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[](http://crossmark.crossref.org/dialog/?doi=10.1016/j.aci.2017.12.002&domain=pdf)A look at the time delays in CVSS vulnerability scoring

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# a r t i c l e i n f o

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# a b s t r a c t

This empirical paper examines the time delays that occur between the publication of Common Vulnerabilities and Exposures (CVEs) in the National Vulnerability Database (NVD) and the Common Vulnerability Scoring System (CVSS) information attached to published CVEs. According to the empirical results based on regularized regression analysis of over eighty thousand archived vulnerabilities, (i) the CVSS content does not statistically influence the time delays, which, however, (ii) are strongly affected by a decreasing annual trend. In addition to these results, the paper contributes to the empirical research tradition of software vulnerabilities by a couple of insights on misuses of statistical methodology.

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1. Introduction

Software vulnerabilities are software bugs that expose weak- nesses in software systems. The CVSS standard is used to classify the severity of known and disclosed vulnerabilities. Once the clas- sification and evaluation work has been completed for a vulnera- bility identified with a CVE, the structured and quantified severity information is stored to vulnerability databases. Moti- vated by a recent empirical evaluation [[16]](#_bookmark30), this paper examines the time delays between the publication of CVEs and the usually later publication of CVSS information. The scope is restricted to NVD and the second revision of the CVSS standard.

The use of CVSS is mandated and recommended by many state agencies for assessments in different security-critical domains [[36]](#_bookmark31), including but not limited to medical devices [[38]](#_bookmark31) and the payment card industry [[2]](#_bookmark16). The standard has been also incorporated into different governmental security risk, threat, and intelligence systems. Furthermore, CVSS information is used in numerous different commercial products [[16]](#_bookmark30), ranging from vul- nerability scanners and compliance assessment tools to automated penetration testing and intrusion detection systems.

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CVSS is also widely used in academic research. Typical applica- tion domains include risk analysis [[2,14]](#_bookmark16), security audit frame- works [[4]](#_bookmark18), so-called attack graphs [[7,26]](#_bookmark22), and empirical assessments using CVSS for different purposes [[1,25,31,33]](#_bookmark15). To these ends, a lot of work has been done to improve CVSS with different weighting algorithms [[17,40]](#_bookmark30), among other techniques [[9,30]](#_bookmark23). With some rare exceptions [[13]](#_bookmark26), limited atten- tion has been given for examining how severity assessments are done in practice.

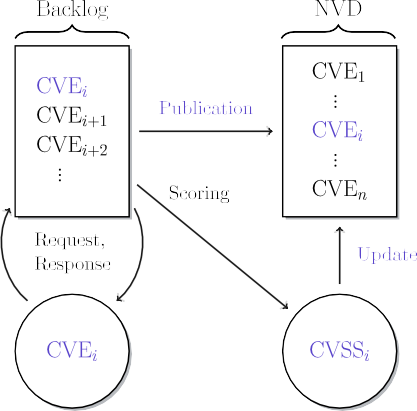
Practical approaches are important because CVSS has faced also challenges. Analogous to problems that have affected CVE assign- ments [[33,34]](#_bookmark31), different practical problems have influenced the severity assignments for CVE-stamped vulnerabilities. Excluding the actual content of the standard, the historical problems related to classification inconsistencies, time delays, and the proliferation of classification standards [[5,24]](#_bookmark19). Some of these problems have continued to exist. For instance, proliferation has continued in recent years; new standards have been introduced for classifying software misuse and configuration vulnerabilities [[3]](#_bookmark17). Some coun- tries [[45]](#_bookmark37) and companies [[43]](#_bookmark32) have also introduced their own severity metrics. To examine whether also the problem with time delays is still present—as has been suspected [[18]](#_bookmark30), a brief remark is required about the CVE and CVSS publication processes in the con- text of NVD. Although the available documentation about these processes is limited [[28]](#_bookmark33), the sketch presented in [Fig. 1](#_bookmark0) is not a far-fetched analytical speculation.

The process starts when security researchers, vendors, and other related actors request CVEs for vulnerabilities they have dis- covered or made aware of. These request-response dynamics are handled by the non-profit MITRE corporation. As is common in

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Fig. 1. A simplified model for CVSS processing.

software engineering, MITRE presumably maintains a backlog for the CVEs assigned, some of which may be even rejected for inclu- sion to NVD. Although the structure of the backlog is unknown, a simple FIFO (first-in, first-out) might be considered in order to con- nect the speculation to a recent theoretical work [[10]](#_bookmark24). In any case, eventually the vulnerabilities accepted for archiving are published in NVD. In parallel to the coordination and archiving work related to CVEs, vulnerabilities are evaluated for their severity by the NVD

RQ3 *Does the answer to RQ2 hold when also the annual trend is controlled for?*

According to the empirical results, only the answer to RQ1 is positive. For predicting the time delays, the CVSS content is largely noise. The statistical effect (RQ2) also fades away once the annual trend is controlled for (RQ3). To elaborate how these conclusions are reached, the remainder of this paper is structured into three sections. Namely: Section [2](#_bookmark1) introduces the dataset and the opera- tionalization of the variables used, Section [3](#_bookmark9) outlines the statistical methodology and presents the empirical results along the way, and Section [4](#_bookmark21) finally discusses the findings.

1. Setup

To outline the setup for the analysis, the following discussion will address the operationalization of the delay metric examined the covariates used to model the metric.

* 1. *Response*

Following the so-called vulnerability life cycle research tradi- tion [[25,33]](#_bookmark30), the interest relates to a time difference

D*i* = sCVSS*i* — sCVE*a* ; given (1)

*i*

*i*

team, which largely operates independently from others carrying similar evaluations [[16]](#_bookmark30). Once the evaluation has been completed,

sCVSS*i* P sCVE*a*

## for all *i* = 1; ... ; *n*.

the CVE-referenced vulnerability information is updated in NVD. The time lags between the initial CVE publications and the later CVSS updates constitute the empirical phenomenon examined.

There is another viewpoint to the abstract CVE backlog. This viewpoint originates from the so-called switching costs, which are often high for information technology standards [[37]](#_bookmark31). Such the- oretical costs cover also database maintenance: even small changes made to standards may imply a lot of evaluation work par- ticularly in case old information needs to be updated. This concern was raised also during the 2007 introduction of the second revision of the CVSS standard [[36]](#_bookmark31). In other words, updates can be costly in terms of time and resources—given the nearly ninety thousand vul- nerabilities currently archived in NVD. Therefore, it is relevant to ask the following research question (RQ) about the time lags affect- ing CVSS scoring.

The integer sCVSS*i* denotes the day (timestamp) at which a CVSS

entry was generated for the *i*:th CVE that was published at sCVE*a* . In

*i*

practice, the two timestamps map to the fields cvss:generated- on-datetime and vuln:published-datetime in the NVD’s extensible markup language schema. Although the exact meaning of the fields is undocumented, the time differences can be inter- preted as delays between CVE and CVSS publications.

Of the 89,465 archived vulnerabilities with both CVE and CVSS entries, the condition sCVSS*i* P sCVE*a* fails to satisfy only for 1,375 vulnerabilities. Without loss of generality, these cases were

*i*

excluded. The same applies to CVEs without severity records. At the time of retrieving the NVD content [[27]](#_bookmark34), there were 2,218 vul- nerabilities that were published but still lacked CVSS records. Most of these cases relate either to new vulnerabilities that are still in the pipeline for severity assessments, or to already published CVEs

that were later rejected as inappropriate for archiving. Either way,

RQ1 *Do the time delays between CVE publications and CVSS updates vary systematically according to an annual year- to-year trend?*

Another question relates to the content of the CVSS standard in terms of the vulnerabilities scored. Reflecting the disagreements among experts about the severity of some vulnerability types [[13]](#_bookmark26), it can be hypothesized that the CVSS content itself affects the time delays. Not all vulnerabilities are equally easy (or hard) to classify in terms of severity; hence, some vulnerabilities may take a relatively short (long) time to classify. This reasoning is presented as a second research question, stated as follows.

RQ2 *Do the time delays vary systematically according to the content of the CVSS severity information?*

Finally, a third and final question can be postulated for control- ling the answers to the earlier two questions:

these had to be also excluded in order for D*i* to be defined for all cases observed. In total, the dataset examined contains

*n* = 89; 465 — 1;375 = 88; 090 archived cases. Given these cases,

the distribution of the time delays observed is shown in [Fig. 2](#_bookmark3).

The timelines exhibit a heavy-tailed distribution with extre- mely long right tail. A half of the vulnerabilities observed have seen





Fig. 2. CVE-CVSS publication time delays (Eq. [1](#_bookmark2)).

severity assignments already a day after CVEs were published, but

the standard deviation is still over a year. Most of this deviation is caused by a few extreme outliers for which the severity scores

VECTOR ∈ NETWORK

> >

8> 8>< LOCAL\*

were assigned even a decade after the CVEs were originally published.

To briefly probe these outliers further, [Fig. 3](#_bookmark6). displays the distri- bution of another time difference

EXPLOITABILITY ∈

>>><

>

>>:

COMPLEXITY ∈

LOW\* ADJACENT

HIGH

>>:< MEDIUM

## 8

:8

><

d*i* = sCVSS*i* — sCVE

*i*

where sCVE*b* denotes the vuln:last-modified-datetime field in

NVD. The large amount of negative values indicate that CVEs are

*b* ; (2)

*i*

> AUTHENTICATION ∈

NONE\*

SINGLE

>: MULTIPLE

often updated after these were already published with CVSS infor- mation. Interestingly, 187 outlying cases satisfy d*i* > 0, which may point toward some inconsistencies in database maintenance; CVSS information was generated without updating the corresponding

The rationale for the impact and exploitability metrics relate to different combinatory relationships between the different values the metrics can take. For instance, it is probable that mass-scale attacking tools target less complex vulnerabilities that can be

sCVE*b*

*i*

timestamps. About a quarter of the cases observed satisfy

exploited through a network without performing authentication,

d*i* = 0, meaning that the latest CVE modifications matched the gen- eration of severity information.

* 1. *Covariates*

Two types of covariates are used for modeling the time delays in [(1)](#_bookmark2). The first contains the CVSS information itself. The CVSS (v. 2) standard [[6]](#_bookmark20) classifies the impact of vulnerabilities according to confidentiality, integrity, and availability (CIA). Each letter in the CIA acronym further expands into three categories that characterize the impact upon successfully exploiting the vulnera- bility in question. Thus, the analytical structure behind the impact dimension can be illustrated with a diagram:

8> 8>

NONE\* CONFIDENTIALITY ∈ PARTIAL

8:

> <> COMPLETE

NONE\*

>

>

<> <>

IMPACT ∈ INTEGRITY ∈ PARTIAL NONE\* COMPLETE

>

8:

>

>>: ><

AVAILABILITY ∈ PARTIAL

:

possibly regardless of the impact upon confidentiality, integrity, and availability. There exists also some empirical evidence along these lines [[1]](#_bookmark15). However, the impact and exploitability dimensions both relate to intrinsic characteristics of vulnerabilities; they are constant across time and environments. For instance, EXPLOIT- ABILITY cannot answer to a temporal question about whether an exploit is known to exists for the vulnerability in question [[30,43]](#_bookmark39). The same point extends toward NVD in general [[8]](#_bookmark25). For these and other reasons, the new (v. 3) standard for CVSS enlarges the dimensions toward temporal and environmental metrics.

For the present purposes, however, the impact and exploitabil- ity dimensions are sufficient for soliciting an answers to RQ2. This choice is also necessitated by the paper’s focus on NVD, which does not currently provide full CVSS v. 3 information [[29]](#_bookmark38). Despite of this limitation, a correlation between the six CVSS metrics and D*i* could be expected due to the fairly detailed criteria used for the manual classification. Complex vulnerabilities with severe impact may require more evaluation work than trivial vulnerabilities; a remote buffer overflow vulnerability is usually more difficult to interpret compared to a trivial cross-site scripting vulnerability. Also the reverse direction is theoretically possible; more effort may be devoted for high-profile vulnerabilities [[18]](#_bookmark30). Either way, RQ2 seems like a sensible hypothesis worth asking.

COMPLETE

The three impact metrics measure the severity of a vulnerability on a system after the vulnerability has already been exploited. However, not all vulnerabilities can be exploited; therefore, the CVSS standard specifies also an exploitability dimension for vul- nerabilities. Like with the impact dimension, exploitability expands into three metrics (access vector, complexity, and authen- tication) that can each take three distinct values. The analytical meaning can be again summarized with the following diagram:

With regard to statistical modeling, the three impact metrics

and the three exploitability metrics are included in the models as

so-called dummy variables. For each metric, the reference category is marked with a star in the previous two diagrams. For instance, INTEGRITY is expanded into two dummy variables, INTEGRITY (PARTIAL) and INTEGRITY(COMPLETE), say, the effects of which are compared against INTEGRITY(NONE), which cannot be included in the models due to multicollinearity. The same strategy applies to the metrics used for evaluating RQ1. Namely, the annual

effects are proxied through 18 dummy variables that record the year at which a vulnerability was published according to sCVE*a* . Because only five vulnerabilities were published in the 1980s and

*i*

a negiligle amount (about 1.8 %) in the 1990s, the reference cate- gory for the annual dummy variables is formed by collapsing all vulnerabilities published prior to 2000 into a single group. Given the two CVSS dimensions and the dummy variable approximation

for the annual trend, three model matrices (X1; X2, and X3) are

used in the statistical computation:

8>< M1 : X1 = [1; XIMPACT];



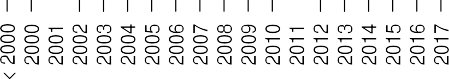
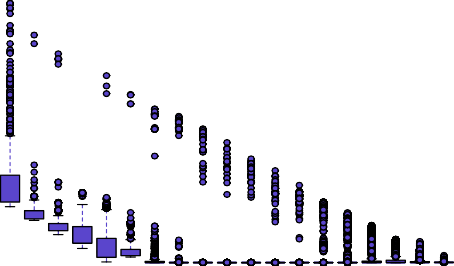
M2 : X2 = [X1; XEXPLOITABILITY];

>: M3 : X3 = [X2; XANNUAL].

(3)

Fig. 3. CVE-CVSS modification time delays (Eq. [2](#_bookmark4)).

called negative binomial model (NBM) instead, although the conventional ordinary least squares (OLS) regression often works well in applied problems when the response is suitably transformed [[15]](#_bookmark29). Thus, instead of [(4)](#_bookmark10), consider that the conditional mean is given by an OLS regression.



## E(ln[D + 1]| X*j*)= E(D~ | X*j*)= X*j*b, (5)

such that

## b^ = min(D~ — X ' D~ — X b) (6)

*a j*b) ( *j*

b



Fig. 4. Annual time delays (based on sCVE*a* ).

*i*

The first model M1 regresses D = [D1, ... , D*n*]' against a constant dummy variables present in the (*n* × 6) matrix XIMPACT. The second represented by a *n*-length vector of ones, 1, and the six impact model is identical except that further six dummy variables are

included for measuring the exploitability dimension. The third and final model includes all information used.

Despite of the growing number of CVEs processed from the circa mid-2000s onward [[32]](#_bookmark31), the time delays for CVSS processing have steadily decreased over the years. As can be seen from [Fig. 4](#_bookmark7), there have been no extreme outliers in recent years, meaning that most of the right tail in [Fig. 2](#_bookmark3) is attributable to older CVEs. A possible but speculative explanation is that the work done to update old CVEs with CVSS (v. 2) information has mostly been completed.

The strong decreasing trend is likely to support a positive answer to the research question RQ1. Given this prior expectation, the main interest in the forthcoming analysis relates to the statis- tical effect of the impact and exploitability metrics when also the annual trend is modeled. One strategy for evaluating the research question RQ3 is to compare the models M1 and M2 against the full information model M3. If the CVSS metrics provide statistical power for predicting D, this power should be visible also when the decreasing annual trend is controlled for.

1. Results

The response D represents a count data vector; each observation in the vector counts the days between CVE and CVSS publications in NVD. Thus, a Poisson regression model provides a natural start- ing point for modeling the time delays. The expected value of the response thus is

E D | X*j* = *e*X*j* b, (4)

where X*j* is a given model matrix from [(3)](#_bookmark5) and b a *k*-length vector of

regression coefficients, including the intercept b1. This conditional mean is always positive.

However, the model assumes that D is distributed from the Poisson distribution, which, in turn, implies that the mean of the time delays should equal the variance of the delays. As can be con- cluded from the numbers shown in [Fig. 2](#_bookmark3), this assumption is clearly problematic in the current setting. While b is still consis-

tently estimated, the apparent overdispersion, Var(D) > E(D),

affects the standard errors of the regression coefficients, and,

hence, the statistical significance of the coefficients. A common solution to tackle the overdispersion problem is to estimate a so-

When applied to the full model matrix X3, the adjusted coeffi- cient of determination is 0.64 for this OLS regression. In other words, the general model performance is quite decent, given the limited amount of information used to model the severity assign-

ment timelines. Moreover, only three coefficients in b^*a* are not sig- nificant at the conventional *p* < 0.05 threshold. By further testing

the joint significance of the dummy variable groups with a *F*-test, all groups are significant at a *p* < 0.001 level. Also the combined forward-stepwise and backward-stepwise algorithm (as imple- mented in the step function for R) retains all coefficients in b^*a* .

As is common in applied problems [[35]](#_bookmark31), the D~ = ln(D + 1) transfor- mation does not account for the high positive skew; therefore,

another test can be computed by using an R implementation [[44]](#_bookmark35) for a consistent covariance matrix estimator [[42]](#_bookmark36). However, the results do not diverge much from the plain OLS estimates; only

one additional coefficient is insignificant at a *p* < 0.05 threshold.

Finally, analogous conclusions can be reached by estimating a negative binomial regression model with the assumption

that Var(D)= E(D)+ /[E(D)]2, where / is a parameter to be estimated [[19,41]](#_bookmark30). By again using an R implementation [[20]](#_bookmark30), only

two coefficients attain *p* P 0.05.

Thus, based on statistical significance, positive answers would be given to all three research questions. This conclusion would be unwarranted, however. Most of the coefficients in the M3 model are close to zero, irrespective of the estimation strategy. Since all covariates are dummy variables (and, hence, have the same scale), this observation can be illustrated in the form of [Fig. 5](#_bookmark11), which plots the OLS coefficients (*y*-axis) against the corresponding NBM coeffi- cients (*x*-axis), omitting the constant b^1. As can be seen, there are some differences between the two regression coefficient vectors, but these differences apply mostly to the annual effects. In partic- ular, the coefficients for the impact and exploitability dimensions are very close to zero without notable differences between the OLS and NBM estimates. The largest absolute coefficient values are obtained for the annual effects from 2005 to 2017. These coef- ficients exhibit also the largest differences between the OLS and the negative binomial estimates.

To examine these observations further, the so-called least abso- lute shrinkage and selection operator (LASSO) provides a good tool.

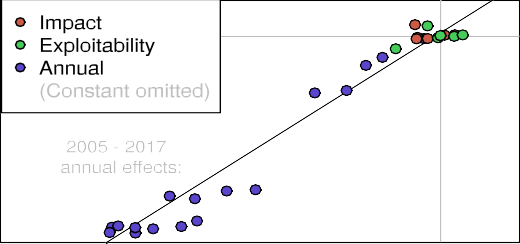


Fig. 5. Coefficients from the OLS and NBM regressions (M3 ).

The LASSO method is a regression model that uses regularization in order to improve prediction accuracy and feature selection. When compared to other regularized regression models, such as the so- called Ridge regression, LASSO can shrink some coefficients exactly to zero. Although the feature selection properties are not entirely ideal for hypothesis testing [[21]](#_bookmark30), this property is desirable for fur-

ther examining whether regularization pushes the coefficients for

If this is the case, there is also no particular reason to consider more complex estimation strategies, such as the so-called group LASSO method [[39]](#_bookmark31). A brief elaboration is required also about the more classical LASSO regressions.

Instead of minimizing the residual sum of squares in [(6)](#_bookmark8), LASSO minimizes penalized sum of squares given by

all of the CVSS metrics toward zero. It should be noted that drop- ^

( 1 X*n* ~

2 X )

ping individual dummy variables based on feature selection is usu- ally unwarranted because interpretation of the coefficients

*ji*

b*b* = min

b

2*n i*=1

(D*i* — x' b)

+ k

*s*=2

*k*

| b*s* |

## , (7)

changes—but if all of the impact and exploitability dummy vari- ables are regularized toward zero, there is not much to interpret.

by (1/2*n*) is done to ease comparisons with different sample where k P 0 is known as the shrinkage factor, and the scaling



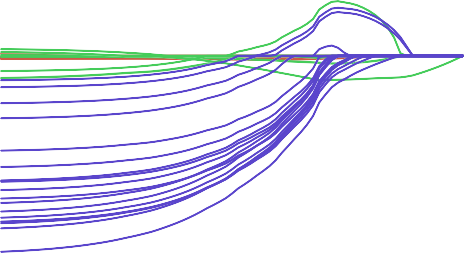
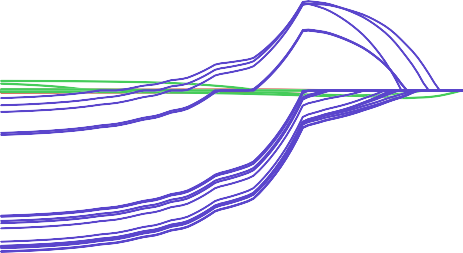


Fig. 6. Gaussian LASSO estimates (b^*b* ). Fig. 7. Poisson LASSO estimates (b^*c* ).

sizes [[12]](#_bookmark27). The penalty is given by the *L*1 norm, that is, the sum of the absolute coefficient values, omitting the constant present in X*j*. If k is zero, the solution reduces to the OLS estimates, and when

k → ∞, all coefficients in b^*b* tend to zero. Despite of the overdisper- sion, the Gaussian LASSO in [(7)](#_bookmark12) can be accompanied with a Poisson

LASSO as an additional robustness check.

The so-called quasi log-likelihood for Poisson regression can be obtained by left-multiplying the logarithm of the expected values

in [(4)](#_bookmark10) by D and subtracting E D | X*j* from the result [[23]](#_bookmark30). Given this

quasi log-likelihood, for the Poisson regression [[12]](#_bookmark27).

## L b | D, X*j* = DX*j*b — exp(X*j*b), (8)

LASSO optimizes

## ^ ( L b | D, X*j* X )

*k*

b*c* = min

b

—

*n*

+ k

*s*=2

| b*s* |

, (9)

apply to historical contexts, and, moreover, the historically long delays affect also academic research.

Second, the positive answer to RQ1 is a negative finding in terms of existing academic research; the historically long time delays presumably translate into selection biases in some existing empir- ical studies using CVSS information. Without naming any particu- lar academic study, consider that a hypothetical article published in the late 2000s used a NVD-based dataset of CVE-referenced vul- nerabilities published between 2000 and 2007, say. The long time delays during this period imply that a lot of the vulnerabilities in the dataset could not have had CVSS information. Consequently, some existing academic studies are exposed to difficult questions related to sample selection and missing values, among other issues. This concern is particularly pronounced regarding studies that examine time-sensitive topics such as vulnerability disclosure.

Third, the results echo the recently raised concern about the misuse of statistical significance in the software vulnerability con-

By again using an R implementation [[11]](#_bookmark28), the results from the

LASSO computations are shown in [Figures 6 and 7](#_bookmark13) for the Gaussian and Poisson specifications. The coefficient magnitudes are shown in the *y*-axes, the lower *x*-axes represent different values of k in loga- rithm scale, and the upper *x*-axes denote the number of coefficients not regularized to zero. The shaded region is based on a 10-fold cross-validation: in each plot, the left endpoint of the region corre- sponds with the value of k that gives the minimum cross-validation error, while the right endpoint is one standard error from this minimum.

In both figures, the models M1 and M2 yield large absolute coef- ficient magnitudes for the CVSS metrics. Furthermore, the coeffi- cients retain their magnitudes rather long as the shrinkage factor increases. For instance, the upper-left plot indicates that none of the impact metrics are regularized to zero in the Gaussian specifi-

cation until about k = exp(—6). However, when the annual affects

are included in M3, all of the CVSS metrics are very close to zero

particularly with respect to b^*b* . Although a couple of exploitability metrics retain their magnitudes within the cross-validation region shown in the lower-right plot in [Fig. 7](#_bookmark14), the same conclusion applies more or less also to the Poisson LASSO model. Furthermore, within the cross-validation regions, both b^*b* and b^*c* compare well to the OLS and NBM coefficient vectors illustrated in [Fig. 5](#_bookmark11). To conclude: when predicting the time delay from CVE publications to CVSS assignments, the actual CVSS content is largely noise; the most rel- evant readily available information comes with the decreasing annual trend.

1. Discussion

This short empirical paper examined the time delays that affect CVSS scoring work in the context of NVD. Three research questions were presented for guiding the empirical analysis based on regres- sion methods. The results are easy to summarize. The CVSS content is correlated with the time delays (RQ2), but the correlations are spurious; the decreasing annual trend affecting the time delays (RQ1) also makes the effects of the CVSS content negiligle (RQ3). Three points are worthwhile to raise about the significance of these empirical findings.

First, the negative answers to RQ2 and RQ3 are positive findings in terms of practical applications using CVSS information. Whether the application context is governmental security intelligence sys- tems or commercial security assessment tools, there is currently no particular reason to worry that a NVD data feed would show significant delays for the CVSS information. Likewise, in 2017, there is no reason to suspect that information for severe vulnera- bilities would tend to arrive later (or earlier) than information for mundane vulnerabilities. However, this conclusion does not

text [[22]](#_bookmark30). It seems that the size of archival material stored to vul-

nerability databases has surpassed a point after which statistical significance starts to lose its usefulness for inference in applied research. The current rate of new vulnerabilities archived—about 17 per day in 2016—implies that the problem with statistical sig- nificance is only going to get worse. The point is particularly important in case CVEs are referenced with other datasets, includ- ing big data outputted by intrusion detection and related systems. The regularized regression models used in this paper offer one solution to consider in further applications, but more research is required to assess the existing biases and the potential means for moving forward.

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