Hiding in Plain Sight: A Longitudinal Study of Combosquatting Abuse

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ABSTRACT

Domain squatting is a common adversarial practice where attackers register domain names that are purposefully similar to popular domains. In this work, we study a specific type of domain squatting called "combosquatting," in which attackers register domains that combine a popular trademark with one or more phrases (e.g., betterfacebook[.]com, youtube-live[.]com). We perform the first large-scale, empirical study of combosquatting by analyzing more than 468 billion DNS records—collected from passive and active DNS data sources over almost six years. We find that almost 60% of abusive combosquatting domains live for more than 1,000 days, and even worse, we observe increased activity associated with combosquatting year over year. Moreover, we show that combosquatting is used to perform a spectrum of different types of abuse including phishing, social engineering, affiliate abuse, trademark abuse, and even advanced persistent threats. Our results suggest that combosquatting is a real problem that requires increased scrutiny by the security community.

KEYWORDS

Domain Squatting; Combosquatting; Network Security; Domain Name System

1 INTRODUCTION

The Domain Name System (DNS) [63, 64], is a distributed hierarchical database that acts as the Internet's phone book. DNS's main goal is the translation of human readable domains to IP addresses. The reliability and agility that DNS offers has been fundamental to the effort to scale information and business across the Internet. Thus, it is not surprising that miscreants heavily rely on DNS to scale their abusive operations.

In fact, domain squatting is a very common tactic used to facilitate abuse by registering domains that are confusingly similar [12] to those belonging to large Internet brands. Past work has thoroughly investigated typosquatting (domain squatting via typographical errors) [13, 33, 48, 54, 67, 90], bit squatting (domain squatting via accidental bit flips) [31, 68], homograph-based squatting (domains that abuse characters from different character sets) [39, 44], and homophone-based squatting (domains that abuse the pronunciation similarity of different words) [69].

A type of domain squatting that has yet to be extensively studied is that of "combosquatting." Combosquatting refers to the combination of a recognizable brand name with other keywords (e.g., paypal-members[.]com and facebookfriends[.]com). While some existing research uses other terms to describe combosquatting domains (i.e.„ "cousin domains" [46]), this work only studies combosquatting in the context of phishing abuse, failing to capture the full spectrum of potential abuse. Thus, even though the general concept of constructing these types of malicious domains is part of the collective consciousness of security researchers, the community lacks a large-scale, empirical study on combosquatting and how it may be abused. Therefore, the security community has little insight into which trademarks domain squatters commonly abuse, how well existing blacklists capture such abuse, and which types of abuse combosquatting is used for.

In this work, we conduct the first large-scale, longitudinal study of combosquatting abuse to empirically measure its impact. By combining more than 468 billion DNS records from both active and passive DNS datasets, which span almost six years, we identify 2.7 million combosquatting domains that target 268 of the most popular trademarks in the US, and we find that combosquatting domains are 100 times more prevalent than typosquatting domains—despite the fact that combosquatting has been less studied. Our study also makes several key observations that help better characterize how combosquatting is used for abuse.

First, we study the *lexical characteristics* of combosquatting domains. We observe that combosquatting lacks generative models and find that, while combosquatting domains vary in overall length,

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50% add at most eight additional characters to the original trademark being abused. Furthermore, 40% of combosquatting domains are constructed by adding a single token (Section 4.2) to the original trademark. Thus, while the pool of potential combosquatting domains is very large, we find that many instances of combosquatting try and limit the overall length of the combosquatting domain. Additionally, we find that combosquatting domains tend to prefer words that are closely related to the underlying business category of the trademark—resulting in combinations that are more targeted than random.

Second, we analyze the *temporal properties* of combosquatting domains and, surprisingly, we see that almost 60% of the abusive combosquatting domains can be found in our datasets for more than 1,000 days—suggesting that these abusive domains can often go unremediated. When combosquatting domains *do* become known to the security community, it is often significantly after the threat was seen in the wild. For example, 20% of the abusive combosquatting domains appear on a public blacklist almost 100 days after we observe initial resolutions in our DNS datasets, and this number goes up to 30% for combosquatting domains observed in malware feeds. To make matters worse, we observe a growing number of queries to combosquatting domains year over year, which is in stark contrast to better known squatting techniques like typosquatting. Thus, combosquatting appears to be an increasingly effective technique used by Internet miscreants.

Third, we discover and analyze numerous instances of combosquatting abuse in the real world. Through a substantial crawling and manual labeling effort, we discover that combosquatting domains are used to perform many different types of abuse that include phishing, social engineering, affiliate abuse, and trademark abuse (i.e., capitalizing on the popularity of trademarks to sell their own products and services). By analyzing publicly available threat reports, we also identified 65 combosquatting domains that were used by Advanced Persistent Threat (APT) campaigns. These findings highlight the wide reaching impact of combosquatting abuse. Finally, we manually analyzed various techniques attackers used to drop malware and counter detection—leading to some interesting discoveries surrounding the use of redirection chains and cookies.

In summary, combosquatting is a type of domain squatting that has yet to be extensively studied by the research community. We provide the first large-scale, empirical study to better understand how attackers use combosquatting to perform a variety of abusive behaviors. Our study examines the lexical characteristics, temporal behavior, and real world abuse of combosquatting domains. We find that not only does combosquatting abuse often appear to go unremediated, but its popularity also appears to be on the rise.

2 BACKGROUND

In this section, we define combosquatting and discuss how it differs from other types of DNS squatting. Additionally, we discuss how combosquatting is used to facilitate many different types of abuse. For example, Internet miscreants use combosquatting to perform social engineering, drive-by-download attacks, malware communication, and Search Engine Optimization (SEO) monetization. Thus, even though combosquatting has not been extensively studied, it has far reaching implications.

2.1 DNS Squatting & Combosquatting

Combosquatting refers to the attempt of "borrowing" a domain name's reputation (or brand name) characteristics by integrating a brand domain with other characters or words. Combosquatting differs from other forms of domain name squatting, like typosquatting and bitsquatting [70], in two fundamental ways: first, combosquatting does not involve the spelling deviation from the original trademark and second, it requires the original domain to be **intact** within a set of other characters. In this paper, we consider a domain name being combosquatting based on the following definition.

Given the effective second level domain name (e2LD) of a legitimate trademark, a domain is considered combosquatting if the following two conditions are met: (1) The domain contains the trademark. (2) The domain cannot result by applying the five typosquatting models of Wang et al. [90].

For example, lets consider the trademark *Example*, such that it is served by the domain name example[.]com and the e2LD of which is *example*. Combosquatting domain names, based on this e2LD, could include any combination of valid characters in the Domain Name System, whether they are prepended or appended to the e2LD. For instance, secure-example[.]com, myexample[.]com, another-coolexample-here[.]com are cases of combosquatting. However, wwwexample[.]com and examplee[.]com are not, since they violate the second clause mentioned earlier. Table 1 shows examples of the different squatting attacks against the youtube[.]com domain name.

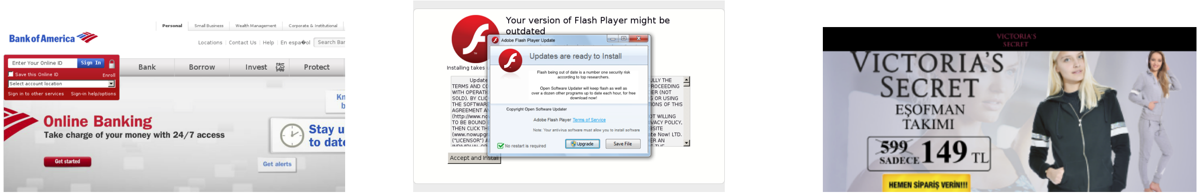
2.2 Combosquatting Abuse

In this section, we discuss the most common types of combosquatting abuse. Despite common beliefs, combosquatting domains are not only used for trademark infringement but are also regularly used in a wide variety of abusive activities—including drive-by downloads, malware command-and-control, SEO, and phishing. We should note that all cases mentioned next were reported to the registrars and law enforcement for remediation.

2.2.1 Phishing. In generic phishing attacks, where obtaining the user's credentials is the final goal of the adversary, the attacker would likely register combosquatting domains close to the targeted organization. For example, in Figure 1a we can see one of those phishing campaigns against Bank of America (BoA) users that employees the bankofamerica-com-login-sys-update-online[.]com domain. It is worth noting that the phishing page that was hosted on this combosquatting domain was nearly identical to the actual BoA website. We argue that this visual similarity, when coupled with

Domain Name	Squatting Type
youtube[.]com	Original Domain
youtubee[.]com	Typosquatting [67]
yewtube[.]com	Homophone-Based Squatting [69]
youtubg[.]com	Bitsquatting [70]
Y0UTUBE[.]com	Homograph-Based Squatting [44]
youtube-login[.]com	**Combosquatting**

Table 1: Examples of the different types of domain name squatting for the youtube[.]com domain name.


Bank of America
Online Banking
Take charge of your money with 24/7 access
Your version of Flash Player might be outdated
Updates are ready to install
VICTORIA'S SECRET
EŞOFMAN TAKIMI
599 SADECE 149 TL
HEMEN SİPARİŞ VERİN!!!

(a) (b) (c)

Figure 1: Examples of combosquatting abuse. (a) A typical phishing campaign against Bank of America using the domain bankofamerica-com-login-sys-update-online[.]com. (b) The airbnbforbeginners[.]com domain uses the AirBnB brand to lure users and drop a malware obfuscated as a Flash Update. (c) An example of trademark abuse against Victoria's Secret using the domain name victoriassecretoutlet[.]org.

the bank's brand name clearly embedded in the combosquatting domain, makes it highly unlikely that everyday users of the web would be able to detect this website as phishing.

2.2.2 Malware. Delivery of malware and drive-by attacks is another interesting case of combosquatting abuse. For example, a combosquatting domain can be used to redirect victims to a page showing fake warnings to lure them into downloading malicious software. Figure 1b shows the domain airbnbforbeginners[.]com being used to lure new AirBnB users. Once users land on the page, a Flash update request is shown to the end user in what looks like a Windows dialogue prompt. Thus, the attack attempts to infect the user by using alerts that suggest Flash Player is outdated and then entice the user to download a malicious update.

In Table 2, we can see malware related domain names that were used as Command and Control (C&C) points for botnets created using popular malware kits (e.g., Zeus). While it is hard to know for sure why attackers decide to use domains that contain popular trademarks, such domains could evade manual analysis of malware communications. The use of combosquatting domain names is not limited to common malware families, like the ones in Table 2. As we will see in Section 3.2, using public reports around targeted attacks and Advance Persistent Threats (APTs), we identified more than 60 APT C&C domains that utilize combosquatting, abusing up to 12 different popular brand names.

2.2.3 Monetization. Next to malicious activities mentioned earlier, combosquatting domains have been heavily exploited in trademark infringement and Search Engine Optimization (SEO). In this monetization category, the combosquatting domains often advertise services similar or related to the original services and products offered by the trademarks being abused. A real world example of such a trademark infringing domain is presented in Figure 1c in which the domain name victoriassecretoutlet[.]org abuses the Victoria's Secret trademark to offer likely counterfeit products at a lower price.

Domain Name	Trademark	Abuse Type
adobejam[.]in	Adobe	Artro C&C
norton360america[.]biz	Norton	Betabot Botnet
googlesale[.]net	Google	Etumbot
indexstatyahoo[.]com	Yahoo	Phoenix Kit
pnbcnews[.]ru	NBC News	Pkybot Botnet
wordpress-cdn[.]org	WordPress	Pkybot Botnet
youtubeee[.]ru	YouTube	Zeus Botnet
google-search[.]ru	Google	Zeus Botnet

Table 2: Examples of combosquatting domains used by malware as Command and Control (C&C) points.

3 MEASUREMENT METHODOLOGY

Measuring the extent of the combosquatting problem is particularly hard because of the almost unlimited pool of potential domains. However, given the definition of combosquatting in Section 2.1, we provide a methodical way to identify combosquatting domains using various datasets. Additionally, we discuss our rationale for selecting trademarks that are most likely to be abused, the type of datasets we use throughout our study, and introduce the necessary notation utilized from this point on.

3.1 Trademark Selection

While all trademarks could be the subject of combosquatting abuse, it is arguably not in the best interest of an adversary to use a less known brand for abuse. In our hypothesis we assume that the adversary would include the trademark name in the effective second level domain (e2LD) as a way to lure victims into clicking and interacting with the combosquatting domain and site.

To that extent, we first need to identify the set of popular domains that are used by major brands (likely to be abused by adversaries). To assemble this list of domains, we extracted the top 500 domain names in the United States (US) from Alexa [14]. Our decision to use only the US-centric popular Alexa domains is due to the underlying datasets we will use for our long-term study (which are mostly US-centric), as we will see in the following section.

Now, even with the top 500 Alexa list, not all domains are appropriate candidates for our combosquatting analysis. This is because (1) there are several brands that employ common words as their brand name and (2) there are several domains and trademarks that are too short to be considered for combosquatting. Table 3 shows a list of trademarks that were ignored in the Alexa Top 500 due to the previous considerations.

We manually inspected all 500 top Alexa domains to exclude domains that fall into the two aforementioned categories. The remaining set contains 246 domains that we will consider in our combosquatting study. We will refer to this list of domains as *seed*

Trademark	Domain	Potential Squat
Apple	apple.com	applejuice[.]com
AT&T	att.com	attorney[.]com, attack[.]com
Bing	bing.com	plumbing[.]com, tubing[.]com
citi (bank)	citi.com	cities[.]com, citizen[.]com
IKEA	ikea.com	bikeandride[.]com
Cisco	cisco.com	sanfrancisco[.]com

Table 3: Trademark examples that have been excluded from our study.

throughout the rest of the paper. The trademarks selected belong to companies that are active in different business categories. Thus, we are able to group them together into 22 categories based on the type of services/products they offer.

We derived this categorization using the Alexa list [14], the TrendMicro [88] website and the DMOZ database [32]. We manually verified the categories and merged any differences between the platforms to create a consistent list. The vast majority of the domains had a stable Alexa rank over time. At the same time, we added seven domains that were a priori chosen in the "Politics" category and 15 for the "Energy" category, following the same process as before. We manually included the energy sector because it is part of the critical infrastructure and the politics because of the US Presidential elections of 2016.

3.2 Datasets

Since our goal is to study combosquatting both in depth and over time, we require a variety of different datasets. Table 4 summarizes the raw datasets used in this study, and Table 5 lists the most important relationships between them. We provide more detail about each of these datasets below.

Passive DNS: The passive DNS dataset (*PDNS*) consists of DNS traffic collected since 2011, above a recursive DNS server located in the largest Internet Service Provider (ISP) in the US. Specifically, this dataset contains the DNS resource records (RRs) from all successful DNS resolutions observed at the ISP, including their daily lookup volume.

Active DNS: We also utilize an active DNS (*ADNS*) dataset, which we obtain daily from the Active DNS project [24]. Since the duration of this dataset is less than a year, it does not have a complete temporal overlap with our *PDNS* dataset. While we will use the *PDNS* and *ADNS* datasets for most measurement tasks, we will also use a variety of smaller datasets to label and measure abuse in these combosquatting datasets. Again, in Table 4 we can see these five different datasets used in this study.

Public Blacklists: We collect historic public blacklisting (*PBL*) information about domains that have been identified by the security community as abusive and placed in various public lists [2–9]. These blacklists have been collected from 2012 until 2016 and overlap with our passive and active DNS datasets.

Advanced Persistent Threats: Using public Advanced Persistent Threat (*APT*) reports [1], we manually extract and verify domain names used in such documented attacks (APT).

Spam Trap: A security company provides us with spam trap [55] data that is labeled using their proprietary detection engine (*SPA*).

Malware Feeds: The same security company and a university provides us with two feeds of domains from dynamic execution of malware samples since 2011 (*MAL*).

Alexa List: To eliminate potentially wrong classification of a domain as abusive (false positive) in the aforementioned datasets, we create a "whitelist" based on the Alexa list. We take the domains that appeared in the top 10,000 of the Alexa list for more than 90 consecutive days in the last five years and create a set of domains as indicators of benign activity (*ALE*).

Certificate Transparency: Google's Certificate Transparency (CT) [10] project provides publicly auditable, append-only logs of certificates with cryptographic properties that can be used to verify the legitimacy of certificates seen in the wild. The official CT website provides a list of known, active logs that can be publicly crawled. We used this list to download all records from those logs up to April 13, 2017. This resulted in a dataset of approximately 271M certificates.

3.3 Linking Datasets

Next, we project the selected trademarks, into the raw datasets presented in Table 4, and derive the trademark–specific datasets, which can be seen in Table 5. The datasets in Table 5 will be used to study the combosquatting problem in depth since 2011. We begin by extracting the Combosquatting Passive (*CP*) and Combosquatting Active DNS (*CA*) set of domains, which reflect combosquatting domains containing at least one of the trademarks of interest in the Passive and Active DNS datasets, respectively. The cardinalities of these two sets are of the order of millions of domain names (2.3M for the *CP* set and 1M for the *CA*), and all combosquatting domain abuse should be bounded by the size of the two sets.

Following the same process, we identify the combosquatting domains in the PBL, APT, Spamtrap, Malware and Alexa sets, deriving C_{pbl}, C_{apt}, C_{spa}, C_{mal} and C_{ale}, respectively. The cardinalities of these sets can be seen in Table 5 where they span from a few domains (C_{apt}) to several tens of thousands of domains (C_{mal} and C_{ale}). Finally, we will define C_{abuse} as the set of domains in all malicious categories of combosquatting domains, namely C_{pbl}, C_{apt}, C_{spa}, and C_{mal}.

4 MEASURING COMBOSQUATTING DOMAINS

In this section we present short and long term measurements revolving around the combosquatting domains in our datasets. We begin by investigating the differences between typosquatting and combosquatting. At the same time we discuss which words attackers choose to combine with popular trademarks more frequently.

[1] `http://tinyurl.com/apt-reports`

Dataset Type	Size	Records	Time Period	Notation
Passive DNS	18.1T	13.1×10^9	2011–01–01 to 2015–10–14	*PDNS*
Active DNS	30.5T	455×10^9	2015–10–05 to 2016–08–19	*ADNS*
Public BLs	26.7G	610×10^6	2012–12–09 to 2016–09–13	*PBL*
APT Reports	N/A	21,927	2008–10–01 to 2016–11–04	*APT*
Spamtrap	35M	965,911	2009–07–17 to 2016–09–13	*SPA*
Malware Traces	34.8G	1.1×10^9	2011–01–01 to 2016–10–22	*MAL*
Alexa	42.9G	1.3×10^9	2012–12–09 to 2016–09–13	*ALE*
Certificate Transparency	842G	271×10^6	2013–03–25 to 2017–04–13	*CERT*

Table 4: Summary of the raw datasets used in this study.

	Passive DNS			**Active DNS**			
α	$\alpha \cap CP$	NoT	NoC	$\alpha \cap CA$	NoT	NoV	**e2LDs Count**
CP							2,321,914
CA							1,022,083
C_{mal}	9,283	179	21	6,886	174	21	9,472
C_{pbl}	3,750	135	21	4,787	128	21	5,844
C_{apt}	59	11	8	56	12	8	65
C_{spa}	2,296	126	20	6,400	148	20	6,400
C_{abuse}	14,965	201	21	17,586	200	21	21,173
C_{ale}	45,619	244	22	37,098	244	22	48,197

Table 5: The combosquatting datasets, and their relational statistical properties. NoT: Number of unique trademarks in a set of domains and NoC: Number of unique business categories in a set of domains. $C_{abuse} = \{C_{mal} \cup C_{pbl} \cup C_{apt} \cup C_{spa}\}$.

Then, we study the temporal properties of the domain names in the combosquatting passive and active DNS datasets. This analysis will help us understand how these combosquatting domains evolved since 2011.

In particular, we observe that the number of combosquatting domain names in our passive and active DNS datasets are steadily increasing; in contrast, the domains in the C_{abuse} set remain stable over time. At the same time, we observer that the security community is lagging behind the detection of malicious combosquatting domains, in many cases up to several months, despite being an obvious target of abuse. Finally, we provide an analysis of the DNS and IP hosting infrastructure that combosquatters tend to employ. The domains in the C_{abuse} set tend to utilize significantly more agile hosting infrastructure, which could be used as a signal to identify abusive combosquatting domains on the rise.

4.1 Combosquatting versus Typosquatting

Since typosquatting is, by far, the most researched type of domain squatting, we begin our discussion of combosquatting by comparing it with typosquatting. Figure 2 shows the number of active typosquatting and combosquatting domains targeting our evaluated trademarks since 2011. To identify typosquatting domains, we use the five typosquatting models of Wang et al. [90] to generate all possible typosquatting domains and search for those domains in our DNS datasets. The left part of the plot is based on our passive DNS dataset while the right part is based on the active DNS dataset. One can clearly see that, even though combosquatting has evaded the attention of researchers, it is significantly more prevalent than typosquatting, with the number of daily combosquatting domains being almost two orders of magnitude larger than the number of typosquatting domains.

In comparison with other types of domain squatting phenomena such as typosquatting, combosquatting has a unique property in that it lacks a generative model. For all other types of domain squatting, researchers can start with an authoritative domain, and by performing character and bit swaps, they can exhaustively list the possible squatting permutations for a given type of domain squatting. For example, the dotted line in Figure 2 indicates the maximum number of typosquatting domains possible when considering the evaluated trademarks and typosquatting models [90]. In combosquatting, however, attackers are free to prefix and postfix a trademark with one or more keywords of their choice, bounded only by the maximum number of characters allowed for any given label by the DNS protocol [65, 66].

Another difference that is closely related to the lack of a generative model, in terms of attack scenarios, has to do with the way attacks are rendered. Typosquatting can be a passive attack for the adversary, who simply must wait until a user accidentally types in a domain. However, combosquatting requires more active involvement from the attacker because, while a user may accidentally type paypa[.]com instead of paypal[.]com, an attacker cannot register paypal-members[.]com and reasonably expect users will accidentally type those eight extra characters. Therefore, miscreants that rely on combosquatting must coerce users (e.g. via spam emails and social networks) to visit combosquatting domains.

To increase the chances that users will interact with their malicious combosquatting domains, attackers can use services like *Let's Encrypt* [56] to both freely and automatically obtain TLS certificates for their domains. In fact, Let's Encrypt has recently come

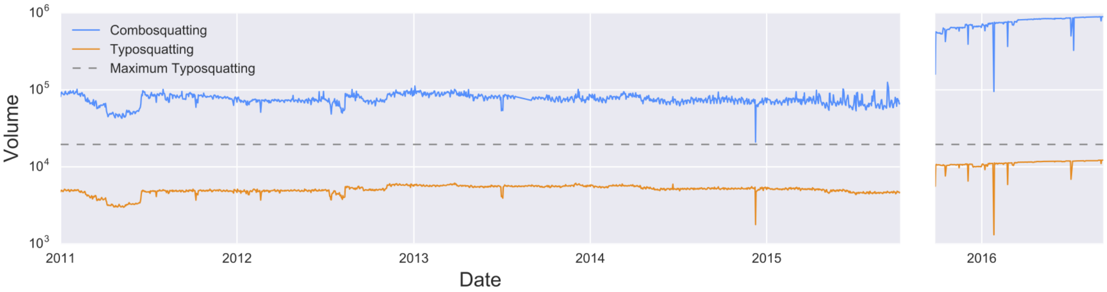


Figure 2: Number of active Combosquatting and Typosquatting domain names per day. The left hand side part of the plot depicts the passive DNS period, whereas the right one reflects domains found in the active DNS dataset.

under criticism for choosing to eschew any sort of security checks before giving domain owners a TLS certificate [11]. To quantify the frequency with which attackers obtain certificates for their malicious domains, we searched the 271 million certificates obtained via the Certificate Transparency append-only log (described in Section 3.2) and discovered that 691,182 certificates were given to a total of 107,572 fully-qualified combosquatting domains related to our trademarks, since 2013, with 41.5% of the certificates being issued by Let's Encrypt. In contrast, only 3,011 certificates were issued for typosquatting domains. This finding further confirms the intuition that typosquatting and combosquatting are two distinct phenomena with different threat models and attack strategies.

In summary, we argue that existing domain squatting detection systems are not taking combosquatting domains into account (since they cannot generate them) and combosquatting requires its own analysis due to the scale of the problem and the different threat models involved.

4.2 Lexical Characteristics

The lack of generative models for combosquatting, makes it hard to proactively create and evaluate domains. Therefore, we utilize the DNS datasets mentioned previously, to identify combosquatting domains and analyze their composition. In particular, we see that adversaries do not usually register lengthy domains and do not use many words when generating the domains. We also find that there are certain words that adversaries favor when generating abusive combosquatting domains. Some words are independent of the trademark's business category, and other words are specific to a single category.

Figure 3a shows the Cumulative Distribution Function (CDF) of the length of all identified combosquatting domains. There we can see that even though an attacker can, in principle, construct very long domains, 60% of the identified combosquatting domains were using less than ten characters and 80% of the combosquatting domains were using less than 22 characters (excluding the original squatted trademark). This provides an early indication that the vast majority of the attackers carefully construct combosquatting domain names without attempting to reach the limits afforded to them by the DNS protocol.

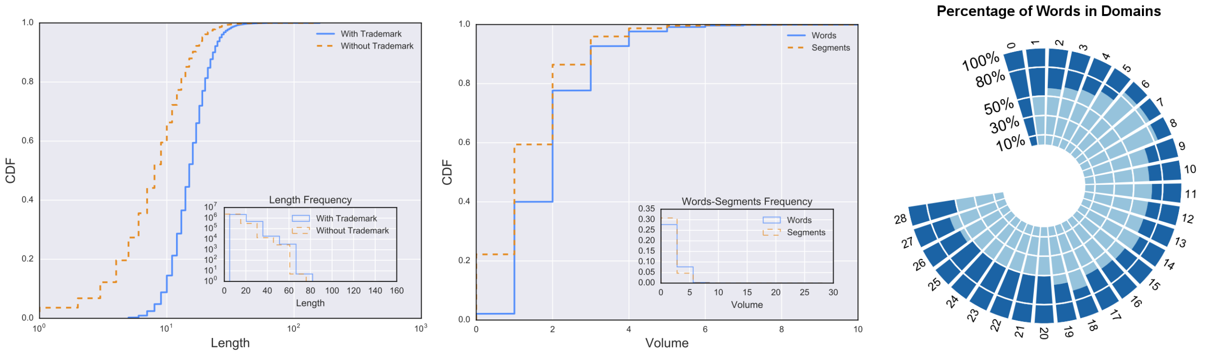
To better understand the construction of combosquatting domains, we extract the non-Top Level Domain (non-TLD) part of each domain (e.g. we extract `facebookfriends` from `facebookfriends[.] com`) and use the *word segmentation* algorithm described in [79]. This algorithm takes a string as input and outputs sequences of that string that have a high probability of being standalone tokens, along with a confidence score for the provided tokenization.

We validate the output tokens provided for each combosquatting domain against four dictionaries: (1) the PyEnchant en_US Python dictionary [76] to identify English words, (2) the *No Swearing* dictionary [16] to identify swearing-related words, and both (3) the SWOPODS [81] and (4) *No Slang* [15] dictionaries to identify slang words in US English. Tokens that are found in any of these dictionaries are referred to as *words* and, when not found, we simply call them *segments*.

Figure 3b depicts a CDF of the number of tokens and number of words that were identified for each domain. We see that almost 80% of the domains have at most two dictionary-words present, and 90% have at most three words. At the same time, we have found a limited number of cases that contain up to 28 words and segments. These results validate our earlier length-based claim that squatters appear to be methodical in their construction of combosquatting domain names. We note that stop words and other short words have not been removed from our datasets because they are frequently used by combosquatting domains.

Figure 3c shows the correlation of segments (cyan) and actual words (blue). Every bin in the radial histogram represents the number of tokens identified in each domain. The presented percentage captures the number of actual words versus segments that we were able to distinguish. As we can see, the middle ranges of token counts (6 to 19) have a lot more segments than words, whereas when the domain consists of fewer tokens, the number of words found in the dictionaries mentioned earlier increases. On average, half of the tokens are words and the other half are segments. This is likely an artifact of the attackers' attempts to register domains that might include typos or several strings close to words, which could be overlooked by the targets, in order to increase their arsenal of combosquatting domains. Consider, for example, the following list of domain names that we identified as combosquatting and all point to a credit card activation campaign.

```
activatemycrbankofamerica[.]com
activatemycrebankofamerica[.]com
activatemycredbankofamerica[.]com
```



(a) *(b)* *(c)*

Figure 3: Lexical Characteristics of combosquatting domains. (a) Length of the Combosquatting domain names, including and excluding the original trademark. (b) CDF of the number of segments and words. We limit the x-axis of the outer plot for the sake of readability. (c) Number of segments used in combosquatting domain names. For each number of segments the percentage of English words is presented in blue color.

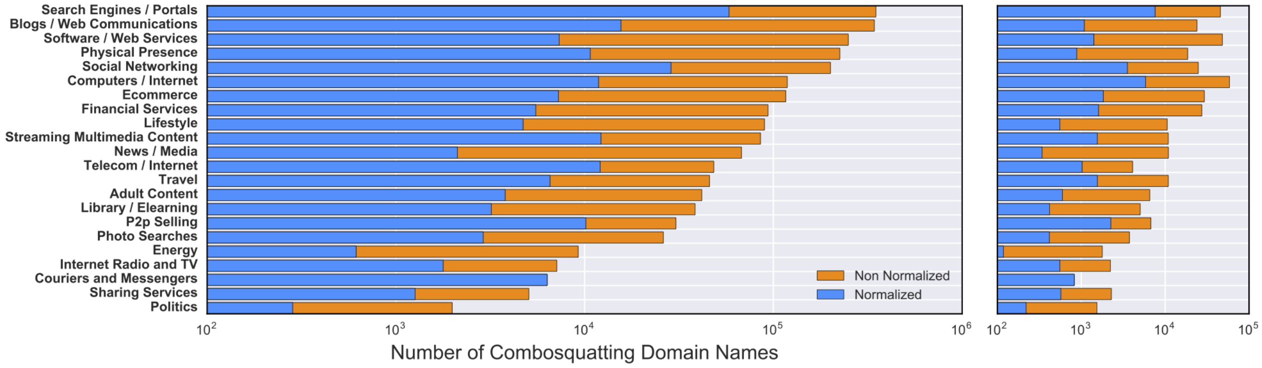


Figure 4: Normalized and absolute size of the combosquatting domains in our datasets per business category.

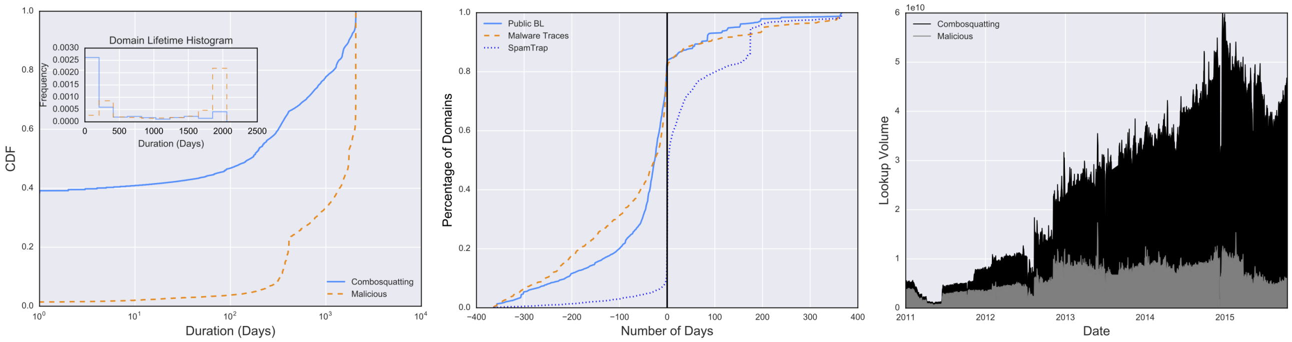
```
activatemycredibankofamerica[.]com
activatemycreditbankofamerica[.]com
activatemycreditcabankofamerica[.]com
activatemycreditcarbankofamerica[.]com
activatemycreditcardbankofamerica[.]com
```

In terms of the words that attackers combine with abused trademarks, the top twenty words across all trademark categories were: *free, online, code, store, sale, air, best, price, shop, head, home, shoes, work, www, cheap, com, new, buy, max,* and *card.* Since the top twenty words represent all of our 22 categories, they include terms that can be found either in one or multiple trademark categories. For example, the word "free" can be found in 12 of the 22 categories, suggesting that attackers commonly combine the word "free" with popular trademarks associated with paid goods (such as shopping, movies, and TV shows) to lure users into interacting with their websites. Contrastingly, certain words appear in a single category of trademarks, such as "cheap" which is found only in the online shopping category.

Due to space limitations, we make Table 10 available in the Appendix that presents the ten most frequent words for each trademark category. We see that many of the popular words closely correlate with the type of trademark being abused, like the words *apple, game* and *phones* being popular in the "Computers/Internet" category and the words *president, vote,* and *elect* being popular in the "Politics" category. The word selection by the adversaries clearly indicates that most registered combosquatting domains have been carefully constructed to match the expected context of each abused trademark. This is a property unique to combosquatting, since any other type of squatting is bounded to the squatted domain name itself. For example, the search space in typosquatting, from which adversaries can choose domain names is bounded to the length of the domain and the characters used, limiting the agility and multiformity of the threat.

4.3 Temporal Analysis

In Section 3.1 we presented our process for selecting the trademarks we use in our study, and in Section 3.2 we discussed the different datasets we use to measure the phenomenon. Using these trademarks and the dataset notation from Table 5, we study the temporal properties of combosquatting domains since 2011. We find that clients are increasingly resolving combosquatting domains and that more than half of all combosquatting domains share a minimum



(a) *(b)* *(c)*

Figure 5: Infrastructure characteristics of combosquatting domains. (a) A CDF of the domain name lifetime in the CP set. (b) The difference between the time a combosquatting domain name was first seen in our datasets and the day it first appeared in a Public Blacklist, the Malware Traces dataset, or the security vendor's spam trap. The plot shows the cumulative volume of domains over time, normalized by the maximum number of domains in each dataset. (c) The DNS lookup volume for the domain names in the CP set vs. the malicious (C_{abuse}) domains.

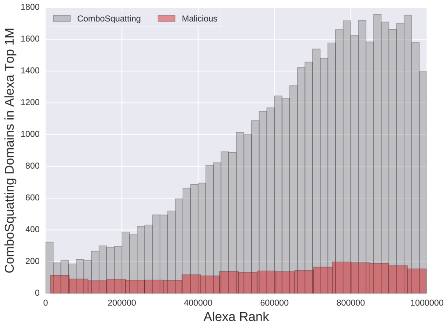


Figure 6: Distribution of the Alexa ranks for combosquatting domains since 2011. The plot depicts the mean rank for the domain names over the period of our C_{ale} dataset.

lifespan of at least three months; in contrast, the majority of abusive domains are active for more than a year. We also see that malicious domains appear in the DNS datasets several months before they appear in our abusive dataset and they even make it into the top thousands ranks in the Alexa list.

Figure 4 shows the number of combosquatting domain names we were able to place in the passive (left) and active (right) DNS datasets. The orange color represents the total number of combosquatting domain names we are able to identify in our datasets for each of the trademark categories. Blue shows the normalized number based on the number of trademarks that appeared in each category. While most of the combosquatting domain names are in "Information Technology" related categories, our dataset is not biased, as the sets CP and CA contain a significant number of domains across all trademarks and business categories.

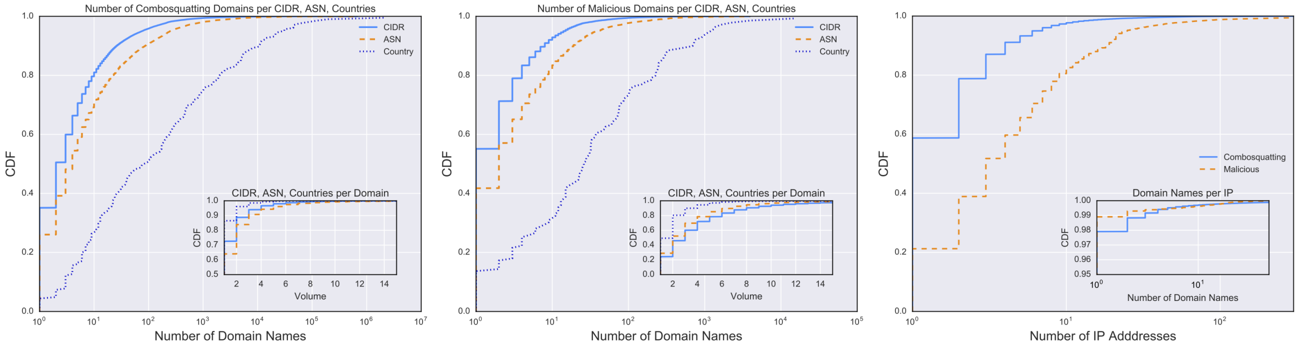
By focusing our attention on the combosquatting passive DNS set, we can see the days in which a combosquatting domain name is available in our datasets. Figure 5a shows the CDF of this lifetime of the domains in the CP set. We measure the lifetime of a combosquatting domain as the number of days between the first and last time we saw it appearing in our passive DNS dataset. Almost 50% of the domain names in the CP set were active for at least 100 days. In the same figure, we can observe the malicious class of combosquatting domain names, which are in the C_{abuse} set (presented earlier in Table 5).

Interestingly, Figure 5a also shows that the lifetime of abusive combosquatting domains is greater than the entire combosquatting passive DNS set. This makes intuitive sense because a large number of abusive combosquatting domains facilitate malicious network communication for prolonged periods of time.

Figure 5b presents how fast the community comes across these combosquatting domains. In the cases of domains from the sets C_{mal} and C_{pbl}, we see that most domains are active several months before they appear in malware traces, or get listed in public black lists. The only exception is the spam trap that the security vendor is operating, where more than 50% of the domain names in the C_{spa} set appear in passive DNS either a few days before, or on the same day that they appear in the spam trap. One reasonable explanation for this behavior is that it is an artifact of the type of abuse (i.e., spam monetization and social engineering) that these combosquatting domains facilitate.

In order to measure the overall popularity of the domains in the combosquatting passive DNS (CP) dataset over time, in Figure 5c we show the DNS lookup volume growth since 2011, according to our PDNS dataset. To put things into perspective, in the same figure, we plot the lookup volume of domains in the C_{abuse} set. It is interesting to observe that while the domains in the CP set have a steady growth over time, the lookup volume of malicious domain names in the set C_{abuse} appears to be nearly uniform. Even though we lack a definite explanation of this behavior, our earlier spam-trap-related results suggest that this almost uniform activity is an artifact of the type of combosquatting abuse (i.e. related to spam and social engineering) that the security industry can reliably detect.

Another interesting observation is related to the Alexa popularity of combosquatting domains. Figure 6 shows the distributions of combosquatting domains across the top 1 million Alexa ranks,



(a) *(b)* *(c)*

Figure 7: Infrastructure distributions for combosquatting Domains. (a) Number of combosquatting domains per CIDR, ASN, and Country for all combosquatting domain names. The inset plot shows the CIDR, ASN, Country Code frequency distribution per combosquatting domain in the CP and CA sets. (b) Number of malicious domains (C_{abuse}) per CIDR, ASN, Countries. The inner plot shows CIDR, ASN, Countries per malicious (C_{abuse}) combosquatting domain. (c) CDFs for the number of IP addresses that domains in the combosquatting (CP and CA) and malicious (C_{abuse}) utilize during their lifetime.

both for combosquatting domains that are known to be malicious (present in any of our abuse datasets) as well as for all of the remaining combosquatting domains. First, we can observe that, as we move from higher to lower rankings, the concentration of generic combosquatting domains increases. Even so, the overall number of combosquatting domains that are present in the top 1 million Alexa list is limited. In terms of the distribution of malicious combosquatting domains, there we see the presence of malicious domains across all Alexa ranks, which suggests that the existing tools for detecting malicious domains are finding only a small fraction of live attacks, regardless of the overall number of combosquatting activity in any given bin of Alexa ranking. We should note that Figure 6 shows aggregate statistics of 20,000 bins in the x-axis. Therefore, the far left domains are cases of combosquatting domains that have made it into any of the top 20,000 Alexa ranks.

4.4 Infrastructure Analysis

So far we have examined how the domains in the combosquatting passive DNS dataset evolved over time. In this section, we turn our attention to the various DNS and IP properties that the domains in the combosquatting passive and active DNS dataset exhibit. We see that the hosting infrastructure of malicious combosquatting domains is concentrated in certain autonomous systems and they are scattered across numerous different CIDRs—which is different from the behavior of combosquatting domains in general.

Figure 7a shows the distribution of Classless Inter-Domain Routing (CIDR) networks, Autonomous Systems (AS), and Country Codes (CC) for the hosting facilities of CP and CA combosquatting domains. As expected, generic combosquatting activity is spread across the globe with no obvious concentrations.

We cannot claim the same for the domains in the C_{abuse} set. In Figure 7b, we can see a higher concentration of malicious combosquatting domains from the C_{abuse} set in a single CIDR and AS. That is, almost 58% of the malicious domains are in one CIDR, where only 38% of all combosquatting domains live in a single network. The preference that malicious domains have a single CIDR/AS can be explained in the following two ways. There are few CIDRs and ASes around the world that will permit the long term hosting of malicious domains. At the same time, such malicious combosquatting domains eventually will be remediated, as we saw earlier in this section. This will practically mean that they will be pointed to a DNS sinkhole or a domain parking page.

With this behavior in mind, we tried to better understand both the bipartite graph between the domains in the combosquatting passive and active DNS datasets, and also in the C_{abuse} set. With Figure 7c we observe that domains in the set C_{abuse} point to hosts that are spread across more distinct CIDRs than the domains in the CP and CA set. While the rotation on malicious IP infrastructure might not be a new observation, in the reduced space of combosquatting domains, this behavior could be used not only as a way to both track combosquatting domains over time, but also to alert us of potentially new abusive ones.

5 COMBOSQUATTING IN THE WILD

So far we have shed light to the combosquatting phenomenon over a period of almost five years. We have shown the complexity of the combosquatting problem by studying its lexical, infrastructure, and temporal properties in Section 4. This section focuses on how combosquatting domains are being used in the wild. We study different aspects of combosquatting abuse, at the time of writing, and show how combosquatting can be used for many different types of illicit activities.

We show that combosquatting domains are currently being used for a variety of attacks (e.g. phishing, affiliate abuse, social engineering, trademark abuse). While we study trademarks spread across different business categories, these attacks affect almost every category. We manually analyze a set of combosquatting domains in order to further examine their network behavior and the countermeasures the adversaries take to evade detection.

5.1 Exploring & Labeling Combosquatting Domains

In order to understand the current status of combosquatting domains and potential attacks rendered using them, we built an infrastructure of 100 *scriptable* browser instances and used them to crawl 1.3 million combosquatting domains, which were all part of CA (active DNS dataset). The 1.3 million domains were comprised of 1.13 million initial seed domains (note that we have slightly more domains than the ones reported in Table 5 since we may crawl multiple subdomains per e2LD). On top of that, we also crawl 200 thousand domains, which included daily registrations of new combosquatting domains and other domains that switched to unknown NS server infrastructure (e.g. non-brand protection companies). Our crawlers were tracking these changes for four weeks and were able to successfully crawl approximately 1.1 million domains.

Due to the sheer size of the collected data and the need of manual verification by human analysts, we approach the dataset we collected through crawling in three sequential steps. First, we scan our entire dataset for evidence of affiliate abuse, i.e., combosquatting domains that redirect users to their intended destination but add an affiliate identifier while doing so. This check will result in the scammer earning a commission from the user's actions [80]. Second, we look in the remainder of the dataset for phishing pages by identifying login forms (from HTML inspection) and focusing on the web pages that are "visually similar" to the legitimate websites. Finally, in order to understand the type of abuse that is neither phishing nor affiliate abuse, we perform a combination of stratified and simple random sampling on our remaining dataset and manually label 8.7 thousand web pages.

All this effort will yield two important points for our study. First, this will help the reader get a sense of how combosquatting is currently used in social engineering and affiliate abuse. Second, we augment the C_{abuse} set of malicious combosquatting domains that escape the threat feeds we used in our study. The next paragraph will provide more details about each step and the discovered abuse.

Affiliate abuse. First, we scan all pages of our crawled corpus focusing on the ones that, through a series of redirections, navigated our crawlers to the appropriate authoritative domains. By excluding domains that, through their WHOIS records and name servers, we identified as clearly belonging to the legitimate owners of the authoritative domains, we manually investigate the rest of the redirection chains and identify 2,573 unique domains that were, for at least one day, involved in affiliate abuse.

Phishing. We scan the HTML code of all the crawled pages that were neither legitimately owned nor abusing affiliate programs, and identify 40,299 unique domains that contain at least one login form. We then proceed to cluster these webpages by their visual appearance using a hamming distance on the hashes produced by a perceptual hashing function, a process which resulted in 7,845 clusters. We then focus on the clusters that contain screenshots that are similar to the look-and-feel of the targeted brands, so as to remove unrelated pages that happen to have login forms. Through this process, we identify 174 domains as conducting phishing attacks. Table 6 shows the trademarks that were attacked by four or more combosquatting domains. Even though this number may appear to be small, these were short-lived *live* phishing domains that we discovered in the wild targeting the users of our investigated trademarks.

Trademark	#Phishing	Example
Facebook	56	facebook123[.]cf
icloud	48	icloudaccountuser[.]com
Amazon	7	secure5-amazon[.]com
Google	8	drivegoogle[.]ga
PayPal	8	paypal-updates[.]ml
Instagram	7	wvwinstagram[.]com
Baidu	4	baidullhk[.]com

Table 6: Examples of domains used for phishing, as discovered by our crawling infrastructure.

Other types of abuse. Last, we focus on the top two Alexa domains of each of the trademark categories (stratified sampling), resulting in the selection of 221,292 combosquatting domains targeting the selected trademarks. Using perceptual hashing in the same way as we did for the identification of phishing pages, we cluster 351 thousand screenshots of websites (note that many of the 221 thousand combosquatting domains were crawled multiple times due to infrastructure changes that were deemed suspicious) into 50 thousand clusters. The trademark responsible for the largest number of clusters (8.3 thousand) was Amazon which, due to its name, "attracts" thousands of combosquatting websites which are not necessarily related to each other, and thus create clustering singletons. To label the screenshots, we randomly sample 10% of the domains of each affected brand and manually label them, resulting in a manual analysis effort of 8.7 thousand screenshots.

The labeling was performed by the authors where each one chose among the following labels: social engineering (surveys, scams such as tech support scam [62], malicious downloads), trademark abuse (websites capitalizing on the brand of the squatted trademarks), unrelated (seemingly benign and unrelated websites), and error/under construction. Finally, the resulting labels are then used to label the entire clusters in which each sampled screenshot belongs. Table 7 shows the overall abuse of the investigated trademarks by consolidating the results of the previous two steps, the manual labeling of the stratified random sample and removing all the authorative domains from the list. Table 8 shows the types of abuse for each category of trademarks by focusing on the abuse of its most popular domain (grey cells denote the most popular type of abuse per trademark category). There we see that while trademark abuse is usually the most popular type of abuse, the exact breakdown varies across categories. For example, for both amazon and homedepot, affiliate abuse is the most popular type of abuse, fueled by the fact that these two services offer affiliate programs to their users.

5.2 Case Studies

On October 30th of 2016, we crawled 505 combosquatting domain names that were hosted on the same infrastructure. That is, the domain names were pointing to the same set of IP addresses on that day according to the active DNS dataset. To better understand how

Unknown	86.6%	Unrelated	11.23%
		Suspicious [1]	88.77%
Malicious	13.39%	Phishing	0.9%
		Social Engineering	13.62%
		Affiliate Abuse	15.56%
		Trademark Abuse	69.9%

[1] Includes under construction, error pages and parking websites.

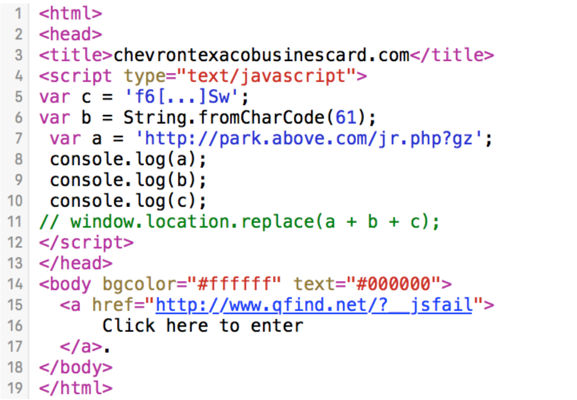
Table 7: Types of combosquatting pages

Category	Trademark	PH	AB	SE	TA
Adult Content	pornhub	0%	5.14%	25.73%	69.11%
Blogging	wordpress	0%	0.06%	2.93%	96.96%
Computers	microsoft	0.32%	11.0%	13.68%	74.39%
E-Shop (Online)	amazon	0.36%	61.65%	1.47%	36.50%
Financial	paypal	6.29%	0.78%	55.11%	37.79%
Radio & TV	netflix	2.29%	5.74%	19.54%	72.41%
E-Learning	wikipedia	0%	0%	32.58%	67.14%
Lifestyle	diply	0%	0%	1.6%	98.4%
News	reddit	1.49%	0%	1.49%	97.01%
Couriers	fedex	0%	3.12%	25%	71.87%
E-Shop (C2C)	craigslist	0%	0%	31.10%	68.89%
Photography	pinterest	0%	0%	5.76%	94.23%
E-Shop (Physical)	homedepot	0%	72.5%	2.5%	25%
Search Engines	google	0.32%	3.58%	23.49%	72.32%
File Sharing	dropbox	2.7%	16.21%	51.35%	29.72%
Social Networks	facebook	5.24%	6.18%	18.74%	69.82%
Software & Web	popads	0%	0%	0%	100%
Streaming	youtube	0%	2.02%	14.5%	83.47%
Telecom	xfinity	2.85%	14.28%	11.42%	71.42%
Travel	airbnb	0%	4.04%	1%	94.95%

Table 8: Types of combosquatting abuse for the most popular investigated domain within each trademark category (PH = phishing, AB = affiliate abuse, SE = social engineering, TA = trademark abuse).

adversaries take advantage of combosquatting domains, we set up a headless crawling engine based on the Python *requests* module, that collects Layer 7 (in the OSI stack) information. Our experimental setup had two phases: first we crawled the domains using the default configuration of the module and then we repeated the process specifying a Chrome *User-Agent*. By comparing crawling results from the two phases, we were able to identify the presence of evasive behavior against our crawlers based on factors like HTTP headers, client's IP address and cookies' presence.

Redirection Games. Most of the domains were associated with a form of redirection, either to a parking page, or to an abuse-related website. A set of 114 domains were performing at least one redirection irrespective of the User-Agent HTTP header. When the User-Agent was not set, 28 domains did not redirect and presented a parking page. This set grew to 127 when User-Agent headers were used. Redirection to the parking page was performed via a child label for the same domain name, following the same naming convention: the child label starts with ww followed by a number (i.e. starbucksben[.]com redirects to ww1.starbucksben[.]com).



```
1  <html>
2  <head>
3  <title>chevrontexacobusinescard.com</title>
4  <script type="text/javascript">
5  var c = 'f6[...]Sw';
6  var b = String.fromCharCode(61);
7   var a = 'http://park.above.com/jr.php?gz';
8   console.log(a);
9   console.log(b);
10  console.log(c);
11 // window.location.replace(a + b + c);
12 </script>
13 </head>
14 <body bgcolor="#ffffff" text="#000000">
15   <a href="http://www.qfind.net/?__jsfail">
16       Click here to enter
17   </a>.
18 </body>
19 </html>
```

Figure 8: The JavaScript redirection performed by some combosquatting domain names. This example is the result of visiting chevrontexacobusinescard[.]com. Line 5 had a 1,838 characters long string.

Moreover, there was a set of 53 domains that was performing HTTP redirection without User-Agent, but JavaScript redirection when the User-Agent was set. In the latter case, the HTTP response contained highly obfuscated JavaScript code similar to the one in Figure 8.

Malware Drops. One interesting example that shows how adversaries are hiding the behavior of a domain from automated systems and crawlers, is http://zillowhomesforsale[.]com. When no User-Agent is present, the domain always redirected to http://ww1.zillowhomesforsale[.]com/, which served us with a parking template. When the User-Agent was set, the redirection would be to either the aforementioned URL or to a completely different domain (i.e. http://rtbtracking[.]com/click?data=Mm[...]Q2&id=8c[...]d3), based on a probabilistic algorithm.

After we identified the attempt of the domains to hide their real behavior, we tried to extract further information. We setup two Virtual Machines (VMs) on a MacBook Pro running Mac OS 10.11.6 and Avast Mac Security 2015 Version 11.18 (46914) with Virus definitions version 16103000. The first VM was an Ubuntu 14.04.1 and the second a Mac OS 10.11.6. We started manually browsing to the domain names mentioned earlier and we identified several instances of malicious websites and URLs we were redirected to.

For example, zillowhomesforsale[.]com this time redirected us to http://www.searchnet[.]com/Search/Loading?v=5 which was blocked by Avast and classified as *RedirMe-inf [Trj]*, a well known trojan (http://malwarefixes.com/threats/htmlredirme-inf-trj/). Similarly, when we browsed to youtubezeneletoltes[.]net we came across an automatic downloader of a disk image file named "FlashPlayer.dmg". It contained a binary that we submitted to VirusTotal for analysis. The results pointed to malware, since 15/54 Antivirus reports were suggesting some type of Trojan or Adware (`http://bit.ly/2ffwyW1`).

Some of the combosquatting domains that we experimented with would redirect us to an authoritative website (not necessarily the one they were abusing), after appending an affiliate identifier in the URL, essentially conducting affiliate abuse. For instance, visiting jcpenneyoulet[.]com lands on http://www.jcpenney[.]com/?cm_mmc=google%20non-[...] and visiting toysrusuk[.]com yields http://www.target[.]com/?clkid=4738[...]. Interestingly, after visiting one of the websites a cookie would be set on the user's browser. If the user attempted to visit another website (from the same set of domains), she would find herself on a parking page [89]. After clearing cookies and repeating the process, the domain would reveal its true nature.

Social Engineering and Phishing. Another type of abuse we identified was related to social engineering and phishing types of attacks. After visiting some domains like stapleseaseyrebates[.]com, we were redirected to http://viewcustomer[.]com/s3/p10/index-20up-p10-cnf-t1-p4.php?tracker=wait.loading-links.com&keyword=staples1[...]. The landing page presented us with a survey for Staples that would supposedly reward us with a gift after completing it, clearly not related to the Staples business in any way. These surveys are meant to collect as much PII as possible from users and subscribe them to potentially paid services [29].

6 DISCUSSION

In Sections 2 through 5, we presented the intuitions behind combosquatting domains, how they are different than other types of domain squatting, and quantified their current level of abuse. Specifically, we found that combosquatting, despite its relative obscurity, is more popular than typosquatting (Section 4.1). Further, we found that combosquatters carefully crafted their domain names to account for the businesses to which the abused trademarks belong to (Section 4.2). By cross-referencing our list of combosquatting domains with popular blacklists, we observed that most domains are active for several months before appearing on these lists (Section 4.3), suggesting the presence of blind spots in the tools used by the security industry. We identified that a few ASes were responsible for the long-term hosting of malicious combosquatting domains (Section 4.4) and witnessed how both common botnets and targeted APTs utilize combosquatting domains to benefit from trademark recognition and remain hidden in plain sight. Finally, by actively crawling 1.3 million combosquatting domains and labeling the results, we witnessed live phishing domains and the abuse of trademarks across all studied business categories (Section 5.1).

Given the magnitude of the combosquatting problem, in this section, we discuss what can be done in terms of countermeasures against combosquatting from the viewpoint of different actors in the domain name ecosystem.

Registrants. A defense that is commonly proposed against traditional types of domain squatting are *defensive registrations.* In defensive registrations, companies can proactively register domains that are likely to be abused (e.g. Microsoft owns wwwmicrosoft[.]com which redirects users to microsoft[.]com) before miscreants have a chance of registering them. Combosquatting, however, is unique in the sense that it lacks a generative model (discussed in Section 4.1). As such, even for companies that can afford a large number of defensive registrations, there is no single algorithm (like the typo models of Wang et al. [90]) that could be used to generate a list of combosquatting domains. Therefore, the burden of protecting against combosquatting domains cannot rest on registrants.

At the same time, we consider it of crucial importance that tradermark owners stop utilizing the practice of registering benign combosquatting domains for their business. For example, the domain paypal-prepaid[.]com belongs to PayPal and advertises the ability to use PayPal to obtain prepaid debit cards. By using these types of domains, companies are indirectly training users that domains that contain their trademark are legitimate, making it harder for every day users to detect the malicious ones (which, as discussed in Section 4.1, will also have TLS certificates). Instead, trademark owners can use filepaths (e.g. www.paypal[.]com/prepaid), subdomains (e.g. prepaid.paypal[.]com) or even TLDs (e.g. prepaid[.]paypal) to advertise their products without the risks associated with the registration of combosquatting domains.

Registrars. Registrars are in the unique position to know which domains users are trying to register before they actually register them. Therefore, we argue that registrars could add extra logic in their fraud-detection systems to flag domains that contain popular trademarks (following a process similar to ours). For each flagged domain, the registrar can either request more information from the users who attempt to register them, or follow up on those domains to ensure that they are not used for malicious purposes. Even though there will always be registrars who do not wish to implement such countermeasures and who turn a blind eye to abuse, over time, these registrars and all the domains registered through them could be treated by domain-intelligence systems as "suspicious." This unwanted labeling will translate to loss of income forcing registrars to either adopt fraud-detection systems, or risk further loss of business.

Third parties. Next to registrars, there exist a wide array of systems [18–20, 41–43] which analyze newly registered domains in an attempt to discover abusive ones before they are weaponized. Similar to the extra step for registrars, we argue that searching for the presence of popular trademarks in newly registered domains can be an extra source of signal that can be exploited to identify malicious registrations.

7 RELATED WORK

DNS Abuse. Weimer et al. [91] proposed collecting passive DNS data for security analysis. Since then, researchers have used passive DNS data to build domain name reputation systems using statistical modeling methods to detect abuse on the Internet [18–20, 25, 59, 74, 77, 92]. More recently, Lever et al. [57] used passive DNS to identify potential domain ownership changes. Hao et al. [43] uses only registration features to build domain reputation system. Liu et al. [58] revealed that dangling DNS records pointing to invalid resources can be easily manipulated for domain highjacking. Chen et al. [28] used passive DNS data to estimate the financial abuse of advertising ecosystem by a large botnet.

Squatting Abuse. Several studies have focused on domain squatting in general. Jakobsson et al. [46, 47] proposed techniques for identifying typosquatting and discovered that websites in categories with higher PPC ad prices face more typosquatting registrations. Wang et al. [90] proposed models for the generation of typosquatting domains from authoritative ones. Agten et al. [13] studied typosquatting using crawled data over a period of seven months finding, among others, that few trademark owners protect themselves by defensively registering typosquatting domains. In addition to typosquatting, Nikiforakis et al. [70] quantify the extent to which attackers are leveraging bitsquatting [31], where random bit-errors occurring in the memory of commodity hardware can redirect Internet traffic to attacker-controlled domains. Their experiments show that new bitsquatting domains are registered daily and monetized through ads, affiliate programs and even malware installations. The authors later performed a measurement of the so-called "soundsquatting", where attackers abuse homophones to attract users and confuse text-to-speech systems [69].

The only work on combosquatting other than this paper is a brief 2008 industry whitepaper [1]. Starting with 30 trademarks and up to 50 generic keywords the authors constructed possible combosquatting domains and then attempted to get traffic data for the 500 domains that were registered. The authors found that most sites were filled with ads, thereby abusing the popularity of trademarks and diluting their revenue. Motivated by the findings of that nine-year-old whitepaper, we performed the experiments described in this paper finding millions of combosquatting domains and analyzing registration and abuse trends over almost six years.

8 CONCLUSION

In this paper, we study a type of domain squatting termed "combosquatting," which has yet to be extensively studied by the security community. By registering domains that include popular trademarks (e.g., `paypal-members[.]com`), attackers are able to capitalize on a trademark's recognition to perform social engineering, phishing, affiliate abuse, trademark abuse, and even targeted attacks. We performed the first large-scale, empirical study of combosquatting using 468 billion DNS records from both active and passive DNS datasets, which were collected over an almost six year time period. Lexical analysis of combosquatting domains revealed that, while there is an almost infinite pool of potential combosquatting domains, most instances add only a single token to the original combosquatted domain. Furthermore, the chosen tokens were often specifically targeted to a particular business category. These results can help brands limit the potential search space for combosquatting domains. Additionally, our results show that most combosquatting domains were not remediated for extended periods of times—up to 1,000 days in many cases. Furthermore, many instances of combosquatting abuse were seen active significantly before they were discovered by public blacklists or malware feeds. Consequently, our findings suggests that current protections do not do a good job at addressing the threat of combosquatting. This is particularly concerning because our results also show that combosquatting is becoming more prevalent year over year. Lastly, we found numerous instances of combosquatting abuse in the real world by crawling 1.3 million combosquatting domains and manually analyzing the results. Based on our findings we discuss the role of different parties in the domain name ecosystem and how each party can help tackle the overall combosquatting problem. Ultimately, our results suggest that combosquatting is a real and growing threat, and the security community needs to develop better protections to defend against it.

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A APPENDIX

A.1 Selected Trademarks

Table 9 depicts the categories and respective number of trademarks for each category we used to identify combosquatting domain names. The second column provides an example of a trademark for each category.

A.2 Most Frequent Words per Category

Table 10 summarizes the ten most frequent words for each trademark category. There, we see that many of the popular words closely correlate with the type of trademark being abused, such as, the words *apple, game,* and *phones* being popular in the "Computers/Internet" category and the words *president, vote,* and *elect* in the "Politics" category.

Moreover, we want to highlight the lists of words in the *Couriers* and *Financial* categories. Several of the trademarks used in both categories have been victims of spear phishing attacks according to Garera et al. [40]. Additionally, words like *tracking, delivery, service,* and *account* are used in both the creation of phishing domains and phishing emails [37]. These results clearly indicate that most registered combosquatting domains have been carefully constructed by attackers to match the expected context of each abused trademark and can be used for a variety of purposes, ranging from trademark abuse to phishing and spear-phishing campaigns.

A.3 Combosquatting APT Domains

Table 11 shows a list of combosquatting domain names related to Advanced Persistent Threats (APT). These domains were found in the public APT reports available at `http://tinyurl.com/apt-reports` and our *CP* and *CA* datasets (Table 5).

Category	Example	Count
Adult Content	youporn[.]com	11
Blogging	blogspot[.]com	22
Computers	adobe[.]com	10
Couriers	fedex[.]com	1
E-Learning	wikipedia[.]org	12
E-Shop (Auctions)	craigslist[.]org	3
E-Shop (Online)	amazon[.]com	16
E-Shop (Physical)	costco[.]com	21
Energy	chevron[.]com	15
File Sharing	dropbox[.]com	4
Financial	paypal[.]com	17
Lifestyle	imdb[.]com	19
News	nytimes[.]com	32
Photography	tumblr[.]com	9
Politics	democraticunderground[.]com	7
Radio & TV	netflix[.]com	4
Search Engines	google[.]com	6
Social Networks	facebook[.]com	7
Software & Web	office365[.]com	34
Streaming	youtube[.]com	7
Telecom	comcast[.]net	4
Travel	expedia[.]com	7

Table 9: Trademark business categories.

Category	**Most Frequent Words**									
Adult Content	free	xxx	porn	sex	gay	live	tube	porno	videos	hot
Blogging	fuck	yeah	love	themes	free	theme	life	blog	best	just
Computers	apple	games	phones	galaxy	phone	office	free	online	support	home
Couriers	office	ground	online	freight	delivery	express	shipping	print	services	service
E-Learning	club	square	school	business	university	health	group	property	online	pilgrim
E-Shop (Auctions)	cars	car	sale	account	south	new	post	posting	san	jobs
E-Shop (Online)	line	store	kindle	online	shop	free	deals	best	lay	card
E-Shop (Physical)	price	sale	store	card	online	prices	home	stores	shop	cheap
Energy	card	cards	online	business	tex	credit	energy	account	chemical	gift
File Sharing	movie	movies	file	free	archive	user	content	login	online	watch
Financial	bank	online	investment	service	account	services	card	worldwide	mortgage	update
Lifestyle	world	land	channel	vacation	games	princess	movie	villa	paris	club
News	news	mike	online	zine	foundation	com	family	new	trust	media
Photography	marketing	photography	photo	buy	time	followers	family	com	photos	best
Politics	president	vote	elect	official	campaign	trump	truth	com	stop	sucks
Radio & TV	free	movies	watch	xxx	movie	chill	account	login	canada	new
Search Engines	plus	mail	search	glass	free	apps	com	play	maps	google
Social Networks	marketing	followers	free	login	buy	account	page	com	business	apps
Software & Web	best	county	new	online	mobile	home	free	sucks	beach	city
Streaming	video	videos	free	download	music	views	converter	best	buy	listen
Telecom	wireless	universal	phone	business	wire	center	online	phones	free	net
Travel	head	island	paris	hotel	garden	inn	hotels	estate	real	beach

Table 10: Most frequent words per trademark category.

Trademark	Domain	APT	Activity Period	Attribution	Reference
Adobe	adobearm[.]com	DarkHotel	5/12 - 11/14	Unknown Actor	[52]
Adobe	adobekr[.]com	Dust Storm	5/10 - 2/16	Unknown Actor	[30]
Adobe	adobeplugs[.]net	DarkHotel	5/12 - 11/14	Unknown Actor	[52]
Adobe	adobeservice[.]net	TooHash	Unknown - 10/14	Chinese Origin	[38]
Adobe	adobeupdates[.]com	DarkHotel	5/12 - 11/14	Unknown Actor	[52]
Adobe	adobeus[.]com	Dust Storm	5/10 - 2/16	Unknown Actor	[30]
Adobe	plugin-adobe[.]com	Saffron Rose	Unknown - 5/14	Iranian Origin	[35]
Amazon	amazonwikis[.]com	Dust Storm	5/10 - 2/16	Unknown Actor	[30]
Delta	deltae[.]com[.]br	Comment Crew	Unknown - 2/13	Unknown Actor	[82]
Delta	deltateam[.]ir	Snake/Uroboros	Uknown - 8/14	Unknown Actor	[53]
Delta	leveldelta[.]com	MiniDuke	2/13 - 5/13	Unknown Actor	[26]
Dropbox	online-dropbox[.]com	Asruex	10/15 - 6/16	Unknown Actor	[49]
Facebook	privacy-facebook[.]me	Pawn Storm	2/16 - 4/16	Unknown Actor	[87]
Facebook	users-facebook[.]com	Saffron Rose	Unknown - 5/14	Iranian Origin	[35]
Facebook	xn--facebook-06k[.]com	Saffron Rose	Unknown - 5/14	Iranian Origin	[35]
Google	all-google[.]com	SpyNet	Unknown - 8/14	Unknown Actor	[60]
Google	drive-google[.]co	Rocket Kitten	Unknown - 11/15	Iranian Origin	[27]
Google	drives-google[.]co	Rocket Kitten	Unknown - 11/15	Iranian Origin	[27]
Google	google-blogspot[.]com	Quartermaster/Sunshop	5/13 - 11/13	Chinese Origin	[36]
Google	google-config[.]com	Comfoo	Unknown - 7/13	Unknown Actor	[78]
Google	google-dash[.]com	Turbo Twist	4/16 - 4/16	C0d0s0 Team	[34]
Google	google-login[.]com	Comfoo	Unknown - 7/13	Unknown Actor	[78]
Google	google-office[.]com	Enfal	Unknown - 9/11	Chinese Origin	[85]
Google	google-officeonline[.]com	Enfal	Unknown - 9/11	Chinese Origin	[85]
Google	google-setting[.]com	Rocket Kitten	Unknown - 11/15	Iranian Origin	[27]
Google	google-verify[.]com	Rocket Kitten	Unknown - 11/15	Iranian Origin	[27]
Google	googlecaches[.]com	ScanBox	9/14 - 10/14	Unknown Actor	[71]
Google	googlenewsup[.]net	Roaming Tiger	Unknown - 7/14	Chinese Origin	[17]
Google	googlesale[.]net	Ixeshe	3/14 - 6/14	Chinese Origin	[21]
Google	googlesetting[.]com	Sofacy	4/15 - 5/15	Russian Origin	[75]
Google	googletranslatione[.]com	Trochilus	6/15 - 1/16	Unknown Actor	[23]
Google	googleupdate[.]hk	Comfoo	Unknown - 7/13	Unknown Actor	[78]
Google	googlewebcache[.]com	ScanBox	9/14 - 10/14	Unknown Actor	[71]
Google	imggoogle[.]com	DarkHotel	5/22 - 11/14	Unknown Actor	[52]
Google	privacy-google[.]com	Saffron Rose	Unknown - 5/14	Iranian Origin	[35]
Google	webmailgoogle[.]com	ScanBox	9/14 - 10/14	Unknown Actor	[71]
Google	xn--google-yri[.]com	Saffron Rose	Unknown - 5/14	Iranian Origin	[35]
iCloud	localiser-icloud[.]com	Pawn Storm	2/16 - 4/16	Unknown Actor	[87]
iCloud	securityicloudservice[.]com	Pawn Storm	2/16 - 4/16	Unknown Actor	[87]
Microsoft	ftpmicrosoft[.]com	Quartermaster/Sunshop	5/13 - 11/13	Chinese Origin	[36]
Microsoft	microsoft-cache[.]com	Turbo Twist	4/16 - 4/16	C0d0s0 Team	[34]
Microsoft	microsoft-security-center[.]com	Suckfly	7/15 - 5/16	Unknown Actor	[84]
Microsoft	microsoft-xpupdate[.]com	DarkHotel	5/12 - 11/14	Unknown Actor	[52]
Microsoft	microsoftc1pol361[.]com	Carbanak	10/14 - 2/15	Unknown Actor	[51]
Microsoft	microsoftmse[.]com	Four Element Sword	10/14 - 4/16	Unknown Actor	[22]
Mozilla	mozillacdn[.]com	Poseidon Group	Unknown - 2/16	Poseidon Group	[22]
Reuters	reuters-press[.]com	Pawn Storm	2/16 - 4/16	Unknown Actor	[87]
Skype	downloadskype[.]cf	PoisonIvy	6/14 - 4/15	Israelian Origin	[72]
Yahoo	cc-yahoo-inc[.]org	Pawn Storm	2/16 - 4/16	Unknown Actor	[87]
Yahoo	delivery-yahoo[.]com	Sofacy II	Unknown - 4/15	Unknown Actor	[73]
Yahoo	edit-mail-yahoo[.]com	Pawn Storm	2/16 - 4/16	Unknown Actor	[87]
Yahoo	help-yahoo-service[.]com	Pawn Storm	2/16 - 4/16	Unknown Actor	[87]
Yahoo	newesyahoo[.]com	Apt Against India	Unknown - 8/13	Unknown Actor	[45]
Yahoo	privacy-yahoo[.]com	Sofacy II	Unknown - 4/15	Unknown Actor	[73]
Yahoo	settings-yahoo[.]com	Sofacy II	Unknown - 4/15	Unknown Actor	[73]
Yahoo	us-mg6mailyahoo[.]com	Strontium	Unknown - 11/15	Unknown Actor	[61]
Yahoo	yahoo-config[.]com	Comfoo	Unknown - 7/13	Unknown Actor	[78]
Yahoo	yahoo-user[.]com	Comfoo	Unknown - 7/13	Unknown Actor	[78]
Yahoo	yahooeast[.]net	Hidden Lynx	Unknown - 9/13	Unknown Actor	[83]
Yahoo	yahooip[.]net	EvilGrab	9/13 - 1/14	Unknown Actor	[86]
Yahoo	yahoomail[.]com[.]co	Saffron Rose	Unknown - 5/14	Iranian Origin	[35]
Yahoo	yahooprotect[.]com	EvilGrab	9/13 - 1/14	Unknown Actor	[86]
Yahoo	yahooprotect[.]net	EvilGrab	9/13 - 1/14	Unknown Actor	[86]
Yahoo	yahooservice[.]biz	DarkHotel	5/12 - 11/14	Unknown Actor	[52]
Yahoo	yahoowebnews[.]com	IceFrog	Unknown - 9/13	Chinese Origin	[50]

Table 11: Combosquatting domains related to APT.