

# Old is Still Gold: A Comparison of Cyber and Regular Consumer Fraud in The United States

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## I. INTRODUCTION

In the United States, a total of more than 25 million people are victims of frauds [1]. These deceptive scams are a major cause of users' economic harm with the added externalities of wasted time and stress. These illicit practices have a part of the underground economy for a while. Initially, individuals were tricked by scam calls, mail or in-person fraudsters, however, the rise of the Internet has provided fraudulent entities with a more streamlined exposure to the overall population. A survey report from 2014 indicated that 47% of the Americans were victims of an online identity theft. Another recent report released by the Federal Trade Commission (FTC) revealed that debt collection, identity theft, and impostor scams contribute towards 56% of the total frauds complaints in 2015 [2]. With the number of Internet users on the rise, the number of cyber frauds is likely to increase over the next couple of years [3]. To deal with the increasing trend, along with the FTC, the Federal Bureau of Investigation (FBI) has also established a similar complaint portal known as the IC3, for the collection of specifically Internet-based fraudulent practices [4]. This emerging trend of deceptive practices necessitates their study in order to evaluate and mitigate the harm caused to victims' individuals.

In this paper, we evaluate the nature of consumer fraud in the United States. Our work provides a comparison between cyber and well as regular frauds. We categorize cyber frauds as all those deceptive practices that victimize users online, while

regular ones comprise of frauds that target individuals over the phone, with mail, or in-person. While we understand that cyber frauds are a major focus of today's research, our comparison-based approach allows us to better understand how they differ from conventional frauds. It also enables us to independently evaluate trends in regular frauds and to see whether fraudsters are adopting online mechanisms to target more individuals. This combined analysis aids us to devise strategic suggestions to develop better fraud reduction methodologies.

To evaluate fraud trends, we use a primary dataset from FTC complaints from the year 2013 and 2014. We also collect demographic information from the US Census Bureau [5]. In addition to data collection, we devise a calibration methodology to identify and separate cyber frauds from the regular ones in the complaint dataset.

Our work provides three main contributions. First, we evaluate the distinctive trends prevalent in cyber and regular frauds in the dataset. This encompasses their reporting numbers and methods. The nature of frauds which are more common in each specific category and the insights on the fraudsters who carry out these specific deceptive activities. Secondly, we look at ethnic, age, education and employment demographics in each specific category and evaluate if certain individuals are more likely to report crimes. Finally, based on our findings we provide suggestive measures that can be taken into account by regulatory agencies to reduce the overall fraud in the United States.

The rest of the paper is structured as follows, section II provides a comprehensive overview of the relevant work. In section III, we elaborate features of the datasets used in our analysis along with a description of our calibration methodology. Section IV summarizes our findings from the data followed by our suggestions to regulatory agencies in V. We conclude our work in section VI and discuss avenues of future research.

## II. RELATED WORK

As our work evaluates both cyber as well as regular frauds, we provide related work that encompasses both of these categories. However, we elaborate more on recent research which focuses on cyber frauds as more individuals are victims of these crimes [1] due to the increased Internet usage trends for sensitive activities. Before the Internet became a primary hub of economic and social activity, researchers measured [6] and developed techniques based on statistical models [7], [8], [9], [10] to detect phone and credit card based frauds. In the past few years, research evaluations have shifted focus towards

Data Field	Field Description
Agency Name	The complaint collection agencies associated with the FTC.
Zip code Information	The zip code of the victim and the fraudulent entity.
Contact Method	The primary channel used by the fraudulent entity to contact the victim e.g. Internet, phone, mail.
Fraud Description	A description of nature the fraud, and its type e.g. credit card, fake product, debt collection.
Fraud & Reporting Date	The dates when the fraud initially occurred and the date on which it was reported.

TABLE I  
THE DESCRIPTION OF THE DATA FIELDS THAT WERE PRIMARILY USED IN THE FOR DATA CALIBRATION AND ANALYSIS

cyber activity [11], [12], [13], [14] due to its high rate and the increased potential for harm.

Even though, term “*cyber fraud*” is usually associated with Computer Science, its recent socio-economic impact has motivated researchers in Economics, Law, and Finance to explore solutions by incorporating methodologies specific to their areas. Ionescu et. al [13] characterize the types and sources of cyber frauds in global digital networks, they link the increase of financial fraud to the prevalent usage of Internet services for financial management and transactions. The authors suggest the involvement of all stakeholders and employees through awareness and training for containing and mitigating fraud. Similarly, Howard et. al [14] study malicious code attacks against financial networks and suggest technical detection and mitigation techniques for financial infrastructure. [12] studies how the cyber criminals have several potential advantages over their opposing law enforcement agencies. They suggest some practical steps to even out the differential gap.

Due to an increase in the overall concern for online fraudulent activity, there has also been state-sponsored research that measures the impact of fraud. Smyth et. al [15] measure the extent of cyber fraud in Canada in 2011. Their work indicates that a major chunk of frauds does not get recorded and suggest a need for a sentinel record fraud data, similar to the FTC complaint center in the US.

Another significant area of research focuses on understanding the demographics of fraud victims. A recent FTC Report [16] uses complaint data to quantify complaint rates and across different ethnic and education groups in the US. [17] also look at how demographics effect the likelihood of an individual to complain about fraud. Researchers in [11] provide a comprehensive survey report that sums the reactions of the victims of an online data breach. They categorize their results in different income, education, age, and ethnic groups. Such research aims to provide organizations with informed insight to better develop policies for consumer rights protection.

In comparison to previous research which individually look at either cyber or regular fraud, w work provides a unique angle of evaluation. We evaluate charectarisitics for both types of cyber and regular frauds and their demographic trends.

### III. DATA AND CALLIBRATION

In this section we explain the charectarisitics of our datasets and the sources they were obtained from. We also provide insight into the essential data processing and callibration methodology that we incorporate to classify and filter the data for a fair evaluation of our questions.

Description	Value
% Cyber Complaints	52.1
% Regular Complaints	47.9
Moth with Most Compliants	July 2013
Moth with Least Compliants	Feb 2013

TABLE II  
T-TEST RESULTS FOR CYBER AND REGULAR FRAUDS IN DIFFERENT PERIODS

#### A. Data Description

1) *FTC Complaint Dataset*: The primary dataset that we use for our evaluation is a corpus of the complaint logs filed at different collections agencies for the FTC during the months Jan, 13 to June, 14. The Dataset comprises of a total of 865K complaints aggregated for cyber as well as regular fraud instances during the time period. Table I shows the fields of the original dataset along with their description summary. For the purposes of brevity, we only include the fields that were used in our analysis.

2) *US Census Datasets*: Zip code information in our complaint dataset allows us to perform demographic analysis of the frauds. We obtain the demographic information associated with zip codes available at the US Census Bureau website [5]. The specific information that we collect is stated below:

- Population density per zip code
- Education and income data <sup>1</sup>
- Age statistics
- Race and ethnic information

As zip codes provide a low level granularity, to aggregate adjacent zip codes we obtain the Zip codes to the Metropolitan Statistical Area (MSA) mappings from [19]. MSA are essentially groups of geographically connected zip codes that demonstrate strong social and economic linkage. While there are more than 40,000 zip codes in the United States there are only 382 distinct MSAs [5].

#### B. Calibration Methodology

As the FTC dataset was aggregated for all fraud channels a major calibration step we perform is to tag each crime complaint as either cyber or regular. An associated challenge for this was our limited view of the fraud description. To perform this calibration we use the **Contact Method** and **Fraud Description** fields from Table I. We flag a complaint as cyber if the victims primary contact method was through

<sup>1</sup>We obtained education data was obtained from [18].

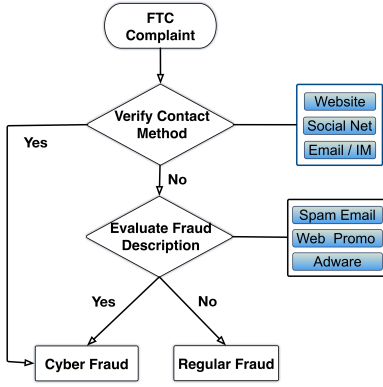


Fig. 1. Classification Methodology for Regular and Cyber Fraud

online media, these are primarily websites, social networks, email and IM. For the remainder of the complaints we look at the description. If the complaint description involves something associated with Internet, we classify it as a cyber fraud regardless of how the victim was initially approached. Figure 1 provides an depiction of our classification methodology. This process provides us with two distinct categories and enables a fair comparison of the frauds.

#### IV. EVALUATION

Our evaluation section can be divided into two main components. First, we look at the different aspects and trends within the complaint dataset and elaborate on certain prominent characteristics between regular and cyber frauds. The second part of our evaluation focuses on an in-depth analysis of the demographics linked with the fraud types.

##### A. Fraud Variation over Time

We initially perform a temporal analysis of the 15-month dataset to evaluate how the fraud reporting varies, over time and explore when a certain fraud is more likely to be reported. As a limitation of our dataset<sup>2</sup>, we use the reporting date as an estimate of fraud count for a specific date. While the overall rate of fraud remains consistent, we observe significant variations in the winter holiday season. To investigate this, we select two distinct, 20 day periods in the dataset; we label them as **Working** (Aug, 15 to Sept, 5) and **Holiday** (Dec 15, to Jan, 5). Figure 2 shows the variation of cyber and regular frauds within the two specific time periods. We observe a significant drop in the frauds during the holiday

<sup>2</sup>The dataset had significant missing values for the date if initial contact of fraud, Figure 4 (a) shows that approximately 70% of reporting dates were within a week of the date when the incident occurred.

Fraud Type	<i>p-value</i>	Coefficient
Cyber	0.014	
Regular	0.003	

TABLE III

T-TEST RESULTS FOR CYBER AND REGULAR FRAUDS IN DIFFERENT PERIODS

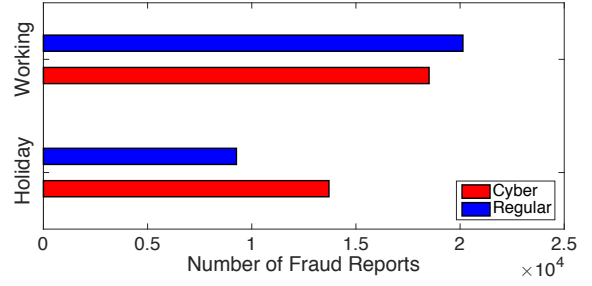


Fig. 2. Cyber and regular fraud variation during regular and holiday season

time period. Individually, cyber fraud decreases by 26% while regular fraud decreases by a much larger value of 56%. We believe that the larger decrease in regular frauds is an overestimate as result of a bias that we explain using additional findings from the next section.

##### B. Fraud Reporting Methods

Consumers have the ability to report complaints to the FTC via several methods and agencies. We aggregate the 26 complaint collecting entities into online and offline categories. For instance, reports made via the Internet complaint center or the FTC complaint assistant and tagged as online, while the ones issued to the FTC call center, publisher clearing house, attorney generals or other regulatory institutions are categorized and offline. Figure 4 provides the distribution of how individuals opt to report cyber and regular crimes. Approximately 82% of cyber fraud victims used an online complaint facility, and 63% of regular fraud victims reported via offline methods.

A major chunk of regular frauds are reported to offline institutions which have reduced operation during holidays. We believe this significantly contributes to the reduction bias of regular frauds value in Figure 2. To further validate this bias, we perform a t-test for the two fraud categories across the working and holiday time periods. The statistically significant *p-value* for regular frauds in Table III, rejects our null hypothesis of *identical reporting trends between two the two time periods*. Additionally, we also calculate the percent increase in reporting between the last 10 holidays and 10 working days right after. While cyber reports only incase by 37% the increase in regular fraud reports is a staggering 104%.

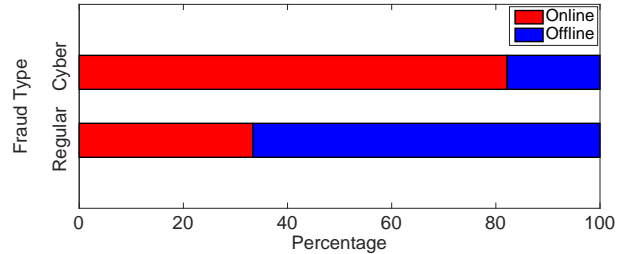


Fig. 3. Distribution of reporting methods in for cyber and regular frauds

The ratio of increases is in line with the proportions (17:66) for offline reporting methods used by cyber and regular fraud victims. We believe that while both types of frauds experience a decrease, the decrease in cyber frauds represents a more accurate trend. These derived insights enable us to suggest more meaningful measures in section V to deal with consumer fraud.

### C. Consumer Reaction Time

We evaluate how quick do the victims of a fraud report an incident. Figure 3 (a) shows the CDF of the number of days between the date when the fraud occurred and when it was first reported to the FTC. We do not observe any difference between the reaction time trends of cyber and regular fraud victims. The graph shows that for both fraud categories, almost 30% of the individuals take more than a week to respond. We believe that this provides ample time window for fraudsters to maliciously act on the assets acquired from individuals. This increased delay can also be a result of individuals discovering they were victimized to a fraud at a later date than the actual incident. One example would be of a credit card theft, when the victims only realize after they see an unauthorized transaction. Unfortunately, we do not have enough information in the dataset to normalize against this trend.

### D. Most Common Frauds

Table IV provides a summary of the top frauds in each category. The significant cyber presence of impostor scams, and sweepstakes in, which have long existed in the regular fraud domain provides evidence that fraudsters are adopting new technology to execute the same frauds. We incorporate this specific insight in our discussion in section. Our results greatly match with the top sources of frauds in the FTC correlate with the frauds stated in an FTC news release in 2016 [2].

Cyber	%	Regular	%
Online Shopping & Sales	14.1	Impostor Fraud	29.8
Impostor Fraud	10.8	Telemarketing	20.1
Unsolicited Email	7.71	Debt Collection	16.1
Counterfeit Check Scams	7.40	Prizes & Sweepstakes	15.5
Prizes & Sweepstakes	7.40	Grants & Credit Loans	4.14

TABLE IV  
TOP FRAUD TYPES

### E. Top Fraudster Locations

Next, we identify the primary locations of the fraudsters within the United States and present our findings in reftopareas. While fraudulent entities are spread throughout, most of the heavy hitters belong to the metropolitan areas. We believe this provides an efficient disguise to the fraudulent entities. Numbers: 29.3% cyber reports and 32.6% regular reports.

We also observe certain areas that have a high cyber to regular fraud ratio and vice versa. The San Francisco, Oakland and San Jose, Santa Clara MSAs have a cyber to regular fraud ratio of 2.21 and 5.13. The popular fraud types in these regions

Metropolitan Area (MSA)	% Cyber	% Regular
New York, New Jersey, Long Island	8.41	7.67
Los Angeles, Long Beach, Santa Ana	6.50	7.09
Washington, Arlington, Alexandria	4.10	5.78
Miami-Fort Lauderdale, Pompano Beach	4.16	5.40
Dallas, Fort Worth, Arlington	2.89	3.36
Chicago, Naperville Joliet	3.17	3.27

TABLE V  
TOP METROPOLEITAN AREAS WHERE FRAUDSTERS ARE BASED

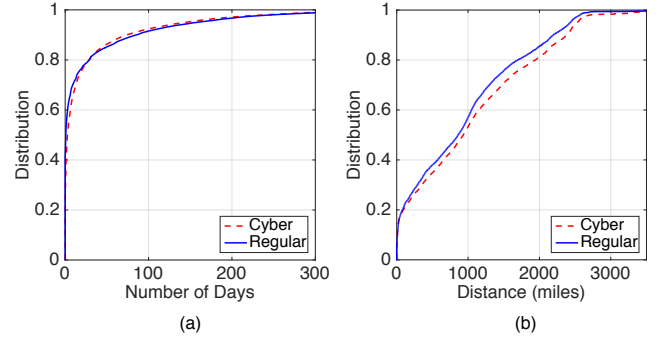


Fig. 4. Distribution of reporting methods in for cyber and regular frauds

are Internet services, unsolicited email, and online shopping. These areas serve as a good medium for cyber fraudsters as it allows them to gel into the surrounding cyber industry. Meanwhile, The Buffalo, Niagara Falls MSA has a regular to cyber fraud ratio of 8.76 with debt collection being the significant outlier. Further investigation reveals that Buffalo has a network of debt collectors which have responsible for multi-million frauds [20], [21].

### F. Fraudster Coverage

In order to understand the operational regions of fraudulent entities, we calculate the distances between consumer and fraudster zip codes. Figure 4 (b) provides a cumulative distribution of the operational radii for cyber and regular fraudsters. This analysis provides insight on whether cyber fraudsters leverage the Internet for more visibility and access to target more distant individuals. With a median distance of 993 and 861 for cyber and regular frauds, we believe that both types of fraudsters follow similar trends. This indicates that a major the Internet based communication does not provide cyber fraudsters with significant advantage over regular ones as they are able to achieve similar operational spans by using phone and mail based communication methods.

### G. Demographic Analysis

To evaluate the effect of prominent demographic features we perform a logistic regression for both cyber and regular complaint rates. Table summarizes our coefficients and their significance. Among ethnicities, our results generate statistically significant results for only Hispanic communities. While the coefficients suggest that frauds decrease for heavier concentrations of Hispanics, a survey study [1] showed that Hispanics and Black communities are more likely to be victims of crimes. The decreasing trend is actually a result of fraud

Observed Variable	Cyber Complaints			Regular Complaints		
	Coefficient	p-value	95% Confidence Interval	Coefficient	p-value	95% Confidence Interval
White (Non-Hispanic)	-0.0042	0.074	[-0.009, 0]	-0.0013	0.128	[0.003, 0]
Black	-0.0058	0.017	[-0.011, -0.001]	0.0017	0.054	[-2.77 <sup>-5</sup> , -0.003]
Asian	-0.0025	0.468	[-0.009, 0.004]	-0.0051	0.00	[-0.008, -0.003]
Hispanic	-0.0026	0.014	[-0.05, -0.001]	-0.0054	0.00	[-0.006, -0.005]
Age	0.0064	0.023	[0.001, 0.012]	0.0281	0.00	[0.026, 0.030]
Income	-2.226 <sup>-6</sup>	8.85 <sup>-7</sup>	[-3.96 <sup>-6</sup> , -4.92 <sup>-7</sup> ]	-3.695 <sup>-6</sup>	0.000	[-4.31 <sup>-6</sup> , -3.08 <sup>-6</sup> ]
Education	0.0155	0.000	[0.013, 0.018]	0.0044	0.00	[0.003, -0.005]
Unemployment	0.0084	0.111	[-0.002, 0.019]	-0.0028	0.138	[-0.006, 0.001]

TABLE VI  
THE DESCRIPTION OF THE DATA FIELDS THAT WERE PRIMARILY USED IN THE FOR DATA CALIBRATION AND ANALYSIS

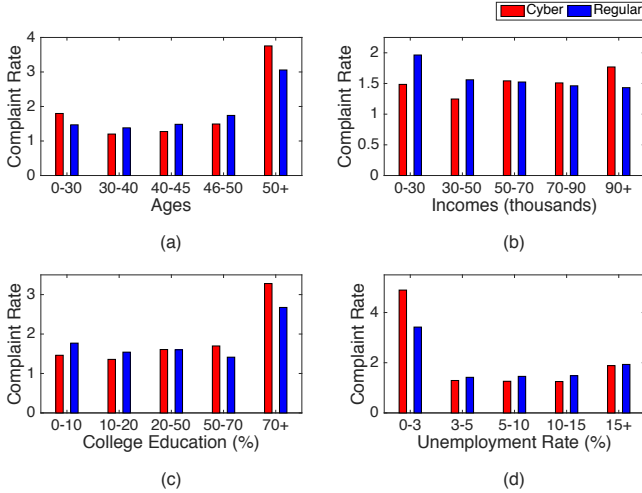


Fig. 5. Cyber and regular fraud trends over age, income, education and unemployment.

underreporting due to cultural reasons, distrust in agencies the lack of awareness and education [22]. We do not observe any comparative difference between the

Other socio economic variables that we take into account are age, income, education an the rate of unemployment. In addition to the regression analysis, we investigate their variation by observing complaint rates across their distributions in Figure 5.

**Age:** While the differences in cyber and regular complaints remain fairly consistent, we observe that individuals greater than 50 years complain significantly more than other age groups. Our significant regression values also corroborate to this trend.

**Education:** Both cyber and regular complaints increase along with education. We associate this trend with greater increased educational awareness among individuals [22]. Another subtle trend, in the increase in cyber to regular complaint ratio from 0.82 to 1.23. We associate this diverging trend to more educated individuals being active the Internet more frequently, and hence being more prone to online fraudpewcollege. Our reasoning is in line with insights from our regression analysis which additionally normalizes for other factors.

We do include income and unemployment in our analysis due to their insignificant correlation values in VI

## V. DISCUSSION

Discussion Goes here

## VI. CONCLUSION

The conclusion goes here. Use our methodololy on more massive datasets. [?]

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