4,177 | 3,230 | 4,177 | 3,230 | 4,177 | 3,230 |
| LR χ^2 | 2575.07 | 833.22 | 2549.38 | 783.67 | 2559.78 | 782.61 |
| Number of VRPs | 156 | | 156 | | 156 | |

Note: the dependent variable is *Nb_Participation*. Negative Binomial Fixed Effects (using dummies for individuals) and Negative Binomial regressions with robust standard errors. Coefficients are Average Marginal Effects. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The number of observations in columns (2), (4), and (6) are reduced because we do not have the information for the *Firm_Size* for every VRPs. Baseline value for *Created_Period* is “Created before 1990”.

one for Specification 2. As expected, the coefficients for *Nb_Words*, *Reward*, and *Scope*—i.e., β_1 and β'_1 in Specification 1 and 2—are all positive and statistically significant. That is, the more detailed the information in a VRP's policy, the more participations it generates. For example, according to the reported average marginal effects in column (3) and (5), when a VRP provides detailed information about the rewards, participation is increased

by 1.6 more participations per month, while giving detailed information about the scope of the contest generates 2.2 more participations per month.

Regarding the control variables, we observe that *Prog_Age* presents a negative coefficient when we account for individual fixed effects, meaning that when everything else remains fixed, the number of participations decreases over the duration of a VRP. We would explain the different sign of the coefficients for *Prog_Age* for column (2), (4) and (6) by the fact that *Prog_Age* also accounts for the attractiveness specific to each VRPs when we do not control for individual fixed effects, and as we have seen in the summary statistics, VRPs that are launched during a longer period of time are likely to generate more participations on the whole. We also observe that the larger the number of active VRPs on the platform (*Platform_Growth*), the less participation a VRP receives. This may be because new hackers are not entering the platform as fast as new VRPs are created and the amount of effort a hacker dedicates to a single VRP reduces with the number of contests that are launched on the platform. As for coefficients for *Firm_Size*, they are positive and always significant, showing that VRPs owned by larger firms generate a larger number of participations. We do not identify any particular trend regarding the industry sector of the organizing company (See Table 12 in the Appendix), or the age of the company, except that companies created after the 90s generate more participations than older companies. US based companies are likely to be more attractive. Lastly, Table 13 in the Appendix presents regression results including the control variable *Lagged_tot_nb_participation* is included. We do not present these regressions as our main results because *Lagged_tot_nb_participation* is highly correlated with a number of other variables, including our dependent variable (See correlation matrix Table 10). However, we observe that VRPs who have generated a higher number of total participation in the past attract more participation (*Lagged_tot_nb_participation*).

Table 14 in the Appendix reports a set of regressions using alternative measures for the Level of information provided by the contest. Columns (1) and (2) report estimation results when we include the three main regressors—*Nb_Words*, *Reward* and *Scope*—altogether within the same regression.¹⁶ Columns (3) to (6) report estimations using two alternative

¹⁶ We consider that there are no multicollinearity concerns. For instance, Variance inflation factor (VIF) for *Nb_Words*, *Reward* and *Scope* are respectively 2.36, 1.78 and 1.62 for regression in column (2)

measures for *Information_Level*: The first is a measure of the *Vocabulary_Diversity* of the written policy. In comparison to *Nb_Words*, this variable counts the number of unique words that are used in the policy while excluding words that are commonly used in English. The second variable is an aggregated measure of *Nb_Words*, *Reward* and *Scope*, that we named *Contract_Completeness*. This variable is equal to $\ln(\text{Nb_Words} + 1) + \text{Reward} + \text{Scope}$. Estimation results using *Nb_Words*, *Reward* and *Scope* altogether are similar to the main results in Table 1, with some minor differences: coefficients all remain positive, the effect of *Nb_Words* remains the same both in its magnitude and statistical significance, while coefficients for *Reward* and *Scope* variables keep their magnitude but are statistically less significant. Regarding the use of the variables *Vocabulary_Diversity* and *Contract_Completeness*, we obtain very similar results with Table 1.

In order to check whether using the number of valid participations as a measure of the number of participations presents bias, we performed the same regressions (Specifications 1 and 2) using an alternative measure of *Nb_Participation*: we used the sum of $\frac{1}{\text{signal}}$ of all valid participations in a given month (*Nb_Participation_2*). As the *Signal* score reflects the probability of a hacker submitting a valid report, *Nb_Participation_2* represents an estimated value of the number of total participations (both valid and rejected participations). Table 15 in the Appendix reports the regression results. We observe that a greater *Information_Level* still positively affects the number of participations. Moreover, neither the magnitude of the effect nor its significance vary significantly by using this alternative definition. We thus conclude that neither ignoring nor accounting for the rejected participations has an identifiable effect on our main findings.

Note that in the preceding regressions we used Negative Binomial regressions that do not include any instruments to deal with the potential reverse causality between the number of participations and the Level of information of a VRP's policy. The next table reports the estimation results using Poisson IV regressions using a control function approach.

Table 2 reports the estimation results when we include the instrumental variables in our regressions, using Specification 1. As specified in Subsection 4.2, we used two instruments: *Acquired* and *PSD2*. The estimation results for the first stage is reported in Table 16 in the Appendix. First

Table 2. Estimation results of the effect of *Information_Level* on *Nb_Participation*—Regressions with IVs.

| | (1) | (2) | (3) |
|--------------------------|--------------------------|-----------------------|----------------------|
| <i>Nb_Words</i> | 0.00353* (0.00188) | | |
| <i>Reward</i> | | 0.912*** (0.252) | |
| <i>Scope</i> | | | 1.595*** (0.455) |
| <i>Prog_Age</i> | -0.245*** (0.0939) | -0.319*** (0.0698) | -0.570*** (0.148) |
| Residuals of First Stage | -0.00120*** (0.00177) | -0.706*** (0.225) | -1.404*** (0.457) |
| Time FE | ✓ | ✓ | ✓ |
| program FE | ✓ | ✓ | ✓ |
| Observations | 4,177 | 4,177 | 4,177 |
| Fstat (excluded instr.) | 187.67 | 124.59 | 44.46 |
| Number of VRPs | 156 | 156 | 156 |

Note: the dependent variable is *Nb_Participation*. Poisson IV regressions with robust standard errors, using a control function approach. Coefficients are Average Marginal Effects. Bootstrapped Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

stage regressions show that the excluded instrument is correlated with the endogenous variable and the Stock-Yogo test is satisfied.¹⁷ Table 17 in the Appendix shows that the over-identification restrictions are also valid, thus we consider our instruments as valid.

As in Table 1, we report the results for the three different measures for *Information_Level* in each pair of columns. We observe that the coefficients for our main explanatory variables all remain positive and statistically significant. Regarding the coefficients for *Reward* and *Scope*, we observe that the magnitude of the effect is smaller when we correct for the simultaneity between hackers' participations and the VRP's demand for participation. That is, providing more detailed information about the reward and the scope generates more participations but part of the effect is due to reverse causality. Nevertheless, we do not observe a large effect from reverse causality.

All in all, our results confirm Hypothesis 1, showing that more information about the VRP's contractual terms, or in other words, less contractual uncertainty, generates more participations.

¹⁷ We have two instruments and F statistics for the excluded instruments are much greater than 19.93 which is the size of nominal 5% Wald test for 2SLS.

5.2. The effect of the Level of information of a VRP's policy on the performance and experience Levels of participants

Table 3 reports the results for estimations that examine the effect of the level of information of a VRP's policy on the performance and

Table 3. Estimation results for the effect of *Information_Level* on participant quality

| Dependent Variable is | Av_Reputation | Av_Signal | Av_Impact |
|-----------------------------|----------------------|----------------------------|----------------------------|
| | (1) | (2) | (3) |
| Nb_Words | -0.809*** (0.176) | -0.000312*** (0.000109) | -0.000942*** (0.000344) |
| Prog_Age | 32.46* (18.03) | 0.0665*** (0.0137) | 0.202*** (0.0426) |
| Lagged_tot_nb_participation | 0.588* (0.350) | 0.000682** (0.000297) | 0.00459*** (0.000887) |
| Time FE | ✓ | ✓ | ✓ |
| program FE | ✓ | ✓ | ✓ |
| Observations | 3,057 | 3,057 | 3,057 |
| VRPs | 156 | 156 | 156 |
| | (4) | (5) | (6) |
| Reward | -500.3** (236.5) | -0.576*** (0.134) | -1.327*** (0.446) |
| Prog_Age | 44.27** (18.29) | 0.0680*** (0.0134) | 0.212*** (0.0419) |
| Lagged_tot_nb_participation | 0.441 (0.361) | 0.000720** (0.000296) | 0.00458*** (0.000892) |
| Time FE | ✓ | ✓ | ✓ |
| program FE | ✓ | ✓ | ✓ |
| Observations | 3,057 | 3,057 | 3,057 |
| | (7) | (8) | (9) |
| Scope | -289.1 (182.8) | -0.0560 (0.123) | -0.134 (0.408) |
| Prog_Age | 41.64** (18.31) | 0.0744*** (0.0137) | 0.227*** (0.0423) |
| Lagged_tot_nb_participation | 0.268 (0.360) | 0.000569* (0.000295) | 0.00424*** (0.000876) |
| Time FE | ✓ | ✓ | ✓ |
| program FE | ✓ | ✓ | ✓ |
| Observations | 3,057 | 3,057 | 3,057 |
| VRPs | 156 | 156 | 156 |

Note: We use Poisson regression for *Av_Reputation*, OLS regressions for *Av_Signal* and *Av_Impact* scores. For all regressions, VRP and time fixed effects are included. Coefficients are Average Marginal Effects for Poisson regression. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

experience levels of participants, using as dependent variables *Av_Reputation*, *Av_Signal*, and *Av_Impact*.

Each triplet of columns in Table 3 reports regression results using the three different measures for *Information_Level* (*Nb_Words*, *Reward*, and *Scope*) and for each column of each triplet, we use the three different measures of participant quality *Av_Reputation*, *Av_Signal*, and *Av_Impact*. As a reminder, *Reputation* represents the experience level of a participant, *Signal* reflects the probability that the participant will submit a valid solution and *Impact* reflects the probability that the participant will submit a valid solution and *Impact* reflects the average severity of the vulnerabilities that are found by the hacker, i.e., how valuable its participation is on average. We use a Poisson regression for *Av_Reputation* while we use linear regressions for *Av_Signal* and *Av_Impact*. Additionally, Table 18 in the Appendix reports the same regressions using standardized values for the dependent variables (i.e., values are rescaled from 0 to 1), so that one can compare the effect of the explanatory variables on the different measures of participant quality.

As expected, the coefficients for *Information_Level* are negative, meaning that less information about the contractual terms, i.e., more uncertainty about getting rewarded, attracts hackers who are more experienced, who find more critical vulnerabilities and who makes less mistakes on average. We also observe that the effect of the amount of information provided in the written policy or detailing the amounts of rewards are statistically significant while the effect of detailing the scope is not. On the other hand, we observe from Table 18 in the Appendix (where values of the dependent variables are rescaled from 0 to 1) that the magnitude of the effect does not vary a lot for the different quality indicators. We also observe that the coefficients for *Prog_Age* are all positive, showing that over time, more skilled and experienced participants are participating on average.

Next, in Table 4, we report the regression results for Specification 1 and 2 using the *Nb_Top_Hackers* as the dependent variable. "Top hackers" are those with *Reputation*, *Signal* and *Impact* scores at the 30th percentile.¹⁸ In Table 4, coefficients for *Information_Level* are mostly negative and are

¹⁸ Other definition for top hackers were tested, such as *Reputation*, *Signal* and *Impact* scores at the 25th percentile, *Reputation* and *Signal* scores at the 25th or 30th percentiles. We obtain similar results for these definitions. Otherwise, we

Table 4. Estimation results for the effect of *Information_Level* on *Nb_Top_Hackers*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|------------------|------------------------|---------------|------------------------|---------------|------------------------|
| | NB FE | NB | NB FE | NB | NB FE | NB |
| <i>Nb_Words</i> | -3.08e-05 (0) | 9.57e-06 (9.21e-05) | | | | |
| <i>Reward</i> | | | -0.175 (0) | -0.0436 (0.0919) | | |
| <i>Scope</i> | | | | | 0.0633 (0) | -0.112 (0.0968) |
| <i>Prog_Age</i> | 0.0164 (0) | 0.0168*** (0.00364) | 0.0140 (0) | 0.0170*** (0.00365) | 0.0194 (0) | 0.0172*** (0.00367) |
| <i>Platform_Growth</i> | | -0.00136 (0.00343) | | -0.000955 (0.00325) | | -0.000139 (0.00334) |
| <i>Firm_Size</i> | | 0.461*** (0.0629) | | 0.463*** (0.0630) | | 0.463*** (0.0631) |
| <i>Managed_byHO</i> | | 0.541*** (0.130) | | 0.537*** (0.129) | | 0.562*** (0.131) |
| <i>Created_in_gos</i> | | 1.146*** (0.287) | | 1.133*** (0.288) | | 1.171*** (0.286) |
| <i>Created_in2000to2007</i> | | 1.022*** (0.226) | | 1.032*** (0.225) | | 1.120*** (0.242) |
| <i>Created_in2008to2010</i> | | 0.615*** (0.146) | | 0.604*** (0.149) | | 0.646*** (0.145) |
| <i>Created_after_2011</i> | | 0.0612 (0.120) | | 0.0518 (0.122) | | 0.0827 (0.114) |
| <i>Based_in_US</i> | | 0.0433 (0.107) | | 0.0536 (0.104) | | 0.0689 (0.105) |
| VRP FE | ✓ | | ✓ | | ✓ | |
| Time FE | ✓ | | ✓ | | ✓ | |
| Industry dummies | | ✓ | | ✓ | | ✓ |
| Observations | 4,177 | 3,230 | 4,177 | 3,230 | 4,177 | 3,230 |
| LR χ^2 | 1408.74 | 557.27 | 1409.02 | 583.23 | 1408.91 | 582.57 |
| Number of VRPs | 156 | | 156 | | 156 | |

Note: the dependent variable is *Nb_Top_Hackers*. *Nb_Top_Hackers* are hackers who have *Reputation*, *Signal* and *Impact* scores at the 30th percentile of all participants on the platform during the month. Negative Binomial FE (using dummies) and Negative Binomial regressions with robust standard errors. Coefficients are Average Marginal Effects. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The number of observations in columns (2), (4), and (6) are reduced because we do not have the information for the *Firm_Size* for every VRP.

not statistically significant. The sign of the effect—the negative coefficients—corroborates the idea that providing more information attracts less successful hackers. This result also rejects the idea that the negative

find a positive sign and no statistical significance for the coefficients of the main explanatory variables when the scores are at a larger percentile.

Table 5. Estimation results for the effect of *Information_Level* on the variance of participant quality

| Dependent Variable is | <i>Sd_Reputation</i> | <i>Sd_Signal</i> | <i>Sd_Impact</i> |
|------------------------------------|-----------------------|---------------------------|---------------------|
| | (1) | (2) | (3) |
| <i>Nb_Words</i> | 0.137*** (0.00299) | 0.000302*** (7.42e-05) | 0.0981 (0.155) |
| <i>Prog_Age</i> | -0.454 (0.343) | -0.00771 (0.00931) | 0.805 (19.50) |
| <i>Lagged_tot_nb_participation</i> | 1.155*** (0.00710) | 0.000288 (0.000203) | 1.375*** (0.424) |
| Time FE | ✓ | ✓ | ✓ |
| program FE | ✓ | ✓ | ✓ |
| Observations | 3,057 | 3,057 | 3,057 |
| VRPs | 156 | 156 | 156 |
| | (4) | (5) | (6) |
| <i>Reward</i> | 81.14*** (3.393) | 0.233** (0.0916) | 143.7 (191.7) |
| <i>Prog_Age</i> | -2.836*** (0.337) | -0.0136 (0.00914) | -0.189 (19.11) |
| <i>Lagged_tot_nb_participation</i> | 1.175*** (0.00711) | 0.000343* (0.000202) | 1.373*** (0.423) |
| Time FE | ✓ | ✓ | ✓ |
| program FE | ✓ | ✓ | ✓ |
| Observations | 3,057 | 3,057 | 3,057 |
| VRPs | 156 | 156 | 156 |
| | (7) | (8) | (9) |
| <i>Scope</i> | 152.3*** (3.177) | 0.152* (0.0841) | 108.2 (175.8) |
| <i>Prog_Age</i> | 0.526 (0.347) | -0.0127 (0.00933) | 0.743 (19.50) |
| <i>Lagged_tot_nb_participation</i> | 1.184*** (0.00703) | 0.000378* (0.000202) | 1.392*** (0.421) |
| Time FE | ✓ | ✓ | ✓ |
| program FE | ✓ | ✓ | ✓ |
| Observations | 3,057 | 3,057 | 3,057 |
| VRPs | 156 | 156 | 156 |

Note: the dependent variable is the Standard Deviation of participant quality (*Av_Reputation*, *Av_Signal*, *Av_Impact* scores) during the month. Poisson regression for *Sd_Reputation*, OLS regressions for *Sd_Signal* and *Sd_Impact* scores. For all regressions, VRP and time fixed effects are included. Coefficients are Average Marginal Effects for Poisson regression. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

effect of higher Level information on average quality comes from a long tail distribution of low-quality hackers. In the meantime, the effect is statistically less significant as we focus on the behavior of more skilled and more experienced participants (the “top hackers”). This difference in statistical significance could be interpreted as less successful hackers are

more sensitive to the degree of information provided by a contest while top hackers are less affected. This has an important practical implication in that changing the Level of information will influence the number of low quality participants rather than that of high quality participants.

While the dependent variable in Table 3 is the measure of the quality itself, we report in Table 5 the regression results for the effect of the *Information_Level* on the variance of participant quality. In Table 5, each triplet of columns reports the regression results using the standard deviation of *Av_Reputation*, *Av_Signal* and *Av_Impact* as dependent variables. The coefficients for *Information_Level* are all positive, corroborating Hypothesis 2. That is, providing more information about the contract increases the variance of participants' performance and experience, while providing less information attracts participants that are more homogenous in their attributes. The coefficients are also always statistically significant except for the case where we use *Scope* as a measure of the Level of information. Additionally, we observe that the coefficients for *Prog_age* are always negative, meaning that participant quality becomes more homogenous over the duration of a VRP.

6. DISCUSSION AND CONCLUSION

The objective of this paper was to see how the main communication tool for a Vulnerability Research Program, its written policy, may affect its efficiency. We particularly focused on the Level of information it provides about the contractual terms. We consider that the Level of information determines the uncertainty perceived by participants about getting compensated and we used three variables that represent different aspects of the Level of information: the length of the VRP's policy, whether it provides detailed information about the reward, and the scope of the contest.

Using a data set covering 4 years of activities, we found that providing more information about the contest generates more participations but also reduces the overall quality of participants and increases the variance of their quality. In particular, participants with a top ranking, i.e., the most skilled and experienced hackers, are not strongly affected by the Level of contractual information. On the contrary, leaving more uncertainty about the rewards and what is expected in exchange is likely to attract more homogenous, more successful and more experienced participants.

As with any empirical work, this paper has some limitations that present opportunities for future research. First, the main dependent variable we use as a measure of the outcome of a VRP is the number of valid participations. As we only observed participations that are rewarded, we are not aware of the number of rejected participations. Although we consider that ignoring the rejected participations does not affect our estimation¹⁹, we also estimate a variety of different models accounting for the *Signal* score in order to compensate for this limitation. Secondly, the number of valid participations equates to the number of vulnerabilities that are found and fixed. It therefore represents the quantitative aspect of the outcome. As for qualitative measures, it would have also been relevant to use the amount of the rewards or the severity of the vulnerabilities. However, this information is not systematically disclosed to public and analyzing only reports that are fully disclosed would present significant selection bias.²⁰ Instead, we used a variety of different models that estimate the effect of the information Level on the performance and experience Levels of participants.

Our work confirms the findings of—which is based on a laboratory experiments on 120 students—in a more robust way, using a “natural setting” from 156 contests involving 184 participants on average. Our approach is unique, as the uncertainty of being compensated is reflected through several measures that reflects the completeness of a contract.²¹ This allows us to have a greater granularity in the degree of uncertainty a contract represents. We show that the self-selection effect also exists and is significant when a worker has to choose among contests with different degrees of contractual uncertainty. Our understanding is that more experienced and more skilled participants are more inclined to take risks (i.e., to select a more uncertain contract) because they are more certain of their ability to succeed and to get a reward. Another interpretation would be that more experienced hackers are more able to assess the needs of the VRP owner even when the VRP does not provide sufficient information either volun-

19 Statistics on the platform show that invalid submissions are relatively constant over time (Zhao et al., 2017).

20 Disclosed reports are usually examples of good practice or an advertising of the VRP that show how it pays well or communicates well.

21 Most research that studies the self-selection effect, including Eriksson et al. (2009), compares variable-pay schemes to “less variable” pay schemes.

tarily or because it lacks experience in managing such contests. This self-selection process is all the more important for contests like VRPs since it has an impact on reducing the triage cost by limiting the number of non-relevant participations.

Our findings also provide interesting insights in terms of managerial implications for companies organizing a VRP, and in the understanding of a bug bounty platform's strategy.

6.1. Managerial implications for VRP owners

We show that the choice of a VRP to reveal more or less information to potential participants leads to a trade-off between having a larger number of participation but attracting less skilled participants and attracting higher quality participants but generating fewer participations. Thus the VRP should strike a balance according to the type of outcome it is looking for. If the VRP is aimed at fixing a maximum number of vulnerabilities and is not specifically looking for the scarcity or originality of vulnerabilities, giving more detailed information and offering more complete contractual terms encourage a maximum number of hackers to participate. Although they would not necessarily be the most skilled, each hacker would provide a certain Level of effort, while the number of participations is maximized. However, if the objective of the VRP is to find the most complex and severe vulnerabilities, our results suggest that leaving more uncertainty helps select the best profiles since only the most skilled and experienced ones would choose VRPs that provide less information.

VRPs can modify their policy anytime they want. Thus, they can start by providing very little information at first in order to attract only the best participants, then provide progressively more details in order to attract additional participants. Besides, our regressions show that older VRPs attract fewer participants. Providing more information could alleviate this effect.

VRP owners also learn over time: they learn how to formulate their needs, how to better evaluate the financial value of a vulnerability, and how to better communicate with hackers. Thus they become more efficient over time, by reducing the marginal cost to handle a report from beginning to end. As the VRP gets more efficient, it can afford to handle a larger

number of participations and may prefer to lessen the Level of screening by providing more information.

VRPs can also combine the use of a minimum quality standard (by managing a private VRP) and the self-selection effect of contractual uncertainty. For instance, one can first run a public VRP and manage the screening Level by controlling the information it provides, then after having processed sufficient participations, it can turn into a private VRP that invites only hackers with a minimum Level of past performance.

It is interesting to note that the platform advises the contrary to companies: it suggests first launching a private VRP with preselected participants (for which it receives an additional service fee) and then going public in a second phase. Indeed, the platform considers that applying a minimum quality standard is the only way to reduce the triage cost. Our findings offer a different perspective.

This raises further questions about whether the platform's goal is aligned with the goal of a VRP.

6.2. The bug bounty platform

Bug bounty platforms take full advantage of their two-sidedness. They benefit from cross-sided network effects between VRPs and hackers: firms launch their VRP on the platform, because they can get access to a large pool of hackers, while hackers benefit from accessing a large number of contests on a single platform, which additionally allows them to maintain a "hacker" profile that cumulates experiences from the different VRPs run on the platform. As it is common in this type of markets, the platform uses an asymmetric pricing strategy, where hackers get free access to the platform, while companies pay a usage fee. Besides, hackers can multi-home while companies usually launch their VRPs on a single platform, as it is costly for them to manage multiple VRPs using distinct platforms. Regarding the usage fee, HackerOne requests a fee proportional to the amount of rewards a VRP pays to hackers (HackerOne requires around 20% of each reward, which also include the taxes). The basic service a company can subscribe to is the access to the web platform and a customized web interface to manage its VRP. The platform also offers a range of services companies can subscribe, related to the management of a VRP: it can

help sort the submitted reports, manage the whole program, pre-select skilled hackers for private VRPs, etc.

As an intermediary between VRPs and participants, the platform stores information that neither VRPs nor the hackers have access to. The platform is best able to analyze hackers' behavior and to create the right incentives so that they work efficiently. It also advises the VRP owners. Although we do not have much information about the advice they offer to VRPs, publicly disclosed information shows that the platform recommends providing detailed information to participants: it points out that being transparent and providing accurate and detailed information helps to create a trusting relationship with hackers.

If we consider that the platform earns mainly from VRP hosting (by receiving a fee proportional to the rewards offered to hackers), the goal of the platform is aligned with those of the VRPs: maximizing the sum of the values of fixed vulnerabilities, or in other words, generating the largest value of transactions. It is then in the platform's interest to reduce the transaction cost and to limit the rate of non relevant participations. In this sense, our findings, which show an alternative way of running a private VRP in order to reduce the triage cost, is worthy of interest for the platform. However, if the platform gains more from services that complement the VRP hosting service, such as managing a VRP from beginning to end or preselecting skilled hackers, its advice and decisions could go against the actual interest of a VRP owner.

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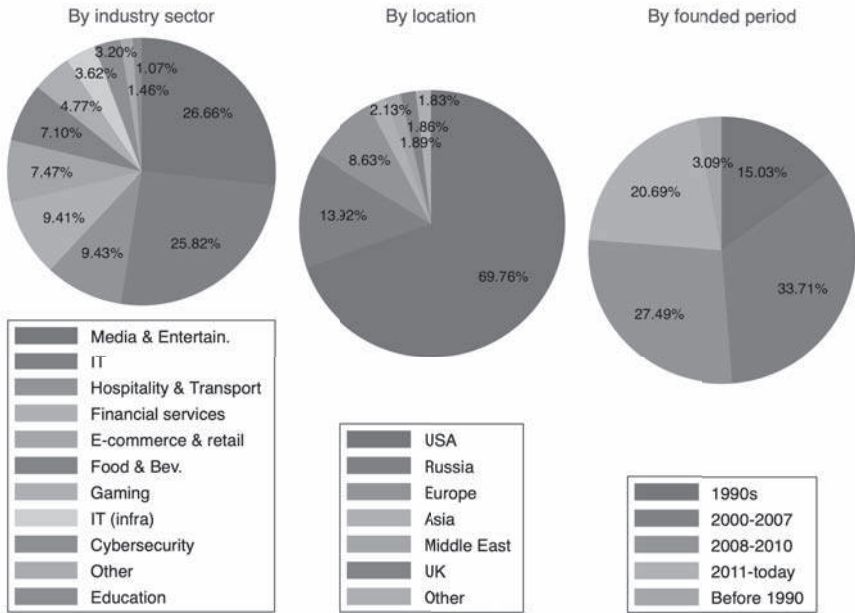
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APPENDIX


Figure 2. Distribution of VRP owners



Tabel 6. Description of variables

| Variable | Description |
|------------------------------------|---|
| <i>Nb_Participation</i> | Total number of valid reports a VRP processed during the month |
| <i>Nb_Top_Hackers</i> | Total number of valid reports submitted by “Top hackers”, i.e., hackers whose <i>Reputation</i> , <i>Impact</i> and <i>Signal</i> scores are at the 30th percentile |
| <i>Av_Reputation</i> | The average <i>Reputation</i> score of the participants to a given VRP at a given month. The <i>Reputation</i> score is an aggregate score of a hackers' contribution in terms of vulnerability severity, relevancy, and quantity |
| <i>Av_Signal</i> | The average <i>Signal</i> score of the participants to a given VRP at a given month. The <i>Signal</i> score is the average relevance of the reports submitted by a hacker |
| <i>Av_Impact</i> | The average <i>Impact</i> score of the participants to a given VRP at a given month. <i>Impact</i> is a measure of the average severity of the vulnerabilities reported by a hacker. |
| <i>Sd_Reputation</i> | Standard deviation of <i>Av_Reputation</i> |
| <i>Sd_Signal</i> | Standard deviation of <i>Av_Signal</i> |
| <i>Sd_Impact</i> | Standard deviation of <i>Av_Impact</i> |
| <i>Nb_Words</i> | Number of words of the written policy at the observed period |
| <i>Reward</i> | A dummy which identifies whether the VRP provides detailed information about the structure and the amount of the rewards during period <i>t</i> |
| <i>Scope</i> | A dummy which identifies whether the policy includes a dedicated section that describes in detail the scope targeted by the contest. |
| <i>Vocabulary_Diversity</i> | Number of unique words used in the written policy, excluding 422 words that are the most commonly used in English. |
| <i>Contract_Completeness</i> | Equal to $\ln(Nb_Words + 1) + Reward + Scope$ |
| <i>Prog_Age</i> | Number of months since the VRP was launched |
| <i>Lagged_tot_nb_participation</i> | Total number of participations to the VRP in the past |
| <i>Firm_size</i> | Categorization of the size of the company which owns the VRP by their number of employees (Small, Medium Size company, Big company) |
| <i>Founded_period dummies</i> | Dummies on whether the VRP owner (the organizing company) was created in 90s, from 2000 to 2007, from 2008 to 2010, or after 2011. |
| <i>Industry dummies</i> | The type of industry the VRP's owner company belongs to |
| <i>Managed_by_HO</i> | A dummy which identifies whether the VRP is fully managed by HackerOne |
| <i>Platform_Growth Based_in_US</i> | The number of active VRPs on the platform at a given period A dummy equal to 1 if the organizing company of the VRP is based in the US (headquarters located in the US) |
| <i>Acquired</i> | A dummy which identifies whether the company that owns the VRP (and thus that finances it) is being <i>Acquired</i> by another company during period <i>t</i> |
| <i>PSD2</i> | A dummy which identifies whether the core activity of the company that owns the VRP <i>i</i> concerns the online or mobile payment sector, whether it is a European company, and whether period <i>t</i> is after January 2018 |

Figure 3. Example of VRP on HackerOne, providing minimal information about the contractual terms: General Motor's VRP



General Motors

www.gm.com • Launched on January 5th, 2016

Policy Hackactivity Thanks Updates (0)
Submit Report

Policy

Committed to Coordination

If you have information related to security vulnerabilities of General Motors products and services, we want to hear from you. Please submit a report in accordance with the guidelines below. We value the positive impact of your work and thank you in advance for your contribution.

Guidelines

GM agrees to not pursue claims against researchers related to the disclosures submitted through this website who:

- do not cause harm to GM, our customers, or others;
- provide a detailed summary of the vulnerability, including the target, steps, tools, and artifacts used during discovery (the detailed summary will allow us to reproduce the vulnerability);
- do not compromise the privacy or safety of our customers and the operation of our services;
- do not violate any criminal law;
- do not violate any other law (other than those that would result only in claims by GM), or disrupt or compromise any data or vehicle that is not their own;
- publicly disclose vulnerability details only after GM confirms completed remediation of the vulnerability and not publicly disclose vulnerability details if there is no completion date or completion cannot be ascertained;
- confirm that they are not currently located in or otherwise ordinarily resident in Cuba, Iran, North Korea, Sudan, Syria or Crimea; and
- confirm that they are not on the U.S. Department of the Treasury's Specially Designated Nationals List.

Out of Scope

1. Reports from automated tools or scans
2. Issues without clearly identified security impact (such as clickjacking on a static website), missing security headers, or descriptive error messages
3. Missing best practices, information disclosures, use of a known-vulnerable libraries or descriptive / verbose / unique error pages (without substantive information indicating exploitability)
4. Speculative reports about theoretical damage without concrete evidence or some substantive information indicating exploitability
5. Forms missing CSRF tokens without evidence of the actual CSRF vulnerability
6. Self-exploitation (e.g., cookie reuse)
7. Reports of insecure SSL / TLS ciphers (unless you have a working proof of concept, and not just a report from a scanner such as SSL Labs)
8. Our policies on presence/absence of SPF / DMARC records
9. Password complexity requirements, account/e-mail enumeration, or any report that discusses how you can learn whether a given username or email address has a GM-related account
10. Missing security-related HTTP headers which do not lead directly to a vulnerability
11. Self Cross-site Scripting vulnerabilities without evidence on how the vulnerability can be used to attack another user
12. Social engineering of GM employees or contractors
13. Any physical attempt against GM property or data centers
14. Presence of autocomplete attribute on web forms
15. Missing secure cookie flags on non-sensitive cookies
16. Denial of Service Attacks
17. Banner identification issues (e.g., identifying what web server version is used)
18. Open ports which do not lead directly to a vulnerability
19. Open redirect vulnerabilities
20. Publicly accessible login panels
21. Clickjacking
22. Content spoofing / text injection

By clicking Submit Report, you consent to Your Information being transferred to and stored in the United States and acknowledge that you have read and accepted the Terms, Privacy Policy and Disclosure Guidelines presented to you when you created your account.

Last updated on May 7, 2016. [View changes](#)

Figure 4. Example of VRP on HackerOne, providing very detailed information about the contractual terms: Slack's VRP

The screenshot displays the Slack Vulnerability Rewards Program (VRP) page on HackerOne. The header includes the Slack logo and tagline: "All your team communication in one place, instantly searchable, and available wherever you go." Below the header, there are navigation links for Policy, Hacktivity, Thanks, and Updates (0), along with social media icons and a "Submit Report" button.

Rewards

| Critical | High | Medium | Low |
|----------|---------|--------|-------|
| \$1,500 | \$1,000 | \$500 | \$100 |

Policy

NEW: Program Update and Guide

Slack is committed to treating our customers' data with the utmost care. As part of this, we encourage security researchers to put our security to the test - and we offer a variety of rewards for doing so. We look forward to continuing to work with the community as we add new features and services.

This page is intended for security researchers. For general information about security at Slack, please see our main website.

Program Rules

- Automated testing is not permitted.
- Follow HackerOne's Disclosure Guidelines.
- Test only with your own team(s) when investigating bugs, and do not interact with other accounts without the consent of their owners.
- You must be the first person to report the issue to us. We will review duplicate bugs to see if they provide additional information, but otherwise only reward the first reporter.
- We award bounties at time of fix, and will keep you posted as we work to resolve them.
- Contacting our support team (feedback@slack.com) about the status of a HackerOne report will result in an immediate disqualification for a bounty for that report.

Bug Bounty Rewards

The following guidelines give you an idea of what we usually pay out for different classes of bugs. Low-quality reports may be rewarded below these tiers, so please make sure that there is enough information for us to be able to reproduce your issue. Step-by-step instructions including how to reproduce your issue starting out by creating a fresh Slack account are preferred. Screenshots and videos are also helpful, but please make sure to not make these public before submitting them to follow our program's rules.

There is no maximum reward - particularly creative or severe bugs will be rewarded accordingly. Depending on the severity of the bug, and the quality of your report, we may pay a lower-tier bug out at a higher level.

Tier 3: Low Severity Bugs \$100 and up

- Mixed content issues
- "Tab-Nabbing" or other (rel="noopener") bugs
- Self-XSS (XSS requiring interaction other than browsing to exploit)
- Server misconfiguration or provisioning errors
- Information leaks or disclosure (excluding customer data)
- And other low-severity issues

Tier 2: Medium Severity Bugs \$500 and up

- Cross-Site Request Forgery on Sensitive Actions or Functions (CSRF/XSRF)
- Broken Authentication affecting a single team
- Privilege Escalation affecting a single team
- SSRF to an internal service, hosted by slack
- Information leaks or disclosure (including customer data)
- And other medium-severity issues

Tier 1: High Severity Bugs \$1000 and up

- XSS

Response Efficiency

91% of reports
Meet response standards

Program Statistics

\$342,166
Total bounties paid
\$1,000 - \$10,000
Top bounty range
737
Reports resolved
385
Hackers thanked

Top hackers

- Jurajk Reputation:1828
- danlec Reputation:1650
- fransrosen Reputation:1288
- Iuji Reputation:1245
- imnarendrabhati Reputation:1057

All Hackers

Figure 4. Rest of Slack's VRP policy

Tier 0: Critical Severity Bugs \$1500 and up

- SQL Injection
- Remote Code Execution
- Privilege Escalation affecting all teams
- Broken Authentication affecting all teams
- SSRF to an internal service, with extremely critical impact (e.g. immediate and direct security risk)
- And other critical-severity issues

What's In Scope

- slack.com
- api.slack.com
- status.slack.com
- Tier-3 and Higher: screenhero.com (and subdomains that explicitly are run by Slack, and are required for the screenhero service to operate)
- Tier-0 bugs only for the following:
 - slackatwork.com
 - slack-redir.net
 - slack-files.com
 - slack-lmgs.com
 - spaces.pm
- Current versions of the official Slack applications for Windows, Mac, Linux, iOS, Android, and Windows Phone
- Apps that are maintained by Slack itself (and *not* 3rd party applications). To identify apps that are in scope for bug bounty, please go to the page for that app (for example, email) and ensure there is no link to "Report this app" under the icon for the application.

Testing notes

- Contacting our support team (feedback@slack.com) about the status of a hackerone report will result in an immediate disqualification for a bounty for that report.
- CSRF: we use a parameter named `crumb` for our CSRF tokens in our production application. CSRF reports that include this parameter in the proof of concept will be marked as invalid.
- Cookie Scope: the only sensitive cookies in the Slack product reside on `.slack.com` and not on other `slack-` domains.

Exclusions

The following bugs are unlikely to be eligible for a bounty:

- Issues found through automated testing
- Vulnerabilities requiring physical access to the victim's unlocked device
- Denial of Service attacks
- Spam or Social Engineering techniques, including SPF and DKIM Issues
- Full-Path Disclosure on any property
- Version number information disclosure
- Third-party applications on the Slack Application directory (identified by the existence of a "Report this app" link on the app's page). Please report issues with these services to the creator of that specific application.
- Clickjacking on pre-authenticated pages, or the non-existence of X-Frame-Options, or other non-exploitable clickjacking issues (An exploitable clickjacking vulnerability requires a) a frame-able page that is b) used by an authenticated user and c) which has a state-changing action on it vulnerable to clickjacking/frame re-dressing)
- CSRF-able actions that do not require authentication (or a session) to exploit
- 3rd-party subdomains of screenhero.com that are not explicitly required for the product to function (e.g. feedback.screenhero.com is not in scope)
- Reports related to the following security-related headers:
 - Strict Transport Security (HSTS)
 - XSS mitigation headers (`X-Content-Type` and `X-XSS-Protection`)
 - X-Content-Type-Options
 - Content Security Policy (CSP) settings (excluding `nosniff` in an exploitable scenario)
- Bugs that do not represent any security risk - these should be reported to feedback@slack.com.
- Issues with other domains or applications owned or related to Glitch or Tiny Speck
- Security bugs in slackhq.com and blog.screenhero.com - these sites runs on Tumblr, so if you find vulnerabilities in the Tumblr service, please see Tumblr's bounty program for reporting details
- Security bugs in third-party applications or services built on the Slack API - please report them to the third party that built the application or service
- Security bugs in software related to an acquisition for a period of 90 days following any public announcement

Table 7. Summary statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|-----------------------------|------|---------|-----------|-----|---------|
| Nb_Participation | 4177 | 6.38 | 10.58 | 0 | 140 |
| Nb_Participation_2 | 4177 | 7.845 | 14.18 | 0 | 191.21 |
| Av_Reputation | 3057 | 2174.74 | 2909.83 | 8 | 36120 |
| Av_Signal | 3057 | 2.46 | 1.80 | -4 | 7 |
| Av_Impact | 3057 | 12.45 | 6.11 | 0 | 37.5 |
| Rescaled Av_Reputation | 3057 | .06 | .081 | 0 | 1 |
| Rescaled Av_Signal | 3057 | .587 | .163 | 0 | 1 |
| Rescaled Av_Impact | 3057 | .332 | .163 | 0 | 1 |
| Nb_Top_Hackers | 4177 | .906 | 2.904 | 0 | 53 |
| Sd_Reputation | 3057 | 1854.95 | 2427.54 | 0 | 25142.6 |
| Sd_Signal | 3057 | 1.59 | 1.16 | 0 | 7.21 |
| Sd_Impact | 3057 | 5.65 | 3.91 | 0 | 25 |
| Nb_Words | 4177 | 493.84 | 457.31 | 0 | 2509 |
| Vocabulary_Diversity | 4177 | 272.66 | 257.01 | 0 | 1292 |
| Reward | 4177 | .349 | .477 | 0 | 1 |
| Scope | 4177 | .430 | .495 | 0 | 1 |
| Contract_Completeness | 4177 | 5.31 | 3.51 | 0 | 9.69 |
| Prog_Age | 4177 | 16.98 | 14.3 | 0 | 64 |
| Lagged_tot_nb_participation | 4177 | 146.49 | 228.28 | 0 | 2420 |
| Managed_by_HO | 4177 | .245 | .43 | 0 | 1 |
| Based_in_US | 4177 | .682 | .466 | 0 | 1 |
| Firm_Size | 3260 | 2.89 | 1.03 | 1 | 4 |
| Platform_Growth | 4177 | 66 | 15.51 | 19 | 89 |
| Acquired | 4177 | .028 | .17 | 0 | 1 |
| PSD2 | 4177 | .052 | .22 | 0 | 1 |

Table 8. Mean values of the dependent variables according to the duration of a VRP

| Duration of a VRP (in months) | Mean value of Nb_Participation | Mean value of Nb_Top_Hackers | Mean value of Av_Reputation | Mean value of Av_Signal | Mean value of Av_Impact |
|-------------------------------|--------------------------------|------------------------------|-----------------------------|-------------------------|-------------------------|
| - 5 | 5.15 | 0.59 | 1722 | 2.70 | 13.37 |
| 5 - 15 | 5.39 | 0.59 | 1743 | 1.95 | 10.19 |
| 15 - 25 | 3.49 | 0.34 | 2048 | 2.33 | 11.51 |
| 25 - 35 | 6.03 | 0.84 | 1815 | 2.37 | 12.02 |
| 35 - 45 | 4.69 | 0.60 | 2184 | 2.30 | 12.28 |
| 45 - 55 | 8.98 | 1.40 | 2275 | 2.39 | 12.74 |

Table 9. Statistics on the number of times a VRP has modified its policy

| | Number of times a VRP added or removed | | | |
|------------|--|-------------------|-------|----------------------|
| | Detailed information about rewards | The scope section | Words | Vocabulary Diversity |
| On average | 1.01 | 0.97 | 5.04 | 5.00 |
| Minimum | 0 | 0 | 0 | 0 |
| Maximum | 3 | 2 | 25 | 25 |

Table 10. Correlation matrix of the principal variables

| | Nb_ Participation | Nb_Top_ Hackers | Nb_ Participation_2 | Av_ Reputation | Av_ Signal | Av_ Impact | Nb_ Words | Reward | Scope | Contract_ Comp. | Vocabulary_ Div. | Prog_ Age | Lagged_ tot_nb_p. | Platform_ Growth |
|-----------------------------|-------------------|-----------------|---------------------|----------------|------------|------------|-----------|--------|--------|-----------------|------------------|-----------|-------------------|------------------|
| Nb_ Participation | 1.0000 | | | | | | | | | | | | | |
| Nb_Top_ Hackers | 0.6422 | 1.0000 | | | | | | | | | | | | |
| Nb_ Participation_2 | 0.9928 | 0.5915 | 1.0000 | | | | | | | | | | | |
| Av_ Reputation | 0.0459 | 0.1799 | 0.0238 | 1.0000 | | | | | | | | | | |
| Av_ Signal | 0.1412 | 0.2571 | 0.0785 | 0.3542 | 1.0000 | | | | | | | | | |
| Av_ Impact | 0.0890 | 0.1559 | 0.0537 | 0.2997 | 0.5904 | 1.0000 | | | | | | | | |
| Nb_ Words | 0.0954 | 0.0234 | 0.0964 | -0.0983 | 0.0136 | -0.0027 | 1.0000 | | | | | | | |
| Reward | 0.0790 | 0.0240 | 0.0814 | -0.0809 | -0.0267 | -0.0429 | 0.5482 | 1.0000 | | | | | | |
| Scope | 0.0559 | 0.0574 | 0.0482 | -0.0246 | 0.0342 | -0.0115 | 0.5186 | 0.2770 | 1.0000 | | | | | |
| Contract_ Completeness | 0.0446 | -0.0178 | 0.0502 | -0.1455 | -0.0393 | -0.0691 | 0.8077 | 0.5951 | 0.6561 | 1.0000 | | | | |
| Vocabulary_ Diversity | 0.0992 | 0.0283 | 0.0994 | -0.0936 | 0.0178 | 0.0030 | 0.9895 | 0.5221 | 0.5324 | 0.7954 | 1.0000 | | | |
| Prog_ Age | 0.0647 | 0.0598 | 0.0527 | -0.0871 | 0.0587 | 0.0415 | 0.2441 | 0.2141 | 0.1969 | 0.3226 | 0.2418 | 1.0000 | | |
| Lagged_tot_nb_participation | 0.4511 | 0.3350 | 0.4228 | 0.0057 | 0.1734 | 0.1030 | 0.1692 | 0.1515 | 0.1217 | 0.1155 | 0.1796 | 0.5629 | 1.0000 | |
| Platform_ Growth | -0.0125 | 0.0078 | -0.0305 | -0.1059 | 0.1510 | 0.0802 | 0.3831 | 0.1807 | 0.2499 | 0.4011 | 0.3770 | 0.4120 | 0.2012 | 1.0000 |

Table 11. Estimation results for the effect of *Information_Level* on the *Nb_Participation*—Using Poisson FE

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-------------------------------|--------------------------|--------------------------|-----------------------|-------------------------|-----------------------|-------------------------|
| | Poisson FE | Poisson | Poisson FE | Poisson | Poisson FE | Poisson |
| <i>Nb_Words</i> | 0.00220*** (0.000147) | 0.00221*** (0.000105) | | | | |
| <i>Reward</i> | | | 1.801*** (0.177) | 0.589*** (0.101) | | |
| <i>Scope</i> | | | | | 1.486*** (0.164) | 0.232** (0.105) |
| <i>Prog_Age</i> | -0.120*** (0.0213) | 0.0660*** (0.00376) | -0.166*** (0.0211) | 0.0637*** (0.00381) | -0.160*** (0.0214) | 0.0677*** (0.00375) |
| <i>Platform_Growth</i> | | -0.0468*** (0.00388) | | -0.0184*** (0.00361) | | -0.0177*** (0.00375) |
| <i>Firm_Size</i> | | 1.908*** (0.0677) | | 2.056*** (0.0688) | | 2.101*** (0.0688) |
| <i>Managed_byHO</i> | | -0.931*** (0.121) | | -1.003*** (0.123) | | -1.054*** (0.122) |
| <i>Created_in_90s</i> | | 8.165*** (0.430) | | 7.402*** (0.421) | | 7.066*** (0.423) |
| <i>Created_in2000to2007</i> | | 1.267*** (0.251) | | 1.461*** (0.260) | | 1.328*** (0.277) |
| <i>Created_in2008to2010</i> | | 0.312 (0.219) | | 0.0948 (0.224) | | -0.157 (0.233) |
| <i>Created_after_2011</i> | | -0.272 (0.235) | | -0.363 (0.240) | | -0.504** (0.252) |
| <i>Based_in_US</i> | | 1.908*** (0.126) | | 2.273*** (0.127) | | 2.240*** (0.129) |
| <i>VRP FE</i> | ✓ | | ✓ | | ✓ | |
| <i>Time FE</i> | ✓ | | ✓ | | ✓ | |
| <i>Industry dummies</i> | | ✓ | | ✓ | | ✓ |
| <i>Observations</i> | 4,177 | 3,230 | 4,177 | 3,230 | 4,177 | 3,230 |
| <i>LR χ^2</i> | 24369 | 11429 | 24242 | 11020 | 24219 | 10991 |
| <i>Number of VRPs</i> | 156 | | 156 | | 156 | |

Note: the dependent variable is *Nb_Participation*. Poisson FE and Poisson regressions with robust standard errors. Coefficients are Average Marginal Effects. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The number of observations in columns (2), (4), and (6) are reduced because we do not have the information for the *Firm_Size* for every VRPs.

Table 12. Estimation results for the effect of *Information_Level* on the *Nb_Participation*—Regressions without IVs —Focus on Industry Sector dummies

| | (1) | (2) | (3) |
|----------------------------------|--------------------------|----------------------|----------------------|
| | NB | NB | NB |
| <i>Nb_Words</i> | 0.00290*** (0.000430) | | |
| <i>Reward</i> | | 1.314*** (0.392) | |
| <i>Scope</i> | | | 1.009*** (0.382) |
| <i>Cybersecurity</i> | -5.862*** (2.264) | -7.641*** (2.804) | -7.560*** (2.709) |
| <i>Ecommerce&Retail</i> | -4.313* (2.316) | -6.502** (2.847) | -6.031** (2.742) |
| <i>Education</i> | -7.714*** (2.621) | -10.39*** (3.036) | -9.939*** (2.936) |
| <i>Financial_services</i> | -5.508** (2.256) | -7.644*** (2.805) | -6.999*** (2.690) |
| <i>Food&Beverage</i> | 2.517 (3.035) | 0.459 (3.477) | 0.742 (3.414) |
| <i>Gaming</i> | -1.722 (2.390) | -4.597 (2.860) | -4.143 (2.757) |
| <i>Hospitality&Transport</i> | 1.745 (2.726) | 0.0463 (3.254) | 0.259 (3.160) |
| <i>IT_General</i> | -3.925* (2.279) | -5.983** (2.822) | -5.385** (2.711) |
| <i>IT_IoT</i> | -6.327*** (2.350) | -8.773*** (2.861) | -8.560*** (2.756) |
| <i>IT_infrastructure</i> | -8.193*** (2.333) | -10.47*** (2.880) | -9.787*** (2.776) |
| <i>Media&Entertainment</i> | -3.437 (2.276) | -5.613** (2.813) | -5.240* (2.709) |
| Observations | 4,177 | 3,230 | 4,177 |

Note: the dependent variable is *Nb_Participation*. Negative Binomial regressions with robust standard errors. Coefficients are Average Marginal Effects. Baseline value for Industry dummies is “Other industry sector”. All control variables are included as in Table 1. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13. Estimation results for the effect of *Information_Level* on the *Nb_Participation*—Including *Lagged_tot_nb_participation* variable

| | (1) | (2) | (3) | (4) | (5) | (6) |
|------------------------------------|--------------------------|--------------------------|------------------------|------------------------|-----------------------|------------------------|
| | NB FE | NB | NB FE | NB | NB FE | NB |
| <i>Nb_Words</i> | 0.00253*** (0.000458) | 0.00290*** (0.000430) | | | | |
| <i>Reward</i> | | | 1.487*** (0.552) | 1.314*** (0.392) | | |
| <i>Scope</i> | | | | | 2.087*** (0.507) | 1.009*** (0.382) |
| <i>Prog_Age</i> | -0.150*** (0.0510) | -0.108*** (0.0189) | -0.199*** (0.0505) | -0.123*** (0.0205) | -0.167*** (0.0512) | -0.115*** (0.0202) |
| <i>Lagged_tot_nb_participation</i> | 0.00201* (0.00121) | 0.0142*** (0.00167) | 0.00252** (0.00122) | 0.0153*** (0.00191) | 0.00235* (0.00121) | 0.0152*** (0.00191) |
| <i>Platform_Growth</i> | | -0.0256* (0.0132) | | 0.00412 (0.0128) | | 0.000682 (0.0132) |
| <i>Firm_Size</i> | | 1.323*** (0.210) | | 1.357*** (0.217) | | 1.419*** (0.216) |
| <i>Managed_byHO</i> | | 0.488 (0.434) | | 0.904** (0.451) | | 0.605 (0.446) |
| <i>Created_in_90s</i> | | 3.084*** (1.116) | | 2.428** (1.163) | | 2.048 (1.259) |
| <i>Created_in2000to2007</i> | | 4.661*** (1.058) | | 4.674*** (1.144) | | 4.088*** (1.252) |
| <i>Created_in2008to2010</i> | | 1.801** (0.863) | | 1.238 (0.939) | | 0.712 (1.027) |
| <i>Created_after_2011</i> | | 1.707* (0.895) | | 1.175 (0.970) | | 0.754 (1.064) |
| <i>Based_in_US</i> | | 2.726*** (0.466) | | 3.304*** (0.479) | | 3.209*** (0.480) |
| VRP FE | ✓ | | ✓ | | ✓ | |
| Time FE | ✓ | | ✓ | | ✓ | |
| Industry dummies | | ✓ | | ✓ | | ✓ |
| Observations | 4,177 | 3,230 | 4,177 | 3,230 | 4,177 | 3,230 |
| LR χ^2 | 2577.84 | 1179.60 | 2553.69 | 1113.47 | 2563.54 | 1109.06 |
| Number of VRPs | 156 | | 156 | | 156 | |

Note: the dependent variable is *Nb_Participation*. Negative Binomial Fixed Effects (using dummies for individuals) and Negative Binomial regressions with robust standard errors. Coefficients are Average Marginal Effects. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The number of observations in columns (2), (4), and (6) are reduced because we do not have the information for the *Firm_Size* for every VRPs. Baseline value for *Created_Period* is Before 1990.

Table 14. Estimation results for the effect of *Information_Level* on the *Nb_Participation*—Using alternative measures for *Information_Level*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|------------------------------|--------------------------|--------------------------|--------------------------|--------------------------|----------------------|------------------------|
| | NB FE | NB | NB FE | NB | NB FE | NB |
| <i>Nb_Words</i> | 0.00230*** (0.000598) | 0.00358*** (0.000542) | | | | |
| <i>Reward</i> | 0.217 (0.650) | 0.856** (0.416) | | | | |
| <i>Scope</i> | 0.933 (0.586) | 0.595 (0.404) | | | | |
| <i>Vocabulary_Diversity</i> | | | 0.00460*** (0.000815) | 0.00492*** (0.000702) | | |
| <i>Contract_Completeness</i> | | | | | 0.424*** (0.0627) | 0.240*** (0.0494) |
| <i>Prog_Age</i> | -0.128* (0.0512) | 0.0485*** (0.0121) | -0.140*** (0.0508) | 0.0468*** (0.0120) | -0.0909* (0.0522) | 0.0456*** (0.0120) |
| <i>Platform_Growth</i> | | -0.0427*** (0.0124) | | -0.0435*** (0.0123) | | -0.0343*** (0.0124) |
| <i>Firm_Size</i> | | 1.846*** (0.201) | | 1.900*** (0.204) | | 1.933*** (0.203) |
| <i>Managed_byHO</i> | | -0.338 (0.411) | | -0.275 (0.405) | | 0.0124 (0.406) |
| <i>Created_in_90s</i> | | 7.523*** (1.364) | | 7.166*** (1.324) | | 7.090*** (1.414) |
| <i>Created_in2000to2007</i> | | 4.200*** (0.945) | | 3.962*** (0.905) | | 3.542*** (0.991) |
| <i>Created_in2008to2010</i> | | 1.760** (0.744) | | 1.725** (0.740) | | 1.062 (0.819) |
| <i>Created_after_2011</i> | | 1.748** (0.777) | | 1.733** (0.776) | | 1.030 (0.853) |
| <i>Based_in_US</i> | | 2.236*** (0.426) | | 2.102*** (0.426) | | 2.526*** (0.423) |
| <i>VRP FE</i> | ✓ | | ✓ | | ✓ | |
| <i>Time FE</i> | ✓ | | ✓ | | ✓ | |
| <i>Industry dummies</i> | | ✓ | | ✓ | | ✓ |
| <i>Observations</i> | 4,177 | 3,230 | 4,177 | 3,230 | 4,177 | 3,230 |
| <i>Number of VRPs</i> | 156 | | 156 | | 156 | |

Note: the dependent variable is *Nb_Participation*. Negative Binomial FE and Negative Binomial regressions with robust standard errors. Coefficients are Average Marginal Effects. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The number of observations in columns (2), (4) are reduced because we do not have the information for the *Firm_Size* for every VRPs.

Table 15. Estimation results for the effect of *Information_Level* on *Nb_Participation*—Alternative measure of *Nb_Participation* accounting for *Signal score*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|-----------------------------|--------------------------|--------------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| | NB FE | NB | NB FE | NB | NB FE | NB |
| <i>Nb_Words</i> | 0.00387*** (0.000671) | 0.00424*** (0.000489) | | | | |
| <i>Reward</i> | | | 2.551*** (0.808) | 1.456*** (0.543) | | |
| <i>Scope</i> | | | | | 3.276*** (0.747) | 1.374** (0.547) |
| <i>Prog_Age</i> | -0.254*** (0.0742) | 0.0592*** (0.0180) | -0.322*** (0.0743) | 0.0528*** (0.0184) | -0.275*** (0.0749) | 0.0585*** (0.0181) |
| <i>Platform_Growth</i> | | -0.0715*** (0.0181) | | -0.0290* (0.0171) | | -0.0345* (0.0178) |
| <i>Firm_Size</i> | | 2.457*** (0.333) | | 2.469*** (0.334) | | 2.542*** (0.330) |
| <i>Managed_byHO</i> | | -0.557 (0.598) | | -0.196 (0.602) | | -0.484 (0.595) |
| <i>Created_in_90s</i> | | 9.795*** (1.931) | | 8.355*** (1.941) | | 7.887*** (2.004) |
| <i>Created_in2000to2007</i> | | 4.917*** (1.208) | | 4.871*** (1.265) | | 4.111*** (1.379) |
| <i>Created_in2008to2010</i> | | 2.071** (1.009) | | 1.189 (1.021) | | 0.580 (1.131) |
| <i>Created_after_2011</i> | | 2.554** (1.086) | | 1.722 (1.093) | | 1.154 (1.201) |
| <i>Based_in_US</i> | | 3.237*** (0.620) | | 3.946*** (0.640) | | 3.868*** (0.643) |
| VRP FE | ✓ | | ✓ | | ✓ | |
| Time FE | ✓ | | ✓ | | ✓ | |
| Industry dummies | | ✓ | | ✓ | | ✓ |
| Observations | 4,177 | 3,230 | 4,177 | 3,230 | 4,177 | 3,230 |
| Number of VRPs | 156 | | 156 | | 156 | |

Note: the dependent variable is *Nb_Participation_2* is the sum of $\frac{1}{Signal}$ of all valid participations in a given month. Negative Binomial FE and Negative Binomial regressions with robust standard errors. Coefficients are Average Marginal Effects. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The number of observations in columns (2), (4), and (6) are reduced because we do not have the information for the *Firm_Size* for every VRPs.

Table 16. First Stage regressions for Table 2

| Dependent variable is: | (1) | (2) | (3) |
|------------------------|----------------------|--------------------------|-------------------------|
| | <i>Nb_Words</i> | <i>Reward</i> | <i>Scope</i> |
| <i>PSD2</i> | 1,613*** (89.13) | 0.723*** (0.0761) | 0.292*** (0.0850) |
| <i>Acquired</i> | 508.7*** (75.21) | 0.827*** (0.0642) | 0.631*** (0.0718) |
| <i>Prog_Age</i> | -19.49*** (1.665) | -0.00675*** (0.00142) | -0.0206*** (0.00159) |
| VRP FE | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ |
| Observations | 4,177 | 4,177 | 4,177 |
| R-squared | 0.732 | 0.818 | 0.787 |
| Number of VRPs | 156 | 156 | 156 |

Note: Linear FE regressions. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Tabel 17. Validity of over-identification restrictions

| Included IVs: | PSD2 & | Only | PSD2 & | Only | PSD2 & | Only | PSD2 & | Only | |
|--------------------------|----------|-----------|----------|--------|----------|--------|----------|--------|--------|
| | Acquired | PSD2 | Acquired | PSD2 | Acquired | PSD2 | Acquired | PSD2 | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Nb_Words | 0.00353 | 0.00251 | 0.0222 | | | | | | |
| Reward | | | | 0.912 | 0.541 | 1.335 | | | |
| Scope | | | | | | | 1.595 | 1.361 | 1.622 |
| Prog_Age | -0.245 | -0.146 | -0.762 | -0.319 | -0.156 | -0.379 | -0.570 | -0.503 | -0.578 |
| residuals from 1st stage | -0.00120 | -0.000374 | -0.0198 | -0.706 | -0.384 | -1.124 | -1.404 | -1.201 | -1.434 |
| VRP FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 4,177 | 4,177 | 4,177 | 4,177 | 4,177 | 4,177 | 4,177 | 4,177 | 4,177 |

Note: the dependent variable is Nb_Participation. Poisson IV regressions with robust standard errors, using a control function approach. Coefficients are Average Marginal Effects. Standard errors and p-values omitted because Bootstrapping is needed.

Table 18. Estimation results for the effect of *Information_Level* on participant quality—Dependent variable are rescaled from 0 to 1

| Dep. var. is | Av_Reputation (1) | Av_Signal (2) | Av_Impact (3) |
|-----------------------------|----------------------------|----------------------------|----------------------------|
| Nb_Words | -2.19e-05*** (5.36e-06) | -2.83e-05*** (9.89e-06) | -2.51e-05*** (9.16e-06) |
| Prog_Age | 0.00196*** (0.000752) | 0.00604*** (0.00124) | 0.00539*** (0.00114) |
| Lagged_tot_nb_participation | 1.12e-05 (1.18e-05) | 6.20e-05** (2.70e-05) | 0.000122*** (2.37e-05) |
| Time FE | ✓ | ✓ | ✓ |
| program FE | ✓ | ✓ | ✓ |
| Observations | 3,057 | 3,057 | 3,057 |
| VRPs | 156 | 156 | 156 |
| | (4) | (5) | (6) |
| Reward | -0.0141 (0.00869) | -0.0524*** (0.0122) | -0.0354*** (0.0119) |
| Prog_Age | 0.00243*** (0.000742) | 0.00618*** (0.00121) | 0.00566*** (0.00112) |
| Lagged_tot_nb_participation | 6.41e-06 (1.19e-05) | 6.54e-05** (2.69e-05) | 0.000122*** (2.38e-05) |
| Time FE | ✓ | ✓ | ✓ |
| program FE | ✓ | ✓ | ✓ |
| Observations | 3,057 | 3,057 | 3,057 |
| VRPs | 156 | 156 | 156 |
| | (7) | (8) | (9) |
| Scope | -0.0107* (0.00628) | -0.00509 (0.0112) | -0.00356 (0.0109) |
| Prog_Age | 0.00233*** (0.000736) | 0.00676*** (0.00124) | 0.00605*** (0.00113) |
| Lagged_tot_nb_participation | 4.56e-06 (1.20e-05) | 5.17e-05* (2.69e-05) | 0.000113*** (2.34e-05) |
| Time FE | ✓ | ✓ | ✓ |
| program FE | ✓ | ✓ | ✓ |
| Observations | 3,057 | 3,057 | 3,057 |
| VRPs | 156 | 156 | 156 |

Note: the dependent variables were standardized (values rescaled from 0 to 1) in order to compare the magnitudes of the effects. We use OLS regressions. For all regressions, VRP and time fixed effects are included. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$