Towards Understanding Crypto Money Laundering in Web3 Through the Lenses of Ethereum Heists

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With the overall momentum of the blockchain industry, crypto-based crimes are becoming more and more prevalent. After committing a crime, the main goal of cybercriminals is to obfuscate the source of the illicit funds in order to convert them into cash and get away with it. Many studies have analyzed money laundering in the field of the traditional financial sector and blockchain-based Bitcoin. But so far, little is known about the characteristics of crypto money laundering in the blockchain-based Web3 ecosystem. To fill this gap, and considering that Ethereum is the largest platform on Web3, in this paper, we systematically study the behavioral characteristics and economic impact of money laundering accounts through the lenses of Ethereum heists. Based on a very small number of tagged accounts of exchange hackers, DeFi exploiters, and scammers, we mine untagged money laundering groups through heuristic transaction tracking methods, to carve out a full picture of security incidents. By analyzing account characteristics and transaction networks, we obtain many interesting findings about crypto money laundering in Web3, observing the escalating money laundering methods such as creating counterfeit tokens and masquerading as speculators. Finally, based on these findings we provide inspiration for anti-money laundering to promote the healthy development of the Web3 ecosystem.

CCS Concepts: • Applied computing \rightarrow Electronic commerce; • Mathematics of computing \rightarrow Exploratory data analysis; • Information systems \rightarrow Information systems applications.

Additional Key Words and Phrases: Money laundering, Blockchain, Cybercriminal, Web3, Transaction behavior

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1 INTRODUCTION

The past decade has witnessed the rapid growth of blockchain and the blockchain-based cryptocurrency ecosystem. The market capitalization of cryptocurrencies has reached a staggering scale, with Bitcoin reaching a market capitalization of \$385 Billion [24]. Meanwhile, with the further development of blockchain technology, there is a global wave of the third iteration of the Internet (Web3). Web3's disruption is built on three essential fundamentals [7]: an underlying blockchain that stores transaction records and ensures the decentralized nature of Web3, smart contracts that represent the logic of the application, and crypto assets (also called digital assets) that can represent anything of value. The shared, co-constructed, assemblable economic system on Web3 brings a richer application ecosystem, a more open economic system, and a larger transaction volume than traditional financial and public blockchains.

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However, any new technology, especially those with a lack of regulation, can be exploited for unscrupulous gain. Since blockchain transactions do not require user identification information, blockchain and its ecosystem have become a hotbed of various cybercrimes and illegal financial activities [33], and the still-developing blockchain-based Web3 is no exception. According to blockchain security firm Certik [26], in the first half of 2022 alone, more than \$2 billion was stolen from Web3 projects as a result of hacking and vulnerabilities. After stealing crypto assets, cybercriminals conceal and disguise them through different channels to make them appear legitimate and then withdraw them, a process known as money laundering. So it is said that money laundering is the subsequent part of all other forms of crypto-based crimes [22, 23]. Therefore, with the frequent occurrence of Web3 security incidents, crypto anti-money laundering (AML) is in a crucial position to be the last line of defense to stop hackers from successfully cashing out and also to deter hackers from committing Web3 crimes at the same time.

Anti-money laundering (AML) is not a new issue, and a wealth of research on the AML issue in traditional financial scenarios have been proposed [8, 11, 13, 19, 32]. In the field of cryptocurrency, the Elliptic dataset [30] is the first open-source Bitcoin money laundering dataset that labels abnormal/normal Bitcoin transactions roughly. But for one, this dataset only has binary labels for money laundering with no other business details, and for two, the Bitcoin platform this dataset focuses on is very different from the Web3 ecosystem which contains rich decentralized applications (DApps). To the best of our knowledge, there is currently no public dataset on Web3 money laundering in academia, nor is there a systematic description and analysis of money laundering on the Web3 ecosystem. It is not clear what the transaction characteristics of these Web3 money laundering accounts are, how the flow of illegal funds in the money laundering ring has achieved the effect of obfuscating the source, and what kind of impact it has on the economy of the Web3 ecosystem. Therefore, this is the question that this paper wants to explore.

However, due to the unique characteristics of Web3 and money laundering practices on it, AML approaches on traditional financial scenarios or bitcoin cannot be directly applied to Web3 due to the following three challenges. (i) The underlying blockchain. Compared with traditional finance, blockchain is decentralized, borderless, and anonymous, without limiting the number of accounts each user can create. This allows cybercriminals to conduct a large number of frequent transactions between accounts under their control, leading to difficult identification of account entities and a large number of anonymous transfers. (ii) Smart contracts and digital assets. Based on blockchain, smart contracts enable various types of digital assets which can be exchanged in the trading platforms. At the same time, Turing-complete smart contracts can represent and execute more complex application logic and functions, leading to more complex transaction patterns. (iii) Decentralized finance (DeFi) [31]. On the one hand, immature DeFi applications gather a large number of assets, attracting the attention of criminals and becoming the hardest hit by asset theft; on the other hand, DeFi services lacking anti-money laundering compliance bring ever-changing means of exchanging coins while also fueling crypto criminals to launder dirty money.

In this paper, we go for the first time to characterize and analyze the crypto money laundering behavior in Web3, taking the largest blockchain platform of Web3 [24], Ethereum, as an entry point. Note that only the information of the accounts where the security incidents occurred is publicly reported, whereas the money laundering accounts where the stolen money is transferred are usually unknown. To this end, we start from the tip of the iceberg - a very small number of accounts of known security incidents - and then dig and expand the malicious addresses of money laundering, in order to carve out the full picture of the security incidents and complete the chain of evidence for the transfer of stolen assets.

Specifically, we first propose an abstract model to describe the process of money laundering and present a heuristic tracing algorithm based on this abstract model to extract money laundering transactions from the massive amount of anonymous blockchain data (**Section** 4). We construct the *first money laundering dataset* (containing over 160,000 addresses) in Web3, called EthereumHeist, and also use a case study to illustrate the effectiveness of the tracing method. With these real data, we conduct in-depth empirical analysis from micro to macro perspectives. (i) From the perspective of individual laundering accounts, we count and analyze what are

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the characteristics of accounts and their transaction behavior in the money laundering process (**Section 5**). (ii) From the perspective of a gang, we model and measure the network of transactions involved in the cases and analyze the difference between money laundering transaction networks and the entire Ethereum transaction network (**Section 6**). (iii) From a more macro perspective, we explore how the flow of money laundered funds affects the economy of the Web3 ecosystem (**Section 7**). Finally, we discuss the AML implications, limitations, and ethical issues of this paper, as well as possible directions for future research. The main contributions are as follows.

- To our best knowledge, we present the *first* dataset and the *first* systematic analysis on crypto money laundering in Web3 through the lenses of Ethereum heists from 2018-2022. Based on a very small number of tagged accounts of hackers, exploiters, and scammers, we adopt an augmented poison policy to trace the untagged money laundering process, which provides a full picture of incidents. Methods for tracing, data collection, and measurement of EthereumHeist can also be reused for other cases. We present the money laundering dataset which can be found at https://www.dropbox.com/.
- We obtain many interesting findings of crypto money laundering in Web3 by adopting feature analysis, graph analysis, and other methods. These findings help us gain new knowledge about the crypto money laundering behaviors in Web3. Particularly, we find that it is common for exploiters to obfuscate stolen funds by swapping tokens through DeFi platforms, and hackers even launder money by creating counterfeit tokens for higher anonymity.
- We conduct an empirical study to understand the economic impact of laundering in the Web3 ecosystem by investigating the evolution of money laundering destination service providers and the market price of crypto assets. Moreover, we present insights for anti-money laundering in the Web3 ecosystem based on trends of money laundering techniques and service providers, in order to promote the healthy development of Web3.

2 BACKGROUND

2.1 Stolen Funds From Web3

The boom in the Web3 ecosystem is driving demand for trading platforms. However, where there is money, that is where thieves are attracted. The sources of stolen funds on Web3 can be broadly classified into three types. **Centralized exchanges** (CEXes), which gather large amounts of money but in most cases have weak defenses, have been coveted by hackers. **DeFi projects**, which are still in the early stage of development, have also been a prime target for hackers in recent years, with DeFi digital assets stolen mainly due to contract vulnerabilities, flash loan attacks, and private key leaks. **Scams** are a more common but under-disclosed type of asset theft. Scammers commit theft of cryptocurrency personal holdings through malicious emails or false propaganda, such as phishing scams, Ponzi scams, etc.

2.2 Money Laundering

Money laundering is the illegal process of transferring funds generated by ill-gotten gains or criminal activities (such as drug trafficking or terrorist financing) in order to conceal and hide the source of the funds. Money laundering typically consists of three main stages: (i) **Placement**: The process of putting the proceeds of crime into the "laundering system". These illicit proceeds are often divided into smaller amounts and placed in multiple accounts to prevent detection by AML systems. (ii) **Layering**: Separation of illicit proceeds from their sources and maximum dispersion through complex multiple, multi-layered financial transactions to disguise leads and hide identities. The higher the frequency of diversion, the more difficult it is for investigators to trace the source through network paths. (iii) **Integration**: This is the final stage of money laundering, which is graphically described as "draining". The funds are integrated into the financial system as if they were legitimate.

3 RELATED WORK

3.1 Anti-Money Laundering Techniques

In traditional financial scenarios, AML techniques can obtain and analyze money laundering data through identitylinked information, as well as various modeling and learning approaches. However, in anonymous blockchain systems, the identity information and the association between accounts are usually not easily accessible. In the world of cryptocurrencies, the first publicly available dataset related to money laundering was the Elliptic dataset, classifying Bitcoin transactions into licit and illicit categories. The Elliptic dataset has attracted much attention and has been widely followed and used in a number of studies [1, 14, 17, 28]. However, the Elliptic dataset remains inappropriate for developing and validating AML techniques on Web 3 for two reasons. First, the Elliptic dataset only has binary labels for money laundering transactions and does not contain further details on the events and stages of money laundering; second, the bitcoin platform that this dataset focuses on has very different transaction behaviors than Web3 because it does not support smart contracts and decentralized applications. Therefore, for AML on Web3, a dataset that represents diverse transactions and behaviors on Web3 is urgently needed to be proposed.

3.2 Financial Security Issues on Blockchain

Security issues abound in the blockchain ecosystem, such as phishing scams, Ponzi schemes, wash trading and DApp attacks, etc. [3–5, 12, 16, 18, 21, 29, 34, 35]. There exist several datasets for anomaly detection and a series of approaches have been put forward to solve these issues. For example, Chen *et al.* [5] collect Ponzi schemes labels¹ and propose a Ponzi contract detection approach. Wu *et al.* [34] propose a network-embedding based method for phishing identification and disclose a phishing scam dataset². Existing efforts are usually focused on the beginning of the security incidents without digging deeper into the money laundering behind them. It has been reported [23] that many security incidents are followed by money laundering to withdraw cash through service providers such as exchanges. As a result, existing research cannot fully understand the whole story of security incidents.

4 STUDY DESIGN & DATA COLLECTION

Our research aims to systematically investigate the characteristics of crypto money laundering in Web3, from an individual account, to the transaction networks formed by money laundering groups, and further, their resulting economic impact on the Web3 ecosystem. To this end, our research is driven by the following research questions (RQs):

- RQ 1 *From a micro perspective, what are the characteristics of accounts and their transaction behaviors in the process of crypto money laundering in Web3?* Previous work lacks the collection of data on crypto money laundering in Web3. We strive for a complete picture of cryptocurrency money laundering accounts that cover each suspicious path and compare their trading features with normal accounts.
- RQ 2 *From a meso perspective, what are the properties of the complex network of transactions formed by crypto money laundering groups?* As previous work has conducted network-based measurements and investigations on the entire Ethereum blockchain [15], we wish to perform network modeling of money laundering groups' transactions to investigate the differences in money laundering networks compared to the entire transaction network.
- RQ 3 From a macro perspective, what is the impact of the flow of crypto money laundering on the economy of the Web3 ecosystem? Several reports [23, 25, 27] have revealed that a large number of stolen assets

¹https://www.kaggle.com/datasets/xblock/smart-ponzi-scheme-labels ²http://xblock.pro/#/dataset/6

have flowed into the Web3 trading platform. Therefore, it is interesting to explore how the inflow of stolen assets will affect the Web3 ecosystem.

4.1 Abstraction Model for Money Laundering

Since our goal is to measure the money laundering process of stolen funds in Web3, we first propose an abstract model of the crypto money laundering process. Formally, the money laundering process of a heist can be defined as a four-tuple: $(\mathcal{P}, \mathcal{L}, \mathcal{I}, \mathcal{T})$, where \mathcal{P}, \mathcal{L} and \mathcal{I} represent the address sets of *placement*, *layering*, and *integration*, respectively (corresponding to the three phases of money laundering mentioned in Section 2.2). \mathcal{T} is a transaction set which represents the involved transactions during the money laundering process, including external, internal and ERC20 token transactions.



Fig. 1. Illustration of crypto money laundering phases in the Web3 ecosystem.

Figure 1 shows a toy example of crypto money laundering in Web3. Specifically, the hacker performs an attack to steal assets and place them in \mathcal{P} , i.e. placement address set. The addresses in \mathcal{P} is the source of the stolen funds, whose tagges can be obtained by consulting the blockchain browser (e.g. Etherscan) or official announcements. After taking \mathcal{P} , the hacker initiates multiple transactions of Ether or ERC20 tokens, passing the money in \mathcal{P} layer by layer into the untagged layering address set \mathcal{L} in the layering phase, cycling back and forth, obfuscating the source. Finally, the stolen funds are aggregated to integration address set \mathcal{I} for cash out. The addresses in \mathcal{I} are usually service providers such as exchanges, DeFi platforms, etc.

4.2 Framework of Dataset Construction

4.2.1 Target Incident Selection. Ethereum has seen many security incidents of crypto asset theft each year since its creation. As of April 27, 2022, the "Label Word Cloud" service on Etherscan has flagged 115 addresses as "Heist"³ related to stolen assets from exchange hacks, scam projects, DeFi exploits, and more. It should be noted that the statistics of Etherscan only account for incidents from "cryptocurrency-native" crimes (i.e. on-chain crimes), in which illicit profits are almost always obtained in the form of cryptocurrency rather than flat currency. Based on the "Heist" list marked by Etherscan, we selected a number of representative incidents by year and amount stolen, and obtained the placement address set \mathcal{P} for each incident. The list of incidents selected by us for this study is shown in Table 1 in Section 4.4.

³https://etherscan.io/accounts/label/heist

Algorithm 1: Heuristic Transaction Tracing Algorithm

Data: placement address set \mathcal{P} , address label library *Lib* **Input**:max. depth of traced layers K, max. number of addresses per layer Ψ , threshold transaction number for unknown services Ω **Result:** layering address set \mathcal{L} , integration address set \mathcal{I} , involved transaction set \mathcal{T} 1 $k \leftarrow 0$; // The tracing depth 2 $Cur_k \leftarrow \mathcal{P}$; // The current suspicious address set 3 while $k \leq K$ and $0 < |Cur_k| < \Psi$ do for $a \in Cur_k$ do 4 $\mathcal{T}_a \leftarrow \text{QuaryTxns}(a);$ 5 **if** DirtyAmount $(\mathcal{T}_a, \bigcup_{i=0}^k Cur_i) > \beta$ **then** 6 if $|T_a| > \Omega$ then 7 $I \leftarrow I \cup \{a\};$ 8 $Cur_k \leftarrow Cur_k - \{a\};$ 9 $T_a \leftarrow \text{FilterTxns}(T_a, \bigcup_{i=0}^k Cur_i);$ 10 else 11 $Cur_{k+1} \leftarrow Cur_{k+1} \cup GetUnfamiliar(\mathcal{T}_a, Lib);$ 12 $I \leftarrow I \cup \text{GetServices}(\mathcal{T}_a, Lib);$ 13 end 14 $\mathcal{T} \leftarrow \mathcal{T} \cup \mathcal{T}_a;$ 15 16 end end 17 $k \leftarrow k + 1;$ 18 19 end 20 $\mathcal{L} \leftarrow \bigcup_{i=1}^{k} Cur_i;$

4.2.2 *Tracing Method.* In order to build a model of the above-mentioned money laundering process of Web3 heists, we need to design strategies to trace transactions and sample the transactions used for money laundering. To this end, we propose a heuristic-based algorithm to identify the money laundering transactions of the heists, as shown in Algorithm 1. The basic idea of the algorithm is the Augmented Poison Policy [18]. That is, the downstream accounts for money laundering are usually also money laundering accounts, only to the service provider as an exit.

Next, we briefly explain each part of the tracing algorithm. The input of the algorithm includes the placement address set \mathcal{P} for each incident, and the tracing parameters: the maximum depth of traced layers K, the maximum number of addresses per layer Ψ , and the threshold transaction number for unknown services Ω . The purpose of setting these parameters is to control the scope of transaction tracing, to avoid an explosion in the number of downstream addresses, and to delineate the conditions for terminating tracing. Transaction tracking starts with the placement address set \mathcal{P} (line 1–2). For any address a in the current address set Cur_k at layer k, query its external, internal and ERC20 transactions, and get the transaction record \mathcal{T}_a (line 5). We assume that the purpose of money laundering is to conceal the origin of illicit funds and thus the process tends to be very low profile and avoids using one address for a large number of transactions. Therefore, money laundering usually involves intensive and large-amount transactions between a group of accounts. We consider the address a with a large number of transactions to be an unknown service address in the aggregation phase rather than the layering phase



Fig. 2. (a) The simplified money flow graph of the Upbit Hack case. Nodes represent accounts, and edges represent transactions. (b) Evaluation of Upbit Hack case.

(lines 6–9), after filtering transactions containing small amounts of dirty money (\leq threshold β). We then retain the transactions between unknown service providers and upstream laundering accounts $\bigcup_{i=1}^{k} Cur_i$ within one week as suspected money laundering transactions (line 10). For address *a* with a small number of transactions, we select the next level of suspicious addresses Cur_{k+1} from recipient addresses of *a*'s outgoing transactions. In particular, we check whether these recipient addresses are known service providers, according the address label library *Lib* If they are, they are added to *I*. Otherwise, they are included in the Cur_{k+1} crawled in the next layer (line 12-13). Then, the transactions of address *a* are added to the transaction set \mathcal{T} (line 15). We keep increasing the depth *k* (line 18) until the depth exceeds the maximum number of layers *K*, or the size of the current addresses set Cur_k exceeds the range $[0, \Psi]$ (line 3). Finally, we merge the addresses of each layer to obtain the final layering address set \mathcal{L} (line 20).

4.2.3 Data Crawling Tools. Crawlers are important means to accomplish the collection of the dataset in this work. Specifically, we used BlockchainSpider [36], an open source crawler toolkit implemented based on the Etherscan API, to obtain the transaction records of accounts, i.e., the QuaryTxns function in line 4, Algorithm 1. Moreover, we utilize the address label library *Lib* in line 12-13 of Algorithm 1. The label library *Lib* consists of two parts: the labels of the service platforms and token contracts. To determine the service providers, we employ "Label Spider" of BlockchainSpider [36] to crawl label addresses associated with exchanges (e.g. "Exchange", "DEX", etc.), mixing services (e.g. "Tornado.Cash") and other label addresses that appear in connection with actual money laundering activities. We obtain more than 260,000 items, which is sufficient to cover money laundering destinations. The token contracts refer to the "ERC20TokenInfo" dataset with more than 313,000 ERC20 tokens, and the "ERC721TokenInfo" dataset with more than 15,000 ERC721 tokens, published by Zheng *et. al.* [38], including contract addresses, token names, token symbols, etc. These can help identify the types of tokens being used for money laundering in token transactions.

4.3 Example: Upbit Hack Case

To show the complexity of crypto money laundering, we visualize the simplified money flow graph of Upbit Hack (without round-trip transactions) in Figure 2(a). Specifically, the root node (i.e., the leftmost node) represents the source of money laundering, (i.e., \mathcal{P}), the following nodes show the layering addresses (i.e., \mathcal{L}), and the links show the tainted money flow through multiple transactions (i.e., \mathcal{T}). Through this case, we can see that crypto money laundering flows are massively intertwined.

Case Name	Case Type	Year	Case Name	Case Type	Year
CoinrailHacker	CEX Hack	2018	LiquidExchangeHacker	CEX Hack	2021
BancorHacker	DeFi Exploit	2018	AlphaHomoraV2Exploiter	DeFi Exploit	2021
SpankChainHacker	Others	2018	bZxPrivKeyExploiter	DeFi Exploit	2021
FakeMetadiumPresale	Scam	2018	CreamFinanceExploiter	DeFi Exploit	2021
BitpointHacker	CEX Hack	2019	EasyfiHacker	DeFi Exploit	2021
CryptopiaHacker	CEX Hack	2019	PolyNetworkExploiter	DeFi Exploit	2021
DragonExHacker	CEX Hack	2019	UraniumFinanceHacker	DeFi Exploit	2021
UpbitHacker	CEX Hack	2019	BadgerDAOExploitFunder	Others	2021
PlusTokenPonzi	Scam	2019	VulcanForged	Others	2021
KucoinHacker	CEX Hack	2020	ATOStolenFunds	CEX Hack	2022
AkropolisHacker	DeFi Exploit	2020	LCXHacker	CEX Hack	2022
HarvestFinanceExploiter	DeFi Exploit	2020	CashioAppExploiter	DeFi Exploit	2022
Lendf.MeHacker	DeFi Exploit	2020	FloatProtocolFuseExploiter	DeFi Exploit	2022
WarpFinanceHacker	DeFi Exploit	2020	DEGOandCocosExploiter	Others	2022
NexusMutualHacker	Scam	2020	Arthur0xWalletHacker	Scam	2022
AscendEXHacker	CEX Hack	2021	Fake_Phishing5041	Scam	2022
BitmartHacker	CEX Hack	2021			

Table 1. The selected incidents in Web3 from 2018-2022.

The lack of ground truth for money laundering addresses makes it difficult to show the effectiveness of our tracing method through large-scale experiments. But the good thing is that Etherscan has a unique case of flagging a hacker's money laundering account, which is the Upbit Hack case⁴ discussed here. Therefore, we start from the source of Upbit Hack case and obtain the suspicious laundering addresses with Algorithm 1 (Here we choose conservative parameters K = 20, $\Psi = 10,000$, $\beta = 0.01$, and $\Omega = 1,000$.)

Then, as given in Figure 2(b), we calculate the precision values with varying tracing depth to verify the effectiveness of our tracing method. We observe that as the depth increases, the number of detected money laundering addresses grows exponentially. Even when the depth reaches 8, the precision is still over 90%. This result suggests that our proposed tracing method is somewhat convincing.

4.4 EthereumHeist Dataset Overview

In this work, based on the above data collection method, we collect a total of 33 representative security incidents that occurred in the Web3 ecosystem from 2018 to 2022 based on Etherscan's "Hesit" tag. As shown in Table 1, there are four main types of Web3 cases collected in our dataset: CEX hack, DeFi exploits, Scams and Others, e.g. exploits of Decentralized Autonomous Organization (DAO), Game Finance (GameFi) and NFT Finance (NFTFi), etc. We take a preliminary data analysis and exploration of the money laundering dataset as follows (The complete statistical table of case information is shown in Appendix):

(i) In terms of duration, these cases range from less than 1 day to about 3 years. It can be found that some of the cases in early years usually last longer, e.g., the Upbit Hack laundering lasted for more than 2 years, while all the cases that lasted as short as one day occurred in 2022. This may be related to the newer means in Web3 - mixing service. For example, in the LCX exchange hack that occurred in 2022, the hacker took

⁴https://etherscan.io/accounts/label/upbit-hack

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Fig. 3. Comparison of trading characteristics.

only about a day to exchange the stolen ERC20 tokens for Ether through a decentralized exchange (DEX), and eventually transferred them all to a mixing service named Tornado.Cash.

- (ii) In terms of the amount involved, the average amount of money laundered in these cases ranges from \$100 thousand to \$1 million, and the highest value reaches \$10 million, which shows that the financial loss due to the cases is still very huge.
- (iii) In terms of the complexity of the cases, we calculate the number of layers (i.e., tracing depth), transaction fees (i.e., gas cost), and the size of transaction set \mathcal{T} of each case. In general, cases with more layers of money laundering have more accounts in \mathcal{L} and transactions in \mathcal{T} , resulting in a larger and more complicated case data, which makes it easier for hackers to hide and conceal the source of stolen funds, but also costs hackers more in transaction fees.

5 RQ1: TRADING FEATURES OF ACCOUNTS

For the laundering accounts of our dataset, we investigate their trading features such as transaction amounts, frequencies, lifespan, etc. To highlight the differences between layering and normal accounts, we also randomly sample the same number of normal accounts as reference objects. After comparing and observing the collected data, we obtain the most significant findings as follows.

5.1 Lifespan

As shown in Figure 3(a), on the one hand, many money laundering accounts have extremely short lifespans, exhibiting a "used-and-dumped" characteristic. Compared to normal accounts, the peak of the lifespan distribution for the money laundering account is more to the left. On the other hand, money laundering accounts with larger lifespans show an irregularly high percentage of jumps, which is because some of the more careful hackers do not transfer stolen funds immediately, but lurk until the wind passes before laundering. For example, the Coinrail hacker⁵ stole assets in 2018 and then lurked for two years until 2020 when the stolen money was transferred out.

5.2 Degree and Frequency

Degree indicating the transaction activeness, i.e., the sum of in-degree and out-degree. It can be concluded from Figure 4(a) that the net transaction follows power law distribution, we also plot the fitted line $y = x^{-\alpha}$ ($\alpha = 1.6$) to

⁵https://cn.etherscan.com/address/0xf6884686a999f5ae6c1af03db92bab9c6d7dc8de

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Fig. 4. Comparison of transaction amount (ETH).

prove this. Due to the threshold we set is 10^3 , we can see from the figure that our data cut at the same point. As for the several points, that fall around 10^4 is because they get a big degree in the placement phase the very first time and escape from our threshold control. Frequency is the number of transactions that an account is involved in per day. Generally, the frequency of a Heist account is evenly distributed over all magnitudes, but when it comes to the account that has a high proportion, we can see they normally have a high transaction frequency.

5.3 Transaction Amount

We calculate and count the inflow, outflow, and net value of layering accounts in each heist, as well as the corresponding average value per transaction of accounts, as shown in Figure 3(b). Note that we filter the account whose transaction value is larger than 1,000 to reduce the bias caused by exchanges with frequent transactions [3]. We find that the transaction amount of layering accounts is significantly larger than normal accounts in almost every indicator. This shows that even though hackers can create accounts without restrictions, the amount of stolen funds is so large that the amount per transaction in the laundering process remains large. As shown in Figure 3(b), the average inflow and outflow value of layering accounts reach over 50 ETH, which is about 3-5 times higher than that of normal accounts. The reason for the smaller net value of laundering may be that as little as possible money is left hackers usually leave as little money in the layering account as possible to reduce the risk of being frozen.

Finding 1. The laundering accounts usually present an extremely short or long lifespan, reflecting the "useand-dump" or "wait-and-see" strategies, respectively. Hackers tend to engage in higher value transactions, but their net transaction amount is smaller. The value flow in and out heist account reaches around 200 ETH on average.

6 RQ2: NETWORK FEATURES OF GROUPS

In the previous section, we describe the similarities and differences in the characteristics of isolated money laundering accounts and normal accounts, so naturally we have the next question, what are the similarities and differences between these money laundering transaction networks and normal transaction networks?

	Self-loop	Reciprocity	Density (s.,undi) ⁷	Density (multidi)	Global cluster	Avg. pathlen
HeistEthNet (Med.)	0.06%	4.62E-02	2.59E-02	2.67E-02	1.37E-02	2.47
HeistEthNet (Avg.)	0.64%	9.78E-02	1.86E-01	7.70E-01	2.71E-02	5.56
TransactionNet [15]	0.13%	3.00E-02	1.24E-07	1.87E-07	1.00E-01	5.33
HeistTokenNet (Med.)	0.02%	4.21E-02	2.83E-02	3.36E-02	7.08E-03	2.44
HeistTokenNet (Avg.)	0.03%	1.01E-01	1.78E-01	3.80E-01	1.15E-02	4.97
TokenNet [15]	0.19%	3.00E-02	2.03E-07	1.87E-07	1.75E-01	3.87

Table 2. Comparison of network properties. ("Med." means median. "Avg." means average).

6.1 Network Modeling

If criminal groups initiate transactions for the purpose of money laundering, then these transaction networks may differ from the normal transaction network of Ethereum. To this end, we first model the money laundering transaction of each case as a network, G = (V, E), E is the edge set containing all transactions in the case, i.e. \mathcal{T} , and V is a node set which denotes the accounts involved in these transactions.

6.2 Global Network Properties

For each money laundering case, we model two networks: the Ether transactions (including external and internal transactions) as HeistEthNet, and the ERC20 token transactions as HeistTokenNet, in order to compare with TransactionNet [15] and TokenNet [15] of the entire Ethereum, respectively. It is worth noting that the entire network [15] may reflect the nature of the normal transaction network, as our money laundering accounts represent a minuscule 0.3% of the entire transaction network (46 million). Comparative results of graph properties are shown in Table 2.

6.2.1 Basic Features. First, we count the *self-loop* ratio of each money laundering network and calculate their statistic. When compared to TokenNet, as expected, the self-loop ratio of HeistTokenNet is smaller because self-loop transactions are not consistent with the purpose of money laundering, i.e., no splitting and diverting. Surprisingly, the average self-loop ratio of HeistEthNet is higher than that of TransactionNet. Our further analysis reveals that it is because the CashioApp Exploiter⁶ left messages to the community through several self-transactions in the input data area, resulting in the high self-loop ratio in this case.

Reciprocity is defined as the ratio of the number of edges pointing in both directions to the total number of edges. We find that the reciprocity of money laundering networks is higher than that of the entire network, which is likely related to the high activity of token swaps in the Web3 money laundering process.

Finally, we report the *density* of networks, following the formulas in the exiting research [15]. As shown in Table 2, both HeistEthNet and HeistTokenNet have more than twice the average density in multidigraph than they have in simple undigraph, with HeistEthNet even reaching 4 times. But in the entire network, the density of TransactionNet in multidigraph is only 1.5 times of that in simple undigraph. This indicates crypto money laundering networks are frequent and dense sub-networks.

6.2.2 Small-world Behaviour. Researchers refer to the property of large network size but small average distance as small world effect. Analogous to social networks, the entire Ethereum blockchain graphs are also small-world [15].

⁶https://etherscan.io/address/0x86766247ba3405c5f15f06b895294200809e9cfb

⁷simple, undirected graph



Fig. 5. (a) Directed motifs: M_1 and M_2 are all connected two-node motifs; $M_3 - M_{15}$ are all 13 connected three-node motifs; M_{16} is the four-node bi-fan motif. (b) Distribution of the various motifs in money laundering networks.

In Table 2, we find that the average shortest *path length* of HeistEthNet and HeistTokenNet is 4-6, the same as that of the entire Ethereum transaction network. However, by calculating the average *clustering coefficient* of the money laundering network corresponding to each case, we find that the money laundering network (both HeistEthNet and HeistTokenNet) has a smaller clustering coefficient than the entire network. This may be because the special purpose of money laundering makes it lose the multi-hub and social characteristics of the entire network. Therefore, although the average shortest path length of the money laundering network is small enough, its clustering coefficient is small, so the money laundering networks do not exhibit the small world phenomenon.

6.3 High-order Motifs Counting

Higher-order structure of networks can be captured by network motifs [2] which are recurring small subgraphs in the network. To characterize higher-order patterns, we count the percentage of directed motifs (described in Figure 5(a)) of the simple, directed money laundering network of each case. Figure 5(b) shows the results for the percentage of each motif in 23 cases (the others encountered out-of-memory errors). Then, we compare with the entire Ethereum blockchain network [15] and obtain some interesting observations:

- (i) The fractions of *closed triangular motifs* are quite low (M₃-M₉) in money laundering networks. This may be because the pattern of closed triangle motifs is a manifestation of assets circulating internally, such as wash trading behavior [29], which is not consistent with the intent to launder assets.
- (ii) On the contrary, *open triangle motifs* are the most frequent motifs that appear in the money laundering network, of which there are three most, i.e. M_{10} - M_{12} . These three motifs correspond exactly to three phases of money laundering: M_{10} belongs to the placement phase, which spreads the illegally obtained stolen money and extends the money path; M_{11} belongs to the layering phase, which continuously passes stolen funds and

makes it more difficult to trace; M_{12} belongs to the aggregation phase, which collects the scattered laundered stolen money for withdrawal.

(iii) In particular, the money laundering network of DeFi exploit cases has more M_{13} - M_{15} motifs, in which the bidirectional edges are most likely related to a classic DeFi action – token trade (also called exchange), i.e., the trader's account sells a certain amount of a certain token in exchange for a certain amount of another token in a liquidity pool of an Automated Market Maker (AMM). To this end, we identify the DeFi token swap action in each case, referring to DEFIRANGER [20]. We find that the number of M_{13} - M_{15} motifs does have a strong correlation with the DeFi token swap action. For example, at least 70 token swaps were identified in money laundering of Cream Finance Exploiter ⁸, and its M_{13} - M_{15} motif fractions are also relatively high.

To further understand the criminal activities of hackers using DEXs/AMMs, we explore and analyze the cross-asset behavior of hackers in the money laundering process and its purpose, and attribute it to the following activitie:

- (i) Swapping tokens to non-freezable assets. For example, Tether (USDT) is a stablecoin pegged to the US Dollar, operated by Tether Limited Inc. USDT issuers may freeze assets held by illegal addresses. As a result, criminals use DEXs to swap freezable assets for non-freezable ones. For example, in the AscendEX Exploit⁹ event that occurred in December 2021, the attackers quickly exchanged \$5.7million worth of USDT stolen through the Curve.Fi service for DAI, USDC, in about two hours and 40 minutes.
- (ii) Swapping tokens for mixing. Many criminals make use of DEXs to swap their stolen tokens to ETH for mixing. For example, in the Bitmart Hack¹⁰ event that occurred in December 2021, the criminal swapped MANA token for ETH in 1 inch DEX, then sent swapped ETH to Tornado.Cash for mixing.
- (iii) Swapping tokens to bridge them to other blockchains. Cross-chain transactions of criminals are cunning behavior to confuse the flow of dirty money. Before Cross-chain transactions, criminals need to swap assets for tokens convertible on bridges. For example, in the Nexus Mutual Hacker event that occurred in December 2020, the stolen ETH was swapped for renBTC, then the renBTC was bridged to the Bitcoin blockchain. RenBTC is a wrapped version of bitcoin on Ethereum which can then be bridged across to the Bitcoin blockchain using RenBridge.

We go a step further to explore Illicit Token Flows for money laundering. We analyze these 33 cases in this paper and find that criminals stole 923 different types of token assets. These different types of assets went through multiple DEXs token swaps (in some cases occurring multiple times), with the more popular destination tokens being: ETH, USDT, WETH, and DAI. the average time for cross-asset behavior to occur was 15 hours after the start of laundering the stolen assets. Some of the more popular DEXs services include Uniswap, 1 inch, etc.

Finding 2. In general, the self-loop ratio of crypto money laundering networks is lower than that of the entire network and the reciprocity is the opposite. The crypto money laundering network in Web3 is a frequent and dense subnetwork, but does not exhibit the small world phenomenon. There exists a large number open triangle interaction patterns but few closed triangle patterns in crypto money laundering networks. Particularly, the open triangles in DeFi exploit cases contain more bidirectional edges, reflecting the method of further obfuscating stolen assets through Defi's token exchange. The use of DEXs/AMMs by crypto criminals is closely associated with exploits in the DeFi projects and hacks of exchanges.

⁸https://etherscan.io/address/0x24354d31bc9d90f62fe5f2454709c32049cf866b

⁹https://etherscan.io/address/0x2c6900b24221de2b4a45c8c89482fff96ffb7e55

¹⁰https://etherscan.io/address/0x39fb0dcd13945b835d47410ae0de7181d3edf270



7 RQ3: ECONOMIC IMPACT OF LAUNDERING

7.1 Service Providers of Laundering Exit

In the aftermath of Web3 security incidents, almost all black money flows to service providers to be washed. Thus, it is necessary to present the percentage and changes of various service providers. For a first impression, in Figure 6(a), we draw a word cloud graph of the service providers involved in collected events. As we can see, the most frequent word is "Uniswap". Uniswap is a decentralized exchange of great name that enables peer-to-peer market making and enables users to trade or swap cryptocurrencies without any involvement with a centralized third party, so it provides a wide platform for criminals to money laundering. Additionally, there are some other typical service providers popular among crypto laundering in Web3. For example, Binance (an eminent centralized exchange), Opensea (the largest NFT marketplace), and SushiSwap (a decentralized exchange similar to Uniswap).

Fig. 6. Illustration of the economic impact of money laundering in terms of destination service providers and marketplace.

To further explore the evolution of service providers involved in money laundering over time, we first divide the service providers into six categories, which are centralized exchanges (CEXes), decentralized exchanges (DEXes), crossing chain services, loan services, mixing services, and others. Then, we draw a stacked bar chart displaying the percentage of various service providers change over time as shown in Figure 6(b).

As can been seen, the preferences of the service providers to which this dirty money goes change over time. On the one hand, centralized exchanges, once the top destination for stolen funds in 2018, phased down in 2019. The reason may be that CEXes have enhanced AML and KYC procedures at the request of the regulatory section in recent years [9, 10]. On the other hand, there is an increase in the share of DEXes, which can infer that DEXes without a centralized third party is more likely to escape law enforcement investigations. Moreover, the share of crossing chain services is growing year by year since 2019, which allows black money to circulate and confuse on multiple chains, indicating that criminals are becoming more crafty. There is even dirty money flowing to lending services such as Aave, Compound, Dydx, etc. By using the liquidity pool of lending services, criminals can not only conceal the source of dirty money and reduce the possibility of being traced, but also earn extra income via providing huge amount dirty money to liquidity pools. In addition, since the inception of the mixing service, Tornado.Cash, in 2019, it has been one of the destinations of dirty money. It can be presumed that it is a



Fig. 7. Transaction volume from Kucoin Hacker vs. ETH price

classic and effective money laundering service, no wonder Tornado.Cash was recently sanctioned by the U.S. OFAC¹¹. In addition, there exist some other kinds of service providers. For example, criminals deposit crypto to Air Wallet, a kind of distributed airdrop and digital wallet platform.

7.2 Crypto Price Drop Caused by Cash-outs

In the previous section, we find that various trading platforms are destinations for dirty money. There is a great possibility that money laundering accounts selling stolen crypto in large quantities to withdraw cash will affect the volatility of the crypto price. Therefore, in this part, we further explore whether hackers sending ETH to various service providers affects the price of ETH. Due to space limitation, here we only show the result of one of the typical cases - Kucoin Hacker¹². From Figure 7, we see that KucoinHackers sent ETH to service providers from April 2021 to May 2022 and there exist 5 apparent spikes of transaction volume, for example, May 2021, December 2021, March 2022 and May 2022. When a transaction spike occurs, which means that the hacker is withdrawing a lot, the price of ETH drops significantly. Therefore, we can presume that a large number of cashouts correlate significantly with the price of ETH drops. This may be because hackers are eager to withdraw cash and then sell ETH at low prices, resulting in a significant drop in the price of ETH.

In addition, we find that the stolen NFTs also face the fate of being sold at low prices. On the day of the Arthur Hot Wallet heist, the hacker directly sold or auctioned off the 17 stolen Azuki NFTs for around 10 ETH, which was significantly lower than the average market price (13 ETH) at the time. One of the biggest price drops was Azuki#606¹³ - from 78 ETH before the heist to 50.15 ETH when it was sold off. Moreover, the hacker transferred the stolen NFT to other wallets before dumping it in order to prevent it from being frozen. On the one hand,

¹¹https://home.treasury.gov/news/press-releases/jy0916

¹²https://etherscan.io/address/0xeb31973e0febf3e3d7058234a5ebbae1ab4b8c23

¹³https://etherscan.io/nft/0xed5af388653567af2f388e6224dc7c4b3241c544/606

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Fig. 8. The Role Fake Tokens Play in Money Laundering.

it is not obvious to distinguish whether the purchaser of the stolen NFT is a hacker-controlled account or an ordinary user, increasing the difficulty of tracing the hacker's money laundering transactions. On the other hand, ordinary users are likely to accidentally purchase these stolen NFTs, resulting in their subsequent blacklisting by the trading platform, which is not conducive to NFT market stability.

Finding 3. A large number of cashouts of hackers correlate significantly with ETH price drops. The hackers send lots of stolen ETH to service providers in order to get back clean flat currency. Hackers dumping stolen NFTs at low prices could lead to a crisis of trust in the NFT programs and increases the risk of freezing the crypto assets of a genuine user of NFT trading platforms. The service providers being used to launder money are changing over time. The phenomenon of decentralized exchanges, cross-chain services, and lending services increasing their share year by year indicates that criminals are becoming more anti-regulatory and are constantly seeking more cunning and stealthier means of money laundering.

8 COUNTERFEIT TOKEN DEPLOYMENT FOR CUNNING LAUNDERING

In addition to money laundering techniques such as layered transfers and cross-chaining, more cunning hackers may disguise themselves as other common players to evade detection in the Web3 ecosystem, where the existence of counterfeit tokens provides the perfect opportunity for hackers to launder money. Researchers [12, 37] have found that counterfeit tokens are prevalent in the Web3 ecosystem because most DEXes do not enforce any rules for token listing. Hackers can easily create counterfeit tokens and liquidity pools, and even disguise themselves as ordinary speculators to launder illicit funds from liquidity pools of counterfeit tokens. To this end, we conduct an empirical analysis based on the counterfeit token dataset provided by Gao *et. al.* [12], and are surprised to find that in **13 of the 33** cases in this paper are related to counterfeit tokens some way.

One notable case is Akropolis Hacker¹⁴ (a DeFi Hacker). By tracing downstream laundering transactions of Akropolis Hacker, we find evidence that this hacker was laundering money by creating counterfeit tokens. As plotted in Figure 8, the main procedures are as follows:

¹⁴https://etherscan.io/address/0x9f26ae5cd245bfeeb5926d61497550f79d9c6c1c

- (i) Using the tracing method mentioned earlier, we see that the hacker cascaded the stolen funds from Akropolis to several accounts under his control (0x1c80¹⁵ and 0x982d¹⁶ identified as "Heist" in our dataset), and transferred funds to another controlled account 0x1f8¹⁷.
- (ii) Subsequently, address 0x1f8 created the fake token RZN (Rizen Token)¹⁸, and a liquidity pool on Uniswap¹⁹ with 594 fake RZN and 0.877 ETH.
- (iii) The hackers then manipulated the liquidity pool through multiple accounts, posing as ordinary speculators and participating in the trading of counterfeit tokens, e.g. address 0x8c4d²⁰ sold 1000 fake RZN and got 300 clean ETH.
- (iv) Finally, the RZN creator removed the liquidity of 2144 RZN coins and 0.25 ETH. The hackers successfully laundered the illegal funds by disguising their addresses as ignorant participants.

Finding 4. Hackers launder money anonymously by creating fake tokens and disguising their addresses as ignorant participants, which is an upgraded method of money laundering in Web3. At the same time, the fake tokens created by hackers simultaneously increase the risk of ordinary users falling for the scams.

9 MONEY LAUNDERING CORE GROUP IDENTIFICATION.

In the previous section of dataset construction, we introduce how to mine downstream unknown money laundering accounts and networks based on the starting hackers, exploiters, and scammers. Here, the target of the identification of core money laundering organizations is to find core account groups with more intensive interactions and frequent capital transactions in the relatively sizeable downstream money laundering network, as a supplement to criminal evidence collection.

In order to achieve this target, on the basis of the money laundering network initially crawled in this paper, we first define the money laundering *suspiciousness* of an account, then use the approximate greedy algorithm to prune the original downstream network and build a minimum priority tree to speed up the iterative process. Through this process, the most suspicious subnetwork can be obtained as the core money laundering network. The main idea of suspiciousness comes from the money laundering characteristics observed in RQ1 and RQ2: Money launderers will create a large and dense subgraph of transfers because money laundering accounts need to transfer a large number of funds in a short period of time to avoid being detected and frozen, resulting in a dense transfer subnetwork.

The suspiciousness of subgraph S = (N, E), where N denotes nodes and E denotes edges, is defined as:

$$g(S) = \frac{f(S)}{|S|},$$

which can be regarded as the result of taking the average value after summing the suspiciousness of each node and edge in the subgraph structure. Generally, f(S) is defined as follows:

$$f(S) = f_N(S) + f_E(S)$$

=
$$\sum_{i \in N} a_i + \sum_{i,j \in N, (i,j) \in E} c_{ij},$$

¹⁵https://etherscan.io/address/0x1c80f8670f5c59aab8e81e954aabb64dabde2710

¹⁶https://etherscan.io/address/0x982dd33d6bc5bf83eedcbcab92e4899c7a

 $^{^{17}} https://etherscan.io/address/0x1f84ba7bacd29e875367688b38ecccb7849b50fa$

¹⁸https://etherscan.io/token/0x9c91310c9bf1c779b667f46322d33bfdc96c1a07

 $^{^{19}} https://etherscan.io/address/0x658b4a15aae288757c41a9b074ab1881d3ecad0c$

²⁰https://etherscan.io/address/0x8c4dedecbe3e8fbcc0501599cb59e7feadd99ffc

Algorithm 2: An approximate greedy algorithm based on a Minimal priority tree.

Data: Initially crawled Laundering Transaction newtwork $G = (U \cup V, E)$ by Algorithm 1, suspiciousness *q* is defined before.

1 X denotes the subgraph of G. **Result:** A densest subgraph with maximum suspiciousness

2 initialization(G, g);

³ construction of priority tree *T* of $U \cup V$;

4 $X_0 \leftarrow U \cup V;$

5 **for** t = 1, ..., m + n **do**

6 $i^* \leftarrow argmax_{i \in X_i} g(X_i \setminus \{i\});$

⁷ update the priorities in tree *T* for all neighbors of i^* ;

8 $X_t \leftarrow X_{t-1} \setminus \{i^*\});$

9 end

10 $X^* \leftarrow argmax_{X_i \in \{X_0, \dots, X_{m+n}\}}$

where a_i denotes node suspiciousness, c_{ij} denotes edge suspiciousness. For simple calculation, we set edge suspiciousness $c_{ij} = 0$ and $a_i = \alpha$ when node *i* is labeled as a heist. In our experiment, we set $\alpha = 49$ to achieve the best result according to the experiment. Note that when it comes to application, the formula of f(S) is general and can be replaced with other formulas according to needs.

The algorithm2 for identification of the money laundering core network is shown as follows:

Step 1: Built a transaction network $G = (U \cup V, E)$, where U is a set of transaction sender with size *m*, and V is a set of recipients with size *n*, *E* indicates transaction records.

Step 2: Build a priorities tree to restore the priorities *P* of each node *i*, calculated as:

$$P_i = f(X_t \setminus \{i\}) - f(X_t).$$

Step 3: Traverse all nodes in U and V, and calculate the suspiciousness after removing the current node i^* .

Step 4: Find out the subgraph with the largest suspiciousness.

Step 5: Update the priorities of nodes.

Step 6: Iterate accordingly until all nodes have been traversed.

Step 7: Get the subgraph X^* with the largest suspiciousness.

Due to limited space, we only show the experimental process and results of the Upbit Hack money laundering case here. First, We built a bipartite graph based on the transaction data. In the case of Upbit Hack, there are 131, 654 nodes in U, 16, 138 of which are labeled as heists, and 482, 775 nodes in V with 16, 536 heists in them. The heists are marked according to the labels we get in the previous experiment. That is, we get a matrix of size $|U| \times |V| = 131, 654 \times 482, 775$. After implementing the algorithm, we get a core network of size $200 \times 1, 332$. For the 200 and 1, 332 nodes extracted from U and V respectively, we calculated the classification results of whether these account has been marked as money laundering: it turns out that the precision of our experiment reached 82.5% and 100% in U and V respectively. Next, we collect the transaction data from our core network. The original transaction network has 2, 348, 180 transactions while the core network we extract has only 45, 811 transactions.

In all, through this method in this article, the money laundering core network of size $200 \times 1,332$ can be extracted from the original Upbit Hack money laundering network of size 16, $138 \times 16,536$, which narrows the scope of suspicion for criminal evidence collection and investigation.

10 ETHICAL CONSIDERATIONS

In this paper, we reveal the first crypto money laundering dataset in Web3, investigating and analyzing the money laundering techniques of hackers, exploiters, scammers, and others. The disclosure and investigation may cause the community to worry about contributing to the "copycat crime" effect, but actually, our research motivation is similar to the studies of Ponzi contracts [5], phishing scams [16], DApp attacks [21], counterfeit tokens [12], etc. The money laundering transactions published in EthereumHeist are only the tip of the iceberg. As shown in this paper, cybercriminals are improving their methods and techniques year by year in the "cat-and-mouse" game of Web3 anti-money laundering, reinforcing the need for investigation and understanding of crypto money laundering in the Web3 ecosystem. This work will facilitate more effective designs of anti-money laundering algorithms based on our interesting findings in the laundering accounts and networks, and further promote the healthy development of the Web3 ecosystem.

As for whether our research involves privacy issues, the answer is NO. First, the data we collect is completely public and can be accessed by anyone on blockchain. Second, our dataset only includes anonymous transaction data on blockchain, but not other data associated with real-life personal information. Therefore, based on these two points, we do not consider that this work will invade the privacy of others, or directly lead to the arrest or prosecution of individuals.

11 DISCUSSION & CONCLUSION

In this paper, we conduct the *first* systematic study to characterize the crypto money laundering in the Web3 ecosystem. We start from a very small number of security incident accounts, collect abundant money laundering transactions, and build a dataset named EthereumHeist. Based on the dataset, we obtain a series of interesting findings of crypto money laundering in Web3 via answering three research questions from micro, meso to macro perspectives, reflecting the feasibility and necessity of Web3 AML. By answering RQ1 and RQ2, we summarize the characteristics at the account level and the network level, e.g. the lifespan and transaction amounts of accounts, and higher order patterns of sub-networks. These findings can help design effective red flag indicators and detective methods for Web3 AML. Furthermore, by answering RQ3 in a data-driven manner, it can be observed that DApps on Web3 such as DEXes, lending services, etc. have been increasingly involved in money laundering activities in recent years. There is also evidence that dumping stolen money in the money laundering process affects price volatility. Therefore, money laundering is detrimental to the stability of the Web3 market, and it is necessary to develop decentralized security protocols based on economic incentives to achieve effective regulation of decentralized platforms in Web3. Coincidentally, the EU Commission has recently launched a public call for tender for a study on "embedded supervision" of DeFi [6].

As a preliminary exploration of Web3 money laundering and limited by space, this paper also has some limitations (discussed in the Appendix), and there are ample opportunities for future work following our dataset and analysis. As the proposed dataset contains lots of accounts and transactions, and empirical results, researchers are able to propose intelligent tracing methods and money laundering subgraph detection based on this dataset, as those based on Elliptic dataset. Moreover, it is interesting to investigate the correlations and interactions between money laundering transactions in different cases, such as the hacks on Upbit and Kucoin, which are both responsible for Lazarus Group [22]. This may provide further insights into the evolution of their money laundering strategies and lead to more accurate money laundering tracing. Last but not the least, researchers can also design strategies and methods based on cross-chain tracing in the Web3 ecosystem to extend the dataset of this paper.

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