# Economics of Security — Market Failures and Policy Interventions

Tycho Teesselink (s1560506) Tariq Bontekoe (s1451278) Æde Symen Hoekstra (s1479679) Ramon Houtsma (s1245228) Group 13 — Phishing

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## 1 Introduction

The security issue that this document covers is phishing. We have a dataset that consists of phishing website records for different companies, e.g. PayPal. We have created a metric that determines how well a company performs on the security level by comparing uptime of a phishing website. An example of this can be seen in Figure 1 for three companies in the dataset. We created this graph by doing a survival analysis [1] per company. Here, the lower the (survival) curve, the better [2]. This metric will be used again later on, to determine what factors play a role in the security performance of these companies. The survival curve tells which ratio of the phishing sites is still up after a certain amount of days.

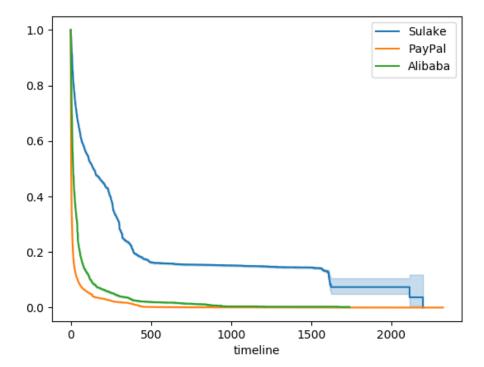


Figure 1: Survival curves for Sulake (creator of the popular game 'Habbo' [3]), PayPal and Alibaba with uptime in days on the x-axis and ratio of phishing sites still up on the y-axis. The shaded area is the 95% confidence interval.

## 2 Actors involved in the Security Issue

In this section we describe what measures three main actors, namely 'Online Service Providers', 'Hosting Providers' and 'Online Service Consumers', could take to mitigate the security issue. For each countermeasure we discuss what effect implementing this countermeasure might have on other actors involved.

#### 2.1 Online Service Providers

When an online service provider is an actor to be targeted by phishing, we mean that their service is attractive to abuse. For example PayPal is an online service provider. When PayPal login information is stolen through phishing their service will be used to transfer money which leads to losses.

#### 2.1.1 Countermeasure

Financial services can buy and install software that tracks payments. Anomalous payments due to stolen login information can be detected with this software and therefore these 'malicious' transactions can be halted before they are processed.

#### 2.1.2 Distribution of Costs and Benefits among the Actors

- Online Service Providers: Service providers will benefit by having fewer fraud cases associated with their services. Furthermore, they save money because of fewer reimbursements to clients. There are costs involved for buying and maintaining fraud detection software, however the trade-off with less overhead with fraud cases and improved reputation for reliability is worth it.
- **Hosting Providers:** Hosting providers are not affected by this countermeasure, since the countermeasure does not target hosted phishing sites.
- Online Service Consumers: Consumers will probably not notice anything, even though they have a lot of benefit by this solution. Some of the costs of this solution might be written off to its service consumers, however this will be relatively little compared to the standard costs. They do have a lot of benefit by this solution however, as for example transactions done when their credentials are stolen may be halted.

#### 2.1.3 Incentive Analysis

Online Service Providers of financial services definitely have incentive to implement this countermeasure. The number of fraud cases will go down, which leads to less overhead with fraud cases, fewer reimbursements, improved reputation for reliability and higher customer satisfaction. Online Service Providers of other types of services, e.g. e-mail services or social networks, will have less incentive to implement fraud detection in transactions. It depends on whether they handle a lot of transactions by customers or not. E-mail providers will benefit the least because they are free or work with subscriptions. Social networks may

have some incentive if they use a virtual currency within their network which users can buy for in-game purchases for example.

#### 2.1.4 Externality Reflection

Implementation of this countermeasure by an online service provider may affect customers and competitors:

- Customers: Customers of the online service provider receive positive externalities in the form of a smaller chance of being a victim of fraud with the service. A negative side-affect may be that their data is being gathered. If a data breach were to happen, this personal data might become known.
- Competitors: Competitors of the online service provider may lose customers to the service provider that implemented the countermeasure, because of the improved perceived service and reputation that are the result of the countermeasure.

## 2.2 Hosting Providers

The hosting providers as an actor are responsible for hosting the phishing sites that target customers of online services. It may be their moral responsibility to not facilitate adversaries with their services. It is a possibility that phishing sites are allowed inadvertently because of insufficient background checking before assigning a domain.

#### 2.2.1 Countermeasure

A more thorough information check before accepting webhosting applications. This means that people, including phishers, have to provide more information than for example just a name, email address and bank account. This will make it less attractive for phishers to register a hosting solution as they have to provide more information which might reveal who they really are.

#### 2.2.2 Distribution of Costs and Benefits among the Actors

- Online Service Providers: Online service providers will not have increased costs. They do however benefit from this countermeasure. As this measure is supposed to lower the amount of phishing websites, they will be less likely to be abused by phishing. This results in less reputational damage that may be incurred during a phishing campaign.
- Hosting Providers: Direct costs for hosting providers will not change much. It may be necessary for some initial development to support this change. Indirect costs may be much higher. People are usually not very keen on sharing a lot of information about themselves. Therefore if more information is required, some people may decide not to apply for a hosting solution at all. This will result in lower revenue for the hosting company itself. The benefit for hosting providers is that their reputation will

be increased. Hosting less phishing websites will show that they are an innovative and healthy organisation within the society.

• Online Service Consumers: Online service consumers can benefit the most from this countermeasure. The purpose of the measure is to protect the consumers by decreasing phishing. They will not see any real increased costs, even if they want to get their own hosting solution. The only extra costs might be of the extra information they have to provide.

#### 2.2.3 Incentive Analysis

Hosting providers may not have a very large incentive to implement this countermeasure. The costs and annoyances that this measure introduces will hinder some of the revenue that these companies can get. One of the main things that distinguishes one hosting provider from others is the ease of use of the platform and the customer friendliness. If such a measure as proposed above is implemented, this might compromise the quality of service and make customers choose a competitor.

#### 2.2.4 Externality Reflection

This countermeasure may also impose negative externalities on the online service consumers. More personal data gathered also means more risk of a privacy breach. A positive externality may be that it is easier to catch the culprits if they still decide to get a hosting solution and host a phishing website. So for example the police may be able to apprehend them quicker.

#### 2.3 Online Service Consumers

Consumers of certain Online Service Providers may be targeted by Phishing Attacks, which trick them into for example revealing their login information. These credentials might give criminals access to for example a bank account. The criminals can then write off money from the consumer's account to themselves in order to make a profit. This will lead to the consumer losing money, which is rather inconvenient for the consumer.

#### 2.3.1 Countermeasure

Consumers could participate in a phishing awareness training. This will help consumers identify phishing websites, which means they are less likely to fill in their personal information and therefore a part of this risk will be mitigated.

#### 2.3.2 Distribution of Costs and Benefits among the Actors

• Online Service Providers: Unless the service provided is a phishing awareness training, this actor will not directly benefit, nor have costs for this countermeasure.

- Hosting Providers: Hosting providers have no costs, and no direct benefits from this countermeasure.
- Online Service Consumers: The online service consumers will bear the costs for this, however they also benefit the most. They will have to pay for the training as well as spend the time taking it.

#### 2.3.3 Incentive Analysis

The online service consumers may have quite some incentive to take a phishing course. By taking such a course, and thus spend a few dollars, they gain a lot more security when browsing the web. It also may prevent users from filling in their information on a phishing site, which will help them even more. The costs that may be required should be seen as an investment rather than sunk costs. However, this may not be the case for all online service consumers. Some users might only use online services once in a while, and therefore it would not be feasible for them to take such a course. It would still be useful, but the costs may outweigh the benefit for them.

#### 2.3.4 Externality Reflection

This countermeasure has a positive effect for online service providers, because less customers will fall victim to phishing sites that target customers of their service. It might also be possible that these consumers can report fishy websites that may be used for phishing. This will help hosting providers in blocking websites more quickly.

## 3 Actor Security Performance

#### 3.1 Factors causing Variance

We suspect that the variance between companies can be explained by their respective maturities in phishing site detection as well as the technological developments in the countries. The former can most likely be explained by the sector in which a company lies as companies in the financial sector have been dealing with these kind of attacks far longer than others. For the latter factor we have chosen to couple countries to continents. One of the reasons for this is that technological progress for countries belonging to the same continent is somewhat similar. This can be seen in Figure 2, which shows the Global ICT Development Index of ITU [4]. Another reason is that it was too hard and elaborate to make a distinction for every country.

Therefore we have the following two factors:

- Sector: We suspect that part of the difference in our metric is explained by the sector in which our companies work. To be more precise we expect a difference between companies from the financial sector and companies from other sectors.
- Continent of headquarters ('residence'): A part of the difference between companies might be explained by their country of residence. As the data is such that it does not contain enough different companies per country to represent each country without a gross bias, we limited the scope to continents as we also expect to see differences there.

#### 3.2 Data

To determine to which continent the companies belong or in which sector they belong, we performed an online search. We mainly used the websites of the company itself, or Wikipedia [5]. We labeled the companies accordingly to what was found and subsequently grouped the data respectively per sector or per continent. We define the continent of a company to be the continent where the main headquarters of the company resides and not as the main market of the company.

The dataset was also cleaned to the extent that most companies that are the same but have different labels are now merged in the same company. Furthermore we did not consider data points on which we could not find appropriate information in order to put them into the right category for our statistical tests. This was done in order to prevent incorrect results and could be done as there were enough different companies per continent in order for the statistical analysis to still be meaningful.

#### 3.3 Statistical Analysis

#### 3.3.1 Sector

A large subset of the companies in our dataset belong to the financial sector, the rest of the companies belongs to a diverse group of other sectors, therefore we have decided to split

based on sector. We split on 'financial' (F), and label the rest as 'other' (O). Subsequently we performed a logrank test to determine whether financial institutions perform better in regard to taking down phishing websites [6, 7]. The way this works is we create an initial hypothesis  $(H_0)$  which says that there is no difference in performance between companies in the financial sectors and companies in other sectors. We accept this hypothesis with a confidence level of 95% if the p-value is greater than 0.05 otherwise we reject it.

The survival curves belonging to each sector can be seen in Figure 5a, and in Figure 5b with a logarithmic scale. The survival curves in the graphs differ quiet a bit. The curve for the financial sector is much lower than the 'other' curve. This would insinuate that financial companies are performing better in regard to taking down phishing websites. This is also apparent in the p-value from the logrank test. Comparing financial against the other sectors resulted in a value of 0.0000 (4 digits precision) therefore we reject the null hypothesis which stated that the two did not differ. Hence, based on these two observations, we expect that companies in the financial sector perform better than the ones in the other sectors.

In addition to the logrank test, we used a Cox proportional hazard model to determine how much, and to confirm that the financial sector performs better than the other sectors. This model can be used to calculate a hazard rate [8, 9]. This rate gives insight into with what percentage the hazard is reduced or increased for a certain category.

This model can only be used when the proportional hazards assumption holds. This can be verified using a logs plot, which plots the log of the survival curve against the log of the time. When these two curves are parallel and hence do not cross, we may assume that the proportional hazards assumption holds. Figure 3 shows the log curves for the financial and other sectors. Because the two curves plotted in this figures are fairly parallel and only cross at the very beginning, it is justified to use the Cox proportional hazards model.

coef	exp(coef)	se(coef)	Z	p	lower 0.95	upper 0.95
0.5660	1.7613	0.0059	96.5332	0.0000	0.5545	0.5775

Table 1: Cox proportional hazards model results for the financial sector (4 digits precision)

The results of this test can be found in Table 1. From these  $\exp(\cos f)$  in results we see that the hazard in the financial sector is reduced by about 76% within the 95% confidence interval when compared to the other sectors. We can therefore conclude that the financial sector indeed performs better than the other sectors combined. However, this does not necessarily mean that it is the best performing sector.

#### 3.3.2 Continent

We also test whether the continent where the company is based, has influence on how quickly phishing websites are taken down. We split the data on six different continents: North-America (NA), South-America (SA), Asia (AS), Europe (EU), Africa (AF) and Oceania (OC). Subsequently we have performed the logrank test again on our initial hypothesis  $(H_0)$  which says that there is no difference in performance between companies in one continent and companies in another continent. We want to compare all possibilities, therefore we perform a pairwise logrank test for all continents.

We have decided to compare continents. The reason for this is that comparing each country could lead to a problem that countries will be represented by only one or two companies which are highly present in the dataset. This will give an unfair bias for each country. We have therefore decided to group similar countries and using continents as a partition of our dataset seemed to make the most sense. This expectation is enforced as countries in the same continent are mostly quite similar on areas such as technological development, GDP, and ICT infrastructure. Moreover, this grouping prevents that some countries which are lower on technological development are underrepresented in the dataset as they are less likely to have submitted data to this dataset. Nevertheless it has to be taken into account that this partition of our dataset will only explain variance. It will be hard to draw conclusions from this as not every country is represented in each continent and also this is a gross oversimplification of the reality. However, given the dataset and the scope this was the best categorization possible that is still able to have explanatory power.

Our initial hypothesis is that there is no difference in performance between companies based in different continents. Based on the results of the logrank test we reject the hypothesis with a confidence level of 95% for all continents. The p-values (Table 2) were not high enough (> 0.0500), which means that the continent of origin for a company is a determining factor on how well they take down phishing websites. We also provided the survival curves for these continents in which you can see that there is indeed a difference between the continents. These can be seen in Figure 6a and with a logarithmic scale in Figure 6b.

	SA	AF	EU	OC	AS
NA	0.0000	0.0000	0.0000	0.0003	0.0000
SA		0.0000	0.0000	0.0000	0.0000
AF			0.0000	0.0000	0.0000
EU				0.0000	0.0000
OC					0.0000

Table 2: p-values for the logrank test with the continents (4 digits precision)

The logrank test however, merely says that there is a difference between the continents, not how much of a difference and therefore which one performs better. Therefore we calculated the hazard rate for each continent when compared to the rest of the world. The results hereof can be found in Table 3.

However, when we use the same visual method to check the proportional hazards that was used in the previous section, we can see in Figure 4 that the proportional hazards assumption does not hold for every pair of curves. For example, the curves in the plot for Oceania, South America and Middle East, cross about halfway. So it is better to not rely on the outcomes of the Cox proportional hazards model for this part.

We see here that only one of the hazard rates is not significant, namely the one belonging to Oceania (OC). Thus for Oceania we do not have a statistically significant result telling us how much of the hazard is increased or decreased for companies in this category. For all the other countries the results are significant and we can see that within the 95% confidence interval companies in North-America, South-America, and Africa have reduced risk (59%, 13% and 39% respectively) and companies in Europe and Asia have increased risk (45% and 19%). This would suggest that indeed this factor plays a role in the performance. However,

we cannot say something about all continents when taking into account that the model is not fully justified for all comparisons.

continent	coef	exp(coef)	se(coef)	Z	р	lower 0.95	upper 0.95
NA	0.4633	1.5893	0.0079	58.2887	0.0000	0.4477	0.4789
SA	0.1211	1.1288	0.0203	5.9802	0.0000	0.0814	0.1608
EU	-0.6049	0.5461	0.0095	-63.5677	0.0000	-0.6236	-0.5863
AF	0.3303	1.3914	0.0526	6.2831	0.0000	0.2273	0.4334
AS	-0.2151	0.8065	0.0195	-11.0390	0.0000	-0.2533	-0.1769
OC	0.0309	1.0314	0.0324	0.9540	0.3401	-0.0326	0.0943

Table 3: Cox proportional hazards model results for different continents (4 digits precision)

#### 3.4 Limitations

There are some limitations to the statistical analysis performed above. One drawback is that the dataset is quite biased, a high percentage of the data comes from the same small set of companies. This leads to the drawback that some companies have a very large influence on the category they fall in. This is a rather hard problem to solve as undersampling some of these companies or adding weights might give too much influence to phishing attacks based on the smaller companies. These latter ones are more likely to be anomalies and hence give unrealistic results, because of this we decided to just take the data as is.

One other possible issue is that for the Cox proportional hazard model we had to use random sampling, for otherwise the gradient descent that is used in this method was too slow. Random sampling is in principle not an issue, but might influence the results a little bit, thus we have weighed the amount of data versus the speed of convergence in order to get a result that is at least very close to the real value.

A final limitation of our results has to do with skewedness of the dataset, for example some continents contain notably more financial companies than others, which means that two properties that are supposed to be independent in practice are somewhat correlated in this dataset.

### 4 Conclusion

We have performed several tests on aggregated data to determine factors that influence the security performance in regard to phishing website takedown. We made a distinction between the financial sector and others. We found that the financial sector performs significantly better than the other sectors combined, since the hazard is reduced by 76%. Reasons for this may be that the financial sector has been dealing with these kinds of problems for much longer than others. Another reason is that their incentive to take down phishing websites is higher, since the expected loss is higher for these types of companies. In general we believe that the sector a company is in, has a determining factor on phishing website takedown performance.

We have also performed the same tests when the data was aggregated per continent. Different continents perform differently in performance of phishing website takedown. We found that when pairwise compared, we can say with 95% confidence that all six continents differ in performance. These results were found statistically significant. We have also found that North-America, South-America and Africa perform better than the rest of the world according to the Cox proportional hazards test, whereas the EU and Asia perform worse. These results are affirmed by the results we found in the survival curve of the continents in general.

One problem with this conclusion is that the data is a little skewed in some cases. Some continents contain a higher ratio of financial compared to other companies, which makes it more likely to perform better in general as per the conclusion of the other test. For example, Europe performs relatively bad compared to the other continents, but when looking at the ratio we obtain 0.70588 for Europe which means there are a lot more 'other' companies than financial in companies for Europe in our dataset whereas for example for South America the dataset only contains financial companies. This may explain the difference we can see in Figure 2 and our results.

## References

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## A Figures

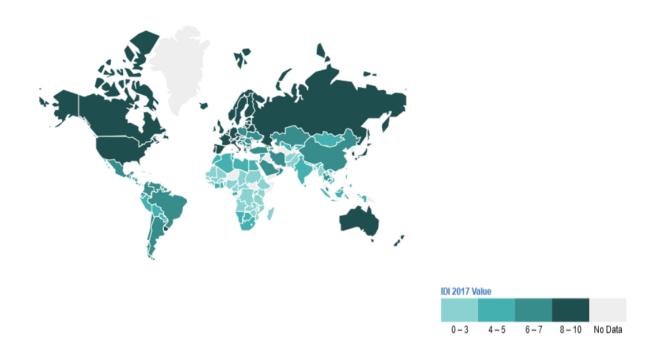


Figure 2: Global ICT Development index per country [4]

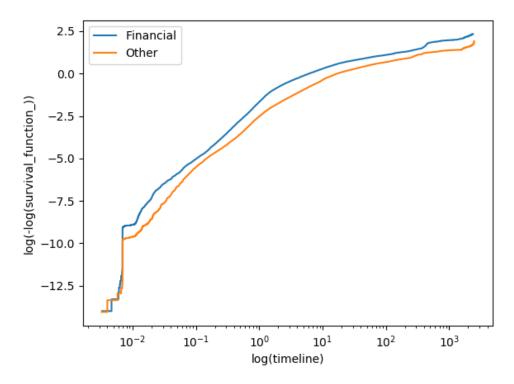


Figure 3: Loglog plot of financial versus other sectors

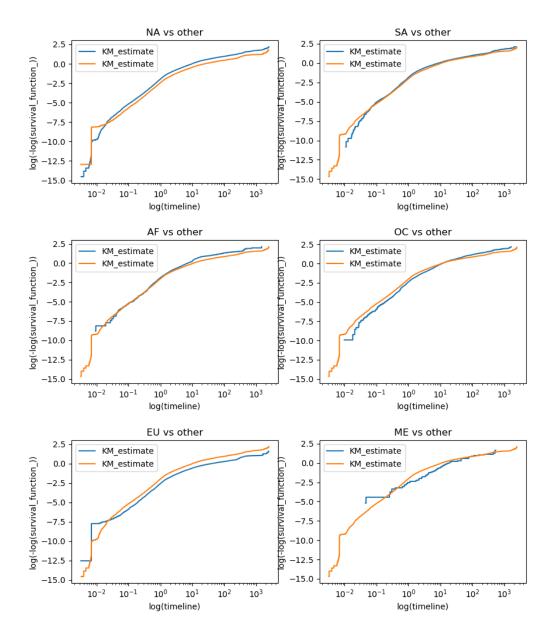
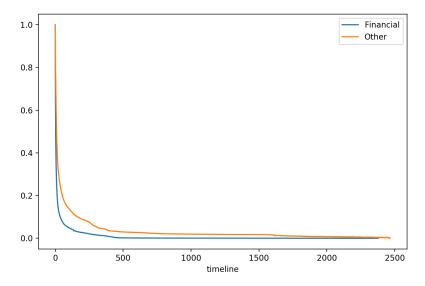
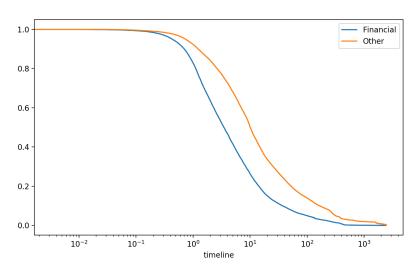


Figure 4: Loglog plot per continent

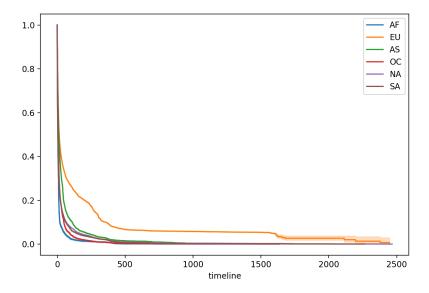


(a) Regular scale for the timeline, where the time is in days

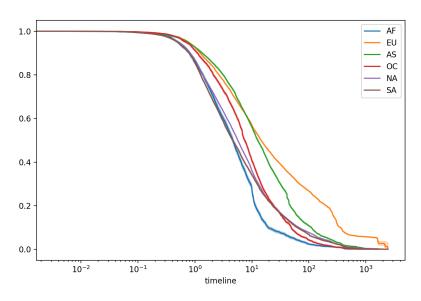


(b) Logarithmic scale, also time in days

Figure 5: Survival curve for companies in the financial sector compared with other sectors



(a) Regular scale for the timeline, where the time is in days



(b) Logarithmic scale, also time in days

Figure 6: Survival curve for companies originating from six different continents