Probing the Mystery of Cryptocurrency Theft: 
an Investigation into Methods for Taint Analysis

Tin Tironsakkul  
School of Mathematical and Computer Sciences  
Heriot-Watt University  
Edinburgh, United Kingdom  
t28@hw.ac.uk

Manuel Maarek  
School of Mathematical and Computer Sciences  
Heriot-Watt University  
Edinburgh, United Kingdom  
m.maarek@hw.ac.uk

Andrea Eross  
School of Social Sciences, Accountancy, Economics and Finance  
Heriot-Watt University  
Edinburgh, United Kingdom  
a.eross@hw.ac.uk

Mike Just  
School of Mathematical and Computer Sciences  
Heriot-Watt University  
Edinburgh, United Kingdom  
m.just@hw.ac.uk

Abstract—Since the creation of Bitcoin, transaction tracking is one of the prominent means for following the movement of Bitcoins involved in illegal activities. Although every Bitcoin transaction is recorded in the blockchain database, which is transparent for anyone to observe and analyse, Bitcoin’s pseudonymity system and transaction obscuring techniques still allow criminals to disguise their transaction trail. While there have been a few attempts to develop tracking methods, there is no accepted evaluation method to measure their accuracy. Therefore, this paper investigates strategies for transaction tracking by introducing two new tainting methods, and proposes an address profiling approach with a metrics-based evaluation framework. We use our approach and framework to compare the accuracy of our new tainting methods with the previous tainting techniques, using data from two real Bitcoin theft transactions and several related control transactions.

Index Terms—Cryptocurrency Crime, Transaction Tracking, Taint Analysis, Address Profiling

1. Introduction

Research into cryptocurrencies remains a fascinating topic in many fields due to the novel implementation of a decentralised digital currency system. While 10 years have already passed, Bitcoin is still the most prominent and valuable cryptocurrency in use. Bitcoin’s high acceptability and pseudonymous privacy capability to protect its users identities still makes Bitcoin attractive to individuals who are looking for a less traceable currency, compared to traditional currencies.

Even though Bitcoin itself is a decentralised peer-to-peer electronic currency that allows individuals to exchange Bitcoins directly without having to rely on a central third-party entity to monitor or control transactions, the majority of its users rely on a controlled third-party entity to facilitate the exchange of Bitcoins. These service entities, such as cryptocurrency exchange services, help facilitate exchanges to real-world currencies or other cryptocurrencies such as Coinbase, or to centralised payment services such as Bitpay.

Cryptocurrency service entities are frequently prime targets for individuals that aim to obtain money illegally. Due to the fact that cryptocurrency services such as cryptocurrency exchange services often store their users’ Bitcoins in their wallet system to operate the transactions or services, the thefts that occur at cryptocurrency services affect both the service and its users. These events can also undermine the whole economy of cryptocurrencies and affect other cryptocurrencies users. Ultimately, such activities can diminish Bitcoins value and its potential to become the official alternative to traditional currencies.

The tracking of Bitcoin transactions remains a formidable challenge due to Bitcoin’s privacy protection system and the rise of new transaction obscuring techniques that allow the individuals engaged in cryptocurrency theft to evade the grasp of law enforcement. While there have been proposals for so-called tainting methods that attempt to track the illegal Bitcoins, there has been little research into evaluation criteria to measure the accuracy of tainting results. In light of the above, this paper contributes the following:

1) We propose two new tainting methods, LIFO and TIHO that seek to recognise a thief’s strategies for tracking evasion;
2) A new approach to tailor tainting with address profiling that only taints transactions up to potential points of theft evasion (e.g., service entities);
3) A set of metrics to evaluate tainting accuracy that we hypothesise to be indicators of cryptocurrency theft behaviour.

We apply our approach and evaluation metrics to examine the effectiveness of several tainting methods, including our two new methods. For each of our six evaluation metrics we introduce a corresponding hypothesis that we use to analyse our results. We used data from two real Bitcoin thefts, as well as a number of control transactions for each theft.

The rest of the paper proceeds as follows. In Section 2, we give the necessary background on Bitcoin and related work on transaction tracking. We then detail our methodology in Section 3 with the new tainting methods we propose (Section 3.1), the address profiling we use to tailor tainting (Section 3.2), the set of tainting metrics we defined (Section 3.3), and the criteria we used to build the
control groups for our experimentation (Section 3.4). We then present in Section 4 the theft cases we investigate, and discuss the results we obtained in Section 5. Section 6 concludes and presents future work.

2. Bitcoin Transaction Tainting

In this section, we provide a brief overview of the Bitcoin system and discuss the tainting methods studied in the previous literature.

2.1. Bitcoin System

The transaction data of Bitcoin is stored in a distributed and transparent transaction ledger system called blockchain, which allows any individual to analyse and visualise every transaction and address in existence [1], [2]. The tracking of the Bitcoin transaction is still not without its challenges, especially in the case of finding the exact ownership and movement of specific Bitcoins. This is due to the fact that, aside from the pseudonymous address system, the possession of Bitcoins in each address exists in the form of unspent transaction outputs (UTXO)3, which are newly created from the sum of inputs2 in that transaction. As a result, when the targeted inputs are combined with other unrelated inputs into new output(s), it is difficult to identify or differentiate the exact distribution and destination of the targeted inputs without having a precise methodology.

The primary purpose of the taint analysis is to overcome this issue by classifying the targeted Bitcoins (e.g., Bitcoins resulting from a known theft transaction) as tainted (or dirty)3, and any address that uses or transfers them will also be considered as tainted addresses. Thus, the tainting method applies a specific rule-set to estimate how the targeted Bitcoins are distributed in the transactions. The idea of taint analysis is frequently associated with the prospect of regulatory systems implementation on cryptocurrencies, in that addresses identified as tainted would immediately be flagged with a warning system by notifying authorities, business entities and other users that the tainted Bitcoins are in circulation. The tainted Bitcoins should not be accepted by other users or businesses and measures would be taken to prevent Bitcoins in quarantine; similar to how the blacklist system works [3], [4].

2.2. Taint Analysis Methods

We identified three tainting strategies or methods for tracking transactions using transaction information from the blockchain: Poison and Haircut methods [3] and FIFO (First In, First Out) method [5]. We review these strategies below.

1. 'Output' is the result of the transaction, which can be used in the subsequent transaction. 'Unspent Transaction Output' (UTXO) is an output that is still unused in any transaction.
2. Input is a reference of the previous transaction’s output that is being used in the current transaction.
3. In this paper, we define the tainted Bitcoins as the Bitcoins that contain any portion of the stolen coins, while clean Bitcoins are Bitcoins that do not contain any portion of tainted Bitcoins.

2.2.1. The Poison Method. The Poison method is a tainting strategy that classifies all of the transaction outputs as tainted outputs in the transactions with any tainted input, regardless of the number of tainted Bitcoins involved [4].

As shown in Fig 1, the number of the tainted Bitcoins will exponentially increase over time as the tainting continues due to the increase in mixing between the tainted and clean Bitcoins that are in circulation.

As shown in Fig 1, the number of the tainted Bitcoins will exponentially increase over time as the tainting continues due to the increase in mixing between the tainted and clean Bitcoins that are in circulation. The argument for the practicality of this method is that the only way the tainted Bitcoins can affect clean Bitcoins is when they are used together as inputs in the same transaction. Hence, there should be minimal risk of tainted Bitcoins becoming mixed with clean Bitcoins for unrelated users provided that they are cautious not to use the tainted or suspicious Bitcoins they receive in the same transaction with their clean Bitcoins. Additionally, if the users do not use the tainted Bitcoins at all, their addresses will also not be classified as tainted addresses (see Section 3.2). Therefore, it is possible for criminals to sabotage Bitcoins possession of other unrelated users by purposely sending them a portion of tainted Bitcoins (so that it becomes mixed with other clean Bitcoins) [4].

However, the argument for this method relies heavily on the common user’s knowledge of the tainted Bitcoins and strict safety precautions. The Poison method is also frequently considered to be too excessive because of the number of Bitcoins impacted. This makes it impractical to be used for both regulation and tracking purposes compared to other tainting methods. Nevertheless, the Poison tainting results can be used as a baseline method for comparison with other methods.

2.2.2. The Haircut Method. This method operates similarly to the Poison method by also classifying all of the resulting output in the transactions that contained tainted inputs as tainted. However, the Haircut method implements an additional rule: instead of being classified as tainted entirely, each output in the transactions that contained tainted inputs will be classified as tainted in proportion [4].

As shown in Figure 2, the Haircut method distributes the inputs based on their proportion in the transaction to each output accordingly. Thus, while both the Poison and Haircut methods consider all of the outputs as tainted in the tainted transactions, the resulting value of the tainted outputs are different. Although, as the mixing between the tainted and clean Bitcoins increases, the tainting result of the Haircut method often accumulates a large number of tainted transactions and addresses.

Figure 1. The Poison Method. The white rectangles represent clean inputs or outputs, while the darker rectangles represent fully tainted ones. For example, in a transaction with a 7 BTC clean input and a 3 BTC tainted input, both of the resulting 9 BTC and 1 BTC outputs will be classified as tainted entirely. The end result is that the number of tainted Bitcoins is now at 10 BTC from initially at 3 BTC.
of cryptocurrency transaction tracking, which is to provide accurate tracking results. This is because the transaction order can be arbitrarily set up in any way possible by the users. The FIFO method that defines the transaction distribution in one specific way might be unable to provide accurate tracking results for more complex transactions. It is also possible for the users to circumvent the FIFO method by reverting their transaction order to misdirect the FIFO tracking of their Bitcoins.

3. Methodology

In this section, we describe our two new tainting methods, followed by our address profiling methods that we use in our tainting analysis. We then present our evaluation metrics for measuring tainting performance. For each evaluation metric we present a corresponding hypothesis.

3.1. Proposed New Tainting Methods

3.1.1. The LIFO Method. The LIFO (Last In, First Out) method is developed based on the assumption that the order-based tainting methods may not be capable to accomplish. TIHO (Taint In, Highest Out) is an alternative method to the FIFO method that operates in the opposite ordering of the FIFO method. LIFO method assumes that the last item that goes in is always the first to goes out.

As shown in Figure 4, when applying LIFO method, the last input in the transaction order would be first to be distributed to the outputs. Next, the LIFO method follows a bottom-up ordering when distributing the inputs. As a result, the first 9 BTC output will contain a portion of the tainted Bitcoins (2 BTC) and the last 1 BTC output will contain any tainted Bitcoins.

As shown in Figure 4, when applying LIFO method, the last input in the transaction order would be first to be distributed to the outputs. Next, the LIFO method follows a bottom-up ordering when distributing the inputs. We implement the LIFO method as a tainting method to evaluate the tracking result of order-based tainting and ascertain whether such tainting techniques can be meaningfully implemented for transaction tracking purpose in the case of cryptocurrency theft transactions.

3.1.2. The TIHO Method. TIHO (Taint In, Highest Out) incorporates a novel tainting classification and the transaction characteristic into the tainting algorithm. This tainting method prioritises the distribution of the tainted inputs to the higher value outputs as shown in Figure 5 below. Hence, we refer to this as a value-based tainting method.

We create this tainting method with the aim to capture larger and more complex transactions that the order-based tainting methods may not be capable to accomplish. TIHO method is developed based on the assumption that the
larger value outputs are usually the main purposes of the transaction, while the smaller value outputs are often change outputs\(^4\) of the transaction.

Although, it should be noted that this assumption does not necessarily apply to every transaction in Bitcoin. For example, in the situation where the users purchase products from merchants using high-value inputs/Bitcoins, similar to using large value banknotes to purchase cheap products, this would mean that the value of the outputs that go to the merchant address would be smaller than the change outputs that go back to the buyers. Hence, the lower value outputs would be the main purpose of the transaction in this example.

3.2. Address Profiling

Although deanonymisation, which aims to reveal the real identity of Bitcoin addresses’ users, is not the goal of this paper, we believe that integrating context-awareness and adaptability capabilities into taint analysis can potentially improve the accuracy of the tracking results. Tainting indiscriminately would miss our goal to understand theft strategies. Therefore, we classify the addresses utilising the information available in the blockchain and tainting results into three categories as follows.

3.2.1. Service Address. As in real life, cryptocurrency services exist in many forms each with different purposes such as cryptocurrency exchange services, online gambling services, E-commerce businesses, marketplace services, CoinSwap services\(^5\) and mixing or tumbling services. We define service address as an address that has exceptionally high transaction activity compared to the other addresses during the same time frame.

We identify service addresses based on the assumption that exceptionally high transaction activity for an address usually indicates that the address is a point of central exchange for other addresses. This is also similar to the concept of degree centrality in network analysis where a high centrality node (a node with many connections to other nodes) often implies that the entity has a large amount of influence to the network and can often be considered as the central hub of exchange for that network [7].

We also consider service addresses to be the end goal or exit point of the tainted Bitcoins. We set the assumption that the ultimate purpose of the stolen Bitcoins is to be exchanged for real-world monetary value. As such when tainted Bitcoins reach the service addresses, we can consider the stolen Bitcoins to ultimately reach its uses and are no longer in the hand of individuals engaged in theft. Therefore, we stop the tainting process for any tainted Bitcoins that reach service address. The classification process and the selection criteria for the service addresses are described in more detailed in Section 5.

Although, it should be noted that as we use only the transaction data from the blockchain for our taint analysis, the tainting method can classify the addresses that belong to service entities in the real world as tainted addresses, especially for the services that also avoid reusing their addresses for privacy purposes.

3.2.2. Tainted Address. A tainted (or dirty) address is as an address that the tainting methods considers to receive the tainted Bitcoins regardless of the amount. As each tainting method utilises different approaches to tracking, each address may be classified differently in each method. Likewise, it is also possible that the tainted addresses may not belong to the theft, as Bitcoins can also be sent to other users’ addresses without having to rely on service entities.

Thus, the tainted address classification in our experiment is different from the tainting classification proposed in the previous literature in that an address would be considered as tainted when it receive any amount of tainted Bitcoins.

3.2.3. Clean Address. A clean address is any address that does not receive any tainted Bitcoin. It should be noted that clean addresses can belong to the theft accomplices depending on how the tainting method operates.

3.3. Tainting Evaluation Metrics

We develop evaluation metrics to assess the tainting methods by utilising information available within the blockchain data. Next, we present our hypotheses for each variable. We discuss these evaluation metrics in the subsections below.

3.3.1. Reused Addresses. Due to the nature of the transactions involving theft, it is expected that the thief would employ transaction obscuring and privacy techniques as much as possible to prevent potential tracking. Avoid utilising the same address(es) multiple times, is one of
the most common privacy techniques, as the Bitcoin system does not only set any limitation on the number of addresses that the users can possess, but also facilitate the ease of creation of the addresses (in a matter of seconds).

We can assume that the thief would be careful enough to attempt to avoid using an address more than once to reduce transaction traceability. Hence, we consider a reused address is an address that has been used in the transaction more than once. As shown in previous research [8], [9], while privacy protection is often considered as one of the most important aspects of Bitcoin among its userbase, many users seem to not be as privacy-conscious as it can be observed from the high number of reused addresses.

This provides us with a valid reason to believe that there is a high chance that the number of reused addresses involved in theft transactions and common transactions is significantly different, giving us the following hypothesis:

H1 The number of reused addresses will be higher in the tainted theft transactions than in the tainted control transactions.

Therefore, the sample theft cases should have a considerably lower number of reused addresses compared to the control groups, and that the tainting method that shows the least number of reused addresses is likely to be more accurate.

For our study, reused address metric does not focus on service addresses and considers only the sent transactions because Bitcoin system allows users to send their Bitcoins to any address without requiring confirmation or permission from the receivers as long as they know the public key of the recipient addresses. This means the receiving transactions may not always be in the control of the addresses' owners, while the sending transaction is always in the control of the sender.

3.3.2. Fresh Addresses. The fresh address is an address that does not have any transaction activity at all before receiving the tainted Bitcoins. To avoid reusing the same addresses multiple times, the thief would need to create new addresses every time the stolen Bitcoins are distributed. Hence, we hypothesise the following:

H2 The tainted theft transactions will have more fresh addresses than those in the tainted control transactions.

Thus, we expect that the tainting method with a higher number of fresh addresses will be more accurate.

3.3.3. Transaction Fee. A Transaction fee is an incentive provided by the transaction sender(s) to miner to prioritise confirming the transaction into the blockchain. The transaction fee is calculated from the difference between input and output value of the transaction [10]. Normally, the recommended transaction fee rate that the miners charge is calculated from the data size of the transaction and the number of transactions that are currently waiting for confirmation at that point of time. Although it is possible for the transaction fees to be zero or lower than the recommended rate as the transaction selection for mining is solely determined by the miners' decision. For example, the miner may decide to confirm transactions with zero transaction fees when few transactions are waiting to be confirmed at that time.

We select the transaction fee as one of the evaluation metrics due to its potential to reveal the difference between transactions that involve an illegal activity and common transactions. The transaction fee variable that we use is the transaction fee value and the ratio of the transaction fee to transaction data size like 1 BTC transaction fee value and 0.5 BTC per byte.

H3 The amount of the transaction fee in tainted theft transactions will be higher than in tainted control transactions.

This hypothesis is motivated by the assumption that the thief will try to obscure his/her transaction trail by rapidly moving the stolen coins; therefore, he/she needs to provide sufficient incentive through the transaction fee to accomplish this. As a result, the tainting strategy with better tracking accuracy should have an overall higher average transaction fee for the tainted transactions according to our hypothesis.

3.3.4. Service Address Reaching. We anticipate that the thief would want to spend the stolen coins as soon as possible to minimise the transaction trail - as the longer the stolen coins are still in his/her possession - the higher the chance for it to be detected.

H4 The tainted theft transactions will reach a service address in higher number.

The tainting strategy that shows the higher number of route to any service address is more likely to be more accurate.

3.3.5. Transaction Frequency. Another common transaction obscuring or privacy technique is to distribute the Bitcoins in smaller amounts to multiple addresses to increase the difficulty of tracking the original Bitcoins. As such, we expect that the number of tainted transactions per day for the sample theft cases will be higher than the control groups.

H5 The number of tainted theft transactions (per day) will be greater than those for the tainted control transactions.

The tainting method providing result with higher transaction frequency is likely to be more accurate.

3.3.6. Number of Addresses per Transaction. Similar to the transaction frequency metric, the majority of the transaction-obscuring techniques often involve a large number of addresses in each transaction whether it be laundering services, coin mixing [11], [12], and CoinJoin technique.

6. A Public key is an identifier of an address that other users use as a reference for sending Bitcoin.
7. A Miner is an individual or a group of individuals that can successfully solve the earliest the block mining challenge provided by the Bitcoin protocol.
8. CoinJoin is a transaction obscuring technique where multiple users share the same transaction whether manually or via a service [13], [14].
The number of addresses per transaction will be greater for the tainted theft transactions than for the tainted control transactions.

The tainting method that shows a higher number of addresses per transaction is expected to be more accurate. It should be noted that the addresses per transaction evaluation metric includes both the input and output addresses in the transaction, and also the addresses with clean inputs in the transactions.

3.4. Control Group Criteria

We select the control groups from the set of all transactions that possess the most similar characteristic as the sample theft case, as we define below. In particular, there are three criteria that we use to select the control groups for each sample theft case:

1) **Time.** We select the common transactions that occur within the same period as the sample theft cases. In this paper, we set the time criteria to be within one month before and one month after the first time the stolen Bitcoins are being distributed.

2) **Transaction value.** We select transactions with similar transaction value as the sample theft cases. In this paper, we set the transaction value range criteria to be between $1,000$ BTC and $\geq 1,000$ BTC, e.g., if the theft is involved in $5,000$ Bitcoins, the transaction value criteria for control groups will be set at between $4,000 - 6,000$ Bitcoins for that particular theft case.

3) **Transaction distribution.** We select the common transactions that possess a closely similar characteristic as the first transaction after the theft transaction. For example, if the first stolen Bitcoin distribution transaction is a one-to-two addresses transaction, the control groups we pick will also be one address to two addresses transaction.

4. Data Collection

We use two historical thefts as the samples for testing the tainting methods. The theft cases we use are the *Bter theft* from 2015 and *Betcoin theft* from 2012.

Bter is a cryptocurrency exchange service located in China. Its service was shut down in 2017 due to the Chinese governments ban on the use of cryptocurrencies. The theft occurred on 14 February 2015 at 04:32AM in which the hacker stole 7,170 Bitcoins from the Bter’s cold wallet address\(^9\) [15]. For simplicity, we refer to the Bter theft case sample as "T1" and to their control groups as "C1".

Betcoin or Betco.in is a gambling service that accepts Bitcoin as its primary medium of exchange. The theft occurred on 11 April 2012 at 10:50AM in which the hacker stole 7,170 Bitcoins from the Betcoin’s cold wallet address\(^9\) [15]. As Betcoin requires the users to send their Bitcoins to the service’s addresses to be held for the betting, the theft of Betcoin also affects other users, similar to the thefts of exchange services. For our experiment, we refer to the Betcoin theft case sample as "T2" and to their control groups as "C2".

For this paper, we restricted the taint analysis of the transactions to be within 15 days from the first stolen Bitcoin distribution transaction of each sample case to limit the computational resources and the time required for evaluation. It is also worth noting that while the theft transaction of T2 happened in 2012, the distribution of the stolen Bitcoins began in 2013 which means that the control groups we chose for this case were from 2013.

4.1. Service Addresses Classification

For each sample theft case, we looked at the number of transactions for every address within the 15 day tainting period. We set the service address classification to be the addresses that have the number of transactions at the top 99th percentile of all the addresses in the time limit. Thus, the criteria for service addresses are any address with more than 24 transactions for T1 and 28 transactions for T2.

We choose the 99th percentile limit in order to reduce the risk of misclassification as the previous research [8], [9] shows that the majority of the addresses normally have less than five transactions throughout their lifetime. This means that the higher criteria limit we select, the less chance the common addresses will be misclassified as service addresses. The previous research also points out that there are still many individuals who reuse their addresses, despite the ease of address creation process. Hence, common addresses can still have enough transaction activity to be in the top percentile.

It is also worth mentioning that choosing the lower criteria limit would mean a higher chance to include services that employ transaction obscuring techniques such as laundering service addresses, which are likely to be involved in some way. We further address our plan for this type of situation in Section 5.

4.2. Control Groups Selection

To select the control groups for each sample theft case, we select the common transactions that fit the control group criteria and that do not appear in the Poison tainting result of the sample cases. As multiple transactions in the same transaction set can fit the criteria (e.g., users sending the same Bitcoins to their addresses in the same way multiple times would make all of the transactions fit the control group criteria), we group the transaction sets together and select only the first transaction of the group to avoid redundant control groups and tainting process. However, this does not eliminate the possibility of transaction merging between the control groups later on in the tainting process.

There are 25 control samples for C1 and 14 control samples for C2 in this experiment. However, we had to slightly adjust the transaction distribution characteristic criteria for T2 as the first distribution transaction has shared inputs with seven other addresses that are directly unrelated to the theft case. As employing this criteria would result in too small number of control groups, we
ease the distribution criteria for T2 to consider only the single input address of the theft transaction. As a result, the transaction distribution characteristic criteria for T2 is the transactions with a single address input and a single address output. The completed list of the control groups’ transaction hash for each case is displayed in Table 1 in the appendix.

5. Results and Discussion

In this section, we present the results and discussion of our taint analyses on the sample theft cases and their control groups. First, we present our findings for T1 followed by T2 along with the control groups’ results in comparison for both theft cases. In the result figures, we abbreviate the word “transaction” as “TX” and “address” as “ADR”. The transaction fee metric is presented in Sat or Satoshis\(^\text{10}\) per byte.

As we incorporate the address profiling into each tainting method, the results would be different from the ones originally proposed in the previous literature. Hence, from this point forward, we indicate the inclusion of the address profiling in the tainting methods with “AP”, (short for address profiling) or “(AP)” after the method name.

As the Poison\(^\text{AP}\) and Haircut\(^\text{AP}\) methods classify every output in the transaction as tainted, albeit with different taint value, the tainted transaction results of both methods would be the same including the addresses involved. Hence, we combine the tainting results of Poison\(^\text{AP}\) method into Haircut\(^\text{AP}\) method in the results.

5.1. The Transaction Frequency Metric

All T1 tainting methods’ results share very similar patterns throughout the whole tainting period and the number of transactions also stay considerably constant between 200 and 700 transactions for the period of interest. Although at one point FIFO\(^\text{AP}\) method results for T1 show the highest transaction frequency with 1,113 transactions on day 11 at the purple dot point as shown in Figure 6, surpassing all other sample results.

Interestingly, there are two C1 cases that possess an extremely high number of transactions per day, as shown by the C1 high case one and two lines in Figure 6. Both results show very different patterns when compared to each other and to the T1 tainting results. While C1 high case two shows extremely high transaction frequency on the first four-day period, the results show a gradual decrease until it reaches the majority of C1 cases on day 8. For C1 high case one results, the transaction frequency abruptly increases on day 6 but rapidly decrease after day 8. Nevertheless, it remains the sample case with highest transaction frequency until the end of tainting except for day 11.

As shown in Figure 7, the results of the transaction frequency display some intriguing patterns for T2 tainting result. Interestingly, there are two C2 cases that also possess the highest number of transaction per day as shown by the C2 high case one and two lines. While both results show similar patterns when compare to other C2 cases during the first 12 day period. Both results suddenly increase on day 13 and become the samples with highest onward.

While there is no transaction activity for T2 during the first eight days, the transaction activity for all of the T2’s FIFO\(^\text{AP}\), LIFO\(^\text{AP}\) and THO\(^\text{AP}\) methods suddenly increase on day 9 and exceed all of the C2 results on day 10 at 150 transactions as marked at the first purple dot point as shown in Figure 7. The number of tainted transactions for the T2’s THO\(^\text{AP}\) method increases further and remains the highest on day 11, as shown at the second dot in Figure 7, while the number of transactions in the other two tainting methods decreases, but nonetheless remain as the highest percentile sample. On day 12, the number of tainted transactions for the T2’s FIFO\(^\text{AP}\) method become

---

10. Sat or Satoshis is the smallest unit in Bitcoin value. One Bitcoin is equal to 100,000,000 Satoshis.
the highest, as shown at the third dot. Interestingly, the number of transactions of the T2’s three tainting methods rapidly decrease afterwards and become more in line with the other C2 cases on day 14.

The sudden increase of the transaction frequency from zero in the first eight-day for the T2 results is behaviour that we did not expect. The explanation we have for this unexpected behaviour is that after waiting for about one year before starting to transfer the stolen Bitcoins, the thief waits for eight more days to check whether there are still tracking attempts or any interest from the public before proceeding further. Although, It is worth mentioning that the year 2013 is the time that the price of Bitcoin rapidly increases for the first time in its history from 10 US dollars in February to around 100 US dollars in April [18]. Therefore, there is a possibility that the thief is merely waiting for the Bitcoin value to rise before deciding to spend the stolen coins.

Both C1 and C2 also have sample cases that show an exceedingly high number of transactions. Our interpretation for the exceptionally high transaction frequency in the control cases is that due to the large transaction value criteria we used to select the control groups, sample the transactions that we select can belong to the service addresses, which would lead to two possibilities of what would happen subsequently as follows.

First, the service addresses transfer the Bitcoins to other addresses that also belong to the services, if the following addresses also match the criteria then the tainting would stop. Second, the service addresses distribute the Bitcoins to their users such as when the users exchange the real-world money for Bitcoins with cryptocurrency exchange services. This would result in widespread distribution of the tracked Bitcoins and exponentially increase the transaction frequency as the Bitcoins keep spreading as seen in the C2 high case one and two in Figure 7, and the C1 high case one in Figure 6 to a degree.

Overall, while the transaction frequency variable results do not exactly match with H5 hypothesis that the sample theft cases would have a higher number of transactions per day than the control groups, and each tainting method results does not reveal the explicit distinction between the theft case samples and their control groups. The results, nonetheless, provide us with an interesting perspective on the theft transactions’ unusual behaviours that can be used in future analysis.

5.2. The Reused, Fresh and Service Addresses

As shown in Figure 8, the percentage of the service, reused and fresh addresses are considerably different between T1 and C1 results. All of the T1 tainting methods results share a similar percentage for reused addresses at around 10% and service addresses at one per cent. The reused address results of T1 tainting methods are also considerably lower than C2. The percentage of fresh addresses are relatively more significant in T1 except for the LIFO\textsuperscript{AP} method at 80%, which is also similar to LIFO\textsuperscript{AP} method result for C1.

As shown in Figure 9, the address type percentage for T2 tainting results reveal quite different patterns than for T1: the percentage of reused addresses for T2 is around 10% higher than for C2 for all four tainting methods, with the LIFO\textsuperscript{AP} method being as high as 25%. The fresh address percentage is also overall slightly higher for T2 results at around 80%, while the C2 results are between 70% and 80%. The service address percentage is similar for T2 and C2, with the FIFO\textsuperscript{AP} method for T2 showing a slightly higher percentage at four per cent compared to the rest.

The reused variable results reveal conflicting yet interesting results for both T1 and T2 cases as shown in Figures 8 and 9 respectively. Both T1 and T2 display very distinctive results from their respective control groups, but in the opposite direction.

Our interpretation on the glaring contrast between the two cases’ results is that it is possible for the stolen coins in T2 to pass through our service address profiling undetected and are already are in the possession of the other users. Another possibility is that the thief employs transaction obscuring technique that distributes the stolen coins in multiple looping patterns to make the analysis of the transaction network more difficult. In any case, the reused addresses results do not exactly match with H1 hypothesis that the sample theft cases would have a lower number of reused addresses than the control groups.

The fresh address variable results for both T1 and T2 cases considerably match with H2 hypotheses that the number of fresh addresses would be higher in theft sample
cases than the control groups, as while all of the FIFO\textsuperscript{AP}, LIFO\textsuperscript{AP} and TIHO\textsuperscript{AP} methods show a higher number of fresh addresses in general compared to their control groups counterpart. However the difference between the two groups is not as significant as we expected, therefore, further analysis is required to ascertain whether the fresh address variable can present a definite contrast in theft transaction cases.

The service addresses variable results show a considerably high number for both T1 and T2 which match with H4 hypothesis that the number of service addresses in the sample theft cases would be high. There are two possible explanations for high service address number as follows; the service addresses that we detect may belong to the types of service directly involved in the transaction obscuring processes like laundering/tumbling services, CoinJoin services and coin mixing services. Another possibility is that the service addresses may be reused addresses of the common users with high enough transaction activity to reach the service address criteria.

Nevertheless, the results still prove there is already a certain number of tainted Bitcoins that manage to reach addresses that are likely to belong to service entities. This means that the integration of address profiling into the tainting method can improve the tainting method accuracy which provides an answer to our second research question of how can the tainting method be improved further for tracking of stolen Bitcoins.

### 5.3. The Number of Addresses per Transaction Metric

As shown in Figure 11, for the addresses per transaction variable, the results do not reveal a distinction between the T2 and C2 as much as for the T1 case.

The addresses per transaction variable results also present a contradiction between T1 and T2 tainting results as shown in Figures 10 and 11 respectively. Our explanation on the contrast between T1 and T2 addresses per transaction variable results is that as the theft distribution transaction for T2 occurred in 2013, there are still not as many complex transaction obscuring methods available at the time that would allow the thief to disguise the transactions in the way as shown in T1 yet. For examples, the CoinJoin method is first purposed in by one of the Bitcoin developers in August 2013 [19].

As a result, while the number of addresses per transaction metric shown in this study yield promising results, the implementation of the number of addresses per transaction metric and H6 hypothesis still need to be revised and investigated further with a larger number of sample cases.

### 5.4. The Transaction Fee Metric

As shown in Figure 12, T1 tainting methods results also do not appear to reveal distinction to C1 results for the transaction fee per byte ratio overall. All of the tainting methods for T1 also share a similar pattern and constantly stay in the lower percentile group with around 25 Sat per byte throughout the whole period of interest.

There are also two C1 cases that possess an extremely high average transaction fee per byte ratio in the C1 high case one and two lines as shown in Figure 12. Both C1 high case one and two show very similar patter during the first six-day period but diverge later on but still stay within 100 - 200 Sat range until the end of our tainting.

As shown in Figure 13, the average transaction fee value in the three tainting methods, FIFO\textsuperscript{AP}, LIFO\textsuperscript{AP} and TIHO\textsuperscript{AP} for T1, show significantly higher fee value than that of T1’s Haircut\textsuperscript{AP} method and all of the C1 tainting methods. The average transaction fee value for T1’s three tainting methods are in between 40,000 - 50,000 Sat range, while C1 tainting results are in between 20,000 - 30,000 Sat range.
As shown in Figure 14, the transaction fee variable yields intriguing results for case T2. While the average transaction fee ratio of T2 tainting results are among the top percentile group when the transactions start appearing on day eight, the transaction fee ratio of the TIHO\textsuperscript{AP} method for T2 drops sharply and becomes the sample case with the lowest transaction fee at 25 Sat per byte in day 11 as pointed out at the purple dot in Figure 14. The average transaction fee ratio for the TIHO\textsuperscript{AP} method increases on day 12 and then becomes the lowest on day 13 at the second purple dot. At the third purple dot on day 14, all of the three tainting methods for T2 have lower transaction fee values than for all of the C2 cases at around 80 Sat per byte.

As shown in Figure 15, although not significantly higher than its control groups as for T1, the average transaction fee value for T2 tainting methods are still as high as for C2 cases. Although, the TIHO\textsuperscript{AP} method for T1 still appear as the lowest of compared to the other T1’s tainting methods and C1 cases. Both of T1 and C1 tainting methods have average transaction fee value between 70,000 - 80,000 Sat range, while the average fee value for T1’s TIHO\textsuperscript{AP} method is at 52,000 Sat.

In general, the transaction fee per size ratio of both T1 and T2 tainting methods are in the lower percentile group when compare to their respective control groups as shown in Figures 12 and 14. Although the results between T1 and T2 are quite different in that the transaction fee ratio results of all T1 tainting methods are remarkably constant among other the lower percentile C1 cases, while T2 shows unstable changes for all of the tainting methods throughout the tainting period especially for TIHO\textsuperscript{AP}.

However, despite the overall low transaction fee ratio for both T1 and T2 which means that both theft cases transactions pay the fee at the lower rate than the majority of their respective control groups, the transaction fee in both cases are still in the higher percentile as shown in Figures 13 and 15.

Our explanation for this difference is that the reason why the transaction fee per size ratio is considerably lower in T1 is due to the fact that the majority of transaction in T1 are considerably larger than the C1 transactions as can be seen from the number of addresses per transaction variable results even though the average transaction fee value in T1 is higher than C1. This interpretation can also be applied for T2 as the number of addresses per
5.5. The Overlapping Tainted Transactions

Figure 16. The number of overlapping tainted transactions between each T1 tainting method. Each circle represents the results of the tainted transaction to each tainting method and the overlapping area represent the tainted transaction results that the tainting methods share. For example, the red circle represent the number of tainted transactions results of T1 tainting method, and the green circle represent the results of FIFOAP method. The yellow overlap area between the two circles represents the number of transactions that both methods classify as tainted.

As shown in Figure 16, all of the tainting methods possess balance portions between overlapping and non-overlapping tainted transaction results for the T1 case. The tainted transaction results of TIHOAP method are slightly more similar to the FIFOAP method than to the LIFOAP method.

As shown in Figure 17, the overall pattern of overlapping transactions’ results for T2 is relatively similar to that of T1. Although the portions of overlapping between each tainting methods are more significant in this case as the the overlapping number between the three tainting methods is larger than each method’s non-overlapping number. Each tainting method still has a considerable portion of tainted transactions that is unshared by the other methods. Interestingly, the FIFOAP and LIFOAP methods share more similarity in the tainted transactions’ results than with the TIHOAP method.

Overall, the three tainting methods FIFOAP, LIFOAP and TIHOAP demonstrate the significantly diverse results of tainting methods for both T1 and T2 cases as shown in Figures 16 and 17. This implies that there is a significant number of mixing involve between the tainted and clean Bitcoins for both sample cases. Ultimately, the tracking results of each tainting method would be completely different in the longer tainting period. The overall tainting results of T1 and T2 are shown in Tables 2 and 3 in the appendix.

6. Conclusion and Future Work

While the privacy that Bitcoin can bring to users is revolutionary in todays modern society, the privacy features can also facilitate the individuals to perform illegal activities or even cause harm to others. In an attempt to combat crime and illegal activities in Bitcoin, tracing the Bitcoins to the end of the blockchain alone would only show who are the unfortunates to be the last holders of tainted Bitcoins chosen by the tainting process. To truly track the crimes in Bitcoin, it is crucial to understand the context of each transaction and address involved.

The variables we use for tainting and evaluation in this paper are information that can be found within the blockchain. Such information cannot be falsified due to the nature of the blockchain. Although it is possible to obtain additional information from the external sources that are available in public such as forums or social media websites [20], there is a risk of the information being either incorrect or purposely falsified, so extra caution must be exercised when handling information from external sources.

The result of our experiment shows that some of the evaluation variable results are in conflict with our hypotheses and there are some contrasts between the results of the two sample theft cases that we study. The evaluation metrics and the hypotheses that we proposed still require further analysis and validation before we can truly measure and evaluate the tracking accuracy of the tainting methods. Additionally, the number of sample theft cases can be expanded further to improve the evaluation results. Nevertheless, the evaluation metrics demonstrate the potential for the future application of illegal activities tracking in cryptocurrency.

Another consideration that should be taken into account is that illegal activities are one of the most important aspects of the Bitcoin economy, considering that as high as 33% of all Bitcoin transactions involve illegal activi-
ties [21]. Thus, the classification of service addresses as an exit point of tainted transactions that utilises only transaction activity may not be sufficient enough, considering the thieves would more likely prefer spending the stolen coins on the exit points with the least chance of being caught, as opposed to official services like cryptocurrency exchange services which could be regulated by governments. As the services or businesses that engage in illegal activities are likely to employ transaction obscuring techniques to protect their users’ privacy, the address profiling should be developed further by incorporating other techniques such as address clustering and network analysis to assist in the address profiling and tainting process. The network analysis result of the tainted transaction network can also be used to discern the flow of complex transactions and the relationship of the addresses that are concealed by transaction obscuring techniques [22].

This paper laid the foundation for our future work on taint analysis to not only discover the most accurate tainting methods but to also improve upon the current transaction tracking strategies. The results of transaction taint analysis can then be used to assist the cybersecurity in combating against cryptocurrency cybercrimes. This will have important implications not only to cybersecurity but to financial regulatory developments.

References

[1] D. McGinn, D. Birch, D. Akroyd, M. Molina-Solana, Y. Guo, and W. J. Knottenbelt, “Visualizing Dynamic Bitcoin Transaction Patterns,” Big Data, vol. 4, no. 2, pp. 109–119, Jun. 2016.

[2] G. Di Battista, V. Di Donato, M. Patrignani, M. Pizzonia, V. Roselli, and R. Tamassia, “Bitconview: Visualization of flows in the bitcoin transaction graph,” in Proc. 12th IEEE Symposium on Visualization for Cyber Security (ViSec 2015), L. Harrison, N. Prigent, S. Engle, and D. M. Best, Eds., 2015, pp. 1–8.

[3] B. Danton, “Bitcoin and Money Laundering: Mining for an Effective Solution,” Indiana Law Journal, vol. 89, no. 1, art. 13, pp. 442–472, 2014.

[4] M. Moser, R. Bohme, and D. Breuker, “Towards Risk Scoring of Bitcoin Transactions,” in Financial Cryptography and Data Security, ser. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2014, pp. 16–32.

[5] R. Anderson, I. Shumailov, and M. Ahmed, “Making Bitcoin Legal,” in Security Protocols XXV, V. Maty, P. venda, F. Stajano, B. Christianson, and J. Anderson, Eds. Cham: Springer International Publishing, 2018, vol. 11286, pp. 243–253.

[6] M. Möser and R. Böhme, “Anonymous alone? measuring bitcoins second-generation anonymization techniques,” in 2017 IEEE European Symposium on Security and Privacy Workshops, 2017, pp. 32–41.

[7] F. Ghafoor and M. A. Niazi, “Using social network analysis of human aspects for online social network software: a design methodology,” Complex Adaptive Systems Modeling, vol. 4, no. 1, pp. 1–14, 2016.

[8] M. Harrigan and C. Fretter, “The Unreasonable Effectiveness of Address Clustering,” in 2016 Intl IEEE Conferences on Ubiquitous Intelligence Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCom/IoP/SmartWorld), Jul. 2016, pp. 368–373.

[9] D. Ron and A. Shamir, “Quantitative Analysis of the Full Bitcoin Transaction Graph,” in Financial Cryptography and Data Security, Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, vol. 7859, pp. 6–24.

[10] S. Nakamoto, “Bitcoin: A Peer-to-Peer Electronic Cash System White Paper,” pp. 1–9, 2009.

[11] T. Rufing, P. Moreno-Sanchez, and A. Kate, “Coinshuffle: Practical decentralized coin mixing for bitcoin,” in European Symposium on Research in Computer Security. Springer, 2014, pp. 345–364.

[12] J. Bonneau, A. Narayanan, A. Miller, J. Clark, J. A. Kroll, and E. W. Felten, “Mixcoin: Anonymity for bitcoin with accountable mixes,” in International Conference on Financial Cryptography and Data Security. Springer, 2014, pp. 486–504.

[13] F. K. Maurer, T. Neudecker, and M. Florian, “Anonymous coinjoin transactions with arbitrary values,” in 2017 IEEE Trustcom/BigDataSE/ICESS, Aug 2017, pp. 522–529.

[14] S. Meiklejohn and C. Orlandi, “Privacy-enhancing overlays in bitcoin,” in Financial Cryptography and Data Security, M. Brenner, N. Christin, B. Johnson, and K. Rohlff, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2015, pp. 127–141.

[15] S. Higgins. (2015) Bter claims 1.75 usd million in bitcoin stolen in cold wallet hack. https://www.coindesk.com/bter-bitcoin-stolen-cold-wallet-hack. [Accessed: 2019-01-13].

[16] Betco.in. (2012) Home of first ever bitcoin poker room. https://betco.in/. [Accessed: 2019-02-05].

[17] Dree12. (2014) List of major bitcoin heists, thefts, hacks, scams, and losses [old]. https://bitcointalk.org/index.php?topic=83794.0. [Online forum comment], [Accessed: 2019-08-13].

[18] O. Beigel. (2019) Complete bitcoin price history graph + related events 2009 - 2020. https://99bitcoins.com/bitcoin/historical-price/. [Accessed: 2019-07-08].

[19] G. Maxwell. (2013) Coinjoin: Bitcoin privacy for the real world. https://bitcointalk.org/?topic=279249. [Online forum comment], [Accessed: 2019-09-02].

[20] M. Fieder, M. S. Kester, and S. Pillai, “Bitcoin transaction graph analysis,” CoRR, vol. abs/1502.01657, 2015. [Online]. Available: http://arxiv.org/abs/1502.01657.

[21] S. Foley, J. R. Karlsen, and T. J. Putni, “Sex, Drugs, and Bitcoin: How Much Illegal Activity Is Financed through Cryptocurrencies?” The Review of Financial Studies, vol. 32, no. 5, pp. 1798–1853, 04 2019.

[22] A. Baumann, B. Fabian, and M. Lischke, “Exploring the bitcoin network.” in WEBIST International Conference on Web Information Systems and Technologies, 2014, pp. 369–374.
**TABLE 1.** THE TRANSACTION HASH OF THE CONTROL TRANSACTION FOR EACH THEFT CASE.

| Bet Bitcoin Theft Case TX Hash (T1) |  |
|------------------------------------|--|
| e29f8a0d963c3d429f7c3d5af026d2c8e8ec2b3d52079e1c8ef71d1f1d445c |  |

**Control TX Hash (C1)**

| Bet Theft Case TX Hash (T2) |  |
|----------------------------|--|
| 21ac34ca629f3a625d5a9bc9c59732f3136e2f2d48 |  |

| TABLE 2. THE RESULTS OF EACH TAINTING METHOD ON CASE T1. |
|----------------------------------------------------------|
| Variables                                               |
| Haircut AP                                              |
| FIFO AP                                                  |
| LIFO AP                                                  |
| TIHO AP                                                  |
| Tainted TX                                              | 502,196 |
| Reused ADR                                               | 5,335 |
| Fresh ADR                                                | 39,612 |
| Avg. ADR Per TX                                          | 5,335 |
| Avg. TX Fee Value (Sat)                                  | 86,542 |

**Variables**

- **Haircut AP:**
  - 502,196
- **FIFO AP:**
  - 5,335
- **LIFO AP:**
  - 39,612
- **TIHO AP:**
  - 5,335
- **Tainted TX:**
  - 86,542
- **Reused ADR:**
  - 25,185
- **Fresh ADR:**
  - 5,335
- **Avg. ADR Per TX:**
  - 5,335
- **Avg. TX Fee Value (Sat):**
  - 86,542

Table 1 shows the complete list of transaction hash of each sample theft case and control sample that we select in this paper for each theft sample case.

Table 2 shows the overall result of each T1 tainting method from 15 days tainting.

Table 3 shows the overall result of each T2 tainting method from 15 days tainting.