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ABSTRACT

Multiple works have leveraged the public Bitcoin ledger to estimate the revenue cybercriminals obtain from their victims. Estimations focusing on the same target often do not agree, due to the use of different methodologies, seed addresses, and time periods. These factors make it challenging to understand the impact of their methodological differences. Furthermore, they underestimate the revenue due to the (lack of) coverage on the target's payment addresses, but how large this impact remains unknown.

In this work, we perform the first systematic analysis on the estimation of cybercrime bitcoin revenue. We implement a tool that can replicate the different estimation methodologies. Using our tool we can quantify, in a controlled setting, the impact of the different methodology steps. In contrast to what is widely believed, we show that the revenue is not always underestimated. There exist methodologies that can introduce huge overestimation. We collect 30,424 payment addresses and use them to compare the financial impact of 6 cybercrimes (ransomware, clippers, sextortion, Ponzi schemes, giveaway scams, exchange scams) and of 141 cybercriminal groups. We observe that the popular multi-input clustering fails to discover addresses for 40% of groups. We quantify, for the first time, the impact of the (lack of) coverage on the estimation. For this, we propose two techniques to achieve high coverage, possibly nearly complete, on the DeadBolt server ransomware. Our expanded coverage enables estimating DeadBolt's revenue at \$2.47M, 39 times higher than the estimation using two popular Internet scan engines.

KEYWORDS

Cybercrime, Bitcoin, Revenue Estimation, DeadBolt ransomware

1 INTRODUCTION

The Bitcoin ecosystem has attracted cybercriminal activities such as ransomware [24, 36, 43, 53, 55, 64, 65], thefts [45], scams [16, 17, 42, 45, 54, 71], human trafficking [56], clippers [31], cryptojacking [37, 67], hidden marketplaces [23, 41, 60], and money laundering [47]. Cybercriminals often request payments in bitcoins from victims that fall for their scams or are infected with their malware. The public nature of the Bitcoin ledger has been leveraged by multiple works to estimate the revenue cybercriminals obtain from victims [17, 24, 36, 37, 41–43, 52–54, 64, 71]. An accurate estimation of the financial impact on victims is fundamental for understanding the cybercrime ecosystem, e.g., for comparing the revenue of different types of cybercrime, such as ransomware versus sextortion. It is also critical for triaging, i.e., assigning adequate investigative resources to each cybercriminal group based on their impact. Underestimating the financial impact of a cybercriminal group may convey the wrong

impression that it is unimportant, removing resources from its analysis and defense and thus allowing its operations to continue unfettered. On the other hand, overestimating the financial impact may wrongly identify small players as dominant, assigning them unnecessary investigative resources.

Starting from a set of *seed* Bitcoin addresses, known to belong to the same cybercriminal group (e.g., ransomware family, Ponzi scheme) or to the same type of cybercrime (e.g., ransomware, sextortion), estimation works apply different methodologies to quantify the financial impact on the victims. Some works simply add deposits to the input seed addresses, while others apply a combination of expansions to discover additional payment addresses (e.g., multi-input clustering [15, 45, 48, 59] and change address heuristics [15, 27, 29, 40, 45]) and filters to remove unrelated addresses and deposits. Estimations focusing on the same target often do not agree, due to the use of different methodologies, seed addresses, and time periods (i.e., block heights). Furthermore, these factors make it very challenging to understand to what degree each methodology step is responsible for differences in the estimation.

In this work, we perform the first systematic analysis on the estimation of cybercrime bitcoin revenue. We quantify the impact in the estimation of the methodology used and the limited seed coverage. In detail, we survey prior estimation works providing a detailed analysis of their methodologies and concrete takeaways. We implement a tool that can replicate the different methodologies. We apply our tool to estimate the same target using 15 methodologies, while fixing the set of seeds and the blockchain height. This allows us to quantify how differences in the methodology affect the estimation. In contrast to what is widely believed, we show that estimations do not always underestimate the revenue. There exist estimation methodologies that can introduce huge overestimation such as those that do not filter seeds that are online wallets in exchanges and those using change address heuristics. We collect 30,424 cybercrime Bitcoin payment addresses from publicly available sources. We use this dataset to compare, using a consistent methodology, the impact of 6 cybercrimes (ransomware, clippers, sextortion, Ponzi schemes, giveaway scams, exchange scams) and of 141 groups running Ponzi schemes, ransomware, and clippers (which replace addresses copied into the clipboard with their own). We observe that the top cybercrime groups by revenue are dominated by ransomware and the most successful ones operate in the ransomware-as-a-service model [46], although there are also Ponzi schemes and clipper families for which we observe more than one million USD revenue. There are also 14 groups whose estimated revenue is below \$20, likely indicating limited coverage on their payment addresses. Our results highlight the limited effectiveness

of existing expansions. The popular multi-input (MI) clustering fails to discover additional addresses for 40% of the 141 groups, likely indicating cybercriminals are actively evading it, while change address expansion introduces large false positives.

An intrinsic issue in cybercrime revenue estimations is that they underestimate the real revenue because they start from a limited set of seeds (oftentimes only one) while the cybercriminals may use a large number of addresses to receive victim payments. To this day, no work has quantified the impact of the (lack of) coverage on the estimation. This requires a vantage point that allows to observe all victim payments. We perform the first quantification of this issue. For this, we focus on the DeadBolt server ransomware family, which infects network-attached storage (NAS) devices [14]. We start by collecting 4,997 DeadBolt payment addresses from two Internet scan engines [21, 63]. We estimate DeadBolt's conversion rate from infections to payments to be 0.7%. A unique characteristic of DeadBolt is that it releases the decryption key on the blockchain upon receiving the victim's payment. We propose two novel techniques, leveraging unique characteristics of DeadBolt's key release transactions, to obtain very high coverage, possibly nearly complete, on the payments DeadBolt receives from victims. Using the 34 seeds with victim payments collected from the scan engines (which MI clustering cannot expand) we would have estimated a very modest revenue of 2.826 BTCs or \$63K. By applying our coverage-expanding techniques, we instead estimate 98.350 BTC, 35 times higher, and our USD estimation is \$2.47M, 39 times higher. The vantage point provided by the scan engines only identifies 2.6% of victim payments due to issues such as scan frequency or infections happening before the scanning begins. Still, Internet scan engines arguably provide higher coverage on server ransomware (i.e., 34 DeadBolt seeds) that is typically available for other groups such as desktop ransomware (i.e., a median of one seed per group). Thus, for other groups, the coverage impact may be even larger.

Our coverage results critically indicate that even if a family or campaign is estimated to have low revenue, it could still have a significant non-measured financial impact on victims. Thus, estimations should also consider other impact metrics beyond the revenue, e.g., the number of family samples observed.

This work provides the following main contributions:

- We perform the first systematic analysis of cybercrime bitcoin revenue estimations. We build a tool that implements the different estimation methodologies and use it to quantify the impact of each methodology step in the estimation. We show that some methodologies can produce huge overestimation.
- We quantify, for the first time, the impact of the (lack of) coverage on the estimation. For this, we propose two novel techniques to achieve high, possibly complete, coverage of the victim payments received by the DeadBolt server ransomware. The USD revenue DeadBolt collects from victims is 39 times larger than what would have been estimated by collecting seeds from two popular Internet scan engines.
- We compare the bitcoin revenue obtained by 6 cybercrimes and 141 cybercriminal groups. Cybercriminals may be actively evading the popular multi-input clustering, which does not discover additional addresses for 40% of groups.

• We have released our estimation tool and DeadBolt dataset [7].

2 BITCOIN REVENUE ESTIMATION

This section surveys prior works that estimate cybercrime bitcoin *revenue* [17, 24, 36, 37, 41–43, 52–54, 64, 71]. These works do not estimate the *profit* the cybercriminals made, as that would require subtracting from the revenue the unknown expenses they incurred [68]. Estimations may target a specific cybercriminal group (e.g., malware family, Ponzi scheme, scam campaign) or a (type of) cybercrime (e.g., ransomware) by aggregating revenue of multiple groups in the same cybercrime (e.g., multiple ransomware families).

At a high level, all the works follow the same approach. They take as input a set of *seed* addresses known to receive victim payments. They optionally expand the seed addresses to obtain an *expanded set* of addresses that belong to the same owners as the seeds. If no expansions are used, the expanded set only contains the seeds. Then, they obtain all the deposits to addresses in the expanded set. Next, they optionally apply filtering to remove unrelated addresses and deposits. This process results in an estimation of BTC revenue. Finally, the BTC amount is converted to fiat currency (typically US Dollars). While the general process is shared, there exist methodological differences at each of the above steps that can lead to differing estimations for the same input seeds.

Table 1 summarizes the 12 surveyed works. To select these works, we first examined papers published since 2009 (the initial Bitcoin protocol release year) in top computer security venues. To identify other articles published in smaller venues and pre-print repositories, we analyzed the references of those initial works. Additionally, we searched on engines like Google Scholar for combinations of keywords, including bitcoin, payments, ransomware, and scam. We limit the selection to papers published on peer-reviewed venues (and technical reports with public datasets) that include an estimation of cybercriminal bitcoin revenue. We exclude works that analyze Bitcoin abuse by cybercriminals but do not include a financial estimation (e.g., [31, 67]), those performing estimations on other cryptocurrencies (e.g., Monero [18, 35]), and those estimating revenue using transaction data not from the Bitcoin blockchain (e.g., [69]). The rest of this section details the above steps using the different parts of Table 1.

2.1 Seeds

We call *payment addresses* to Bitcoin addresses where victims are requested to send their payments. Payment addresses may be obtained from social media (e.g., [64]), threat intelligence reports by security companies (e.g., [24]), by running malware samples on a sandbox (e.g., [36]), from scam emails (e.g., [54]), from Tor hidden services (e.g., [41]), and from scam websites (e.g., [42]). Payment addresses can be split into those that have received some deposit, which are called *seeds*, and those that have not (yet). This determination, and generally the whole estimation, needs to be performed at some particular height of the Bitcoin blockchain. Unfortunately, only two works provide the specific block height used [53, 54]. Most works mention a day, but there are roughly 144 blocks in a day, as a new block is minted every 10 minutes.

Cybercriminals may or may not reuse payment addresses across victims. In the extreme, they could use a single payment address

										Expand			Filtering]	
Work	Year	Crime	Platform	Blk Height	Seeds	Labels	Micro Payments	Seed Clustering	Seeds Available	Multi-input (MI)	Change Address (CA)	Exploration	Value Filtering (VF)	Time Filtering (TF)	Online Wallets (OW)	Double-Counting (DC)	Payment day rate	Methodology
Huang et al. [37]	2014	Cryptojacking	-	2013-11-30	290	10	X	X	X	\checkmark	X	X	X	X	X	X	\checkmark	DD+MI
Spagnuolo et al. [64]	2014	Ransomware	BitIodine	2013-12-15	≥ 12	1	X	X	X	\checkmark	\checkmark	X	\checkmark	×	X	X	X	DD+MI+CA-VF
Liao et al. [43]	2016	Ransomware	-	2014-01-31	2	1	X	X	[43]	\checkmark	\checkmark	X	\checkmark	\checkmark	X	X	\checkmark	DD+MI+CA-VF-TF
Conti et al. [24]	2018	Ransomware	-	2017-12-07	128	20	X	X	[2]	\checkmark	\checkmark	X	\checkmark	\checkmark	X	X	\checkmark	DD+MI+CA-VF-TF
Huang et al. [36]	2018	Ransomware	BlockSci	2017-08-31	25	10	\checkmark	X	X	\checkmark	X	•	\checkmark	X	•	X	\checkmark	DD-OW+MI-VF
Bartoletti et al. [17]	2018	Ponzi	-	-	32	32	X	X	[1]	\checkmark	X	X	X	×	X	X	\checkmark	DD+MI
Lee et al. [41]	2019	Dark Web	BlockSci	2018-04-30	85	-	X	X	X	\checkmark	\checkmark	X	X	X	O	X	\checkmark	DD-OW+MI+CA
Paquet-Clouston et al. [53]	2019	Ransomware	GraphSense	489,181	7,118	35	X	X	[3]	\checkmark	X	X	X	\checkmark	X		\checkmark	DD+MI-TF-DC
Paquet-Clouston et al. [54]	2019	Sextortion	GraphSense	573,989	245	-	X	\checkmark	[4]	\checkmark	X	X	\checkmark	X	O	0	\checkmark	DD-OW+MI-VF-DC
Xia et al. [71]	2020	Exchange scams	-	2019-09-23	66	-	X	\checkmark	[5]	X	X	X	X	X	X	X	X	DD
Oosthoek et al. [52]	2022	Ransomware	-	-	7,321	87	X	X	[20]	×	X	X	X	×	X	X	\checkmark	DD
Li et al. [42]	2023	Giveaway scams	-	2022-07-01	860	-	X	\checkmark	[11]	X	X	X	X	X	X	X	X	DD

Table 1: Related work on estimating cybercrime Bitcoin financial impact. A tick (\checkmark) indicates a property is implemented by the work, a cross (X) no support, a half-filled circle (\bigcirc) partial support, and a dash (-) that the paper does not specify it.

for all victims, or generate a different address for each victim. Oftentimes, a middle ground is used with a (potentially large) pool of payment addresses that are reused with some (potentially low) probability. Payment addresses with deposits are the input seeds to the estimation. The number of seeds ranges from only one up to 7,036 addresses. However, the high number of seeds in two works [52, 53] is due to the outlier Locky ransomware with over 7K addresses. Overall, the median number of seeds per group is 1 (measured on the dataset in Section 3.4). Seeds are the critical starting point for any estimation. To enable replicability, authors should release the seeds used, which happens for 8 of the 12 works.

One challenge when each victim is assigned a unique payment address is that only a small fraction of payment addresses receives payments and thus can be used as seeds. For example, in their sextortion paper, Paquet Clouston et al. [54] extracted 12,533 payment addresses, but only 2% had deposits. Furthermore, for some address collection methods like running malware on a sandbox or collecting emails marked as spam (prior to the user receiving them), if the address is unique for each victim then none of the collected payment addresses would have payments, as there are no real victims. To address this situation, Huang et at. [36] perform micro-payments to payment addresses. Micro-payments simulate the payment of a victim, but their value is much smaller than the requested payment value. Their goal is incentivizing the cybercriminals to move the micro-payment so that it can reveal other payment addresses through the expansions presented in Section 2.2. For example, a micro-payment of a few hundred satoshis is small enough that to move those funds the recipients need to combine them with other Unspent Transaction Outputs (UTXOs) in a multi-input (MI) transaction so that the transaction fee can be paid. This enables discovering those additional inputs through MI clustering, as described in Section 2.2. The larger the micro-payment, the larger the incentive for the cybercriminals to move the gifted funds. However, cybercriminals could ignore any payments not matching the expected values.

Seeds may be labeled with the group to which they belong, which allows to perform separate estimations for each group. For example, the label may capture the malware family that uses the seed, obtained from external reports or from the AV labels of the samples [62]. But, some collection methods such as visiting Tor hidden services [41], visiting scam websites [42, 71], and examining spam emails [54] may collect addresses that belong to different groups. To perform per-group estimates, these works first need to cluster the addresses using external information such as the content of the websites or the spam emails. When seeds are unlabeled and no clustering is performed, it is only possible to provide an estimation of the type of cybercrime all addresses are associated with (e.g., the Dark Web [41]). The quality of the labels is fundamental to the estimation. If a seed is incorrectly labeled, that will inflate the estimation of its group.

Some works extract Bitcoin addresses from Web pages using regular expressions [41, 42, 71]. Since Bitcoin addresses are hashes, such regular expressions may generate false positives. It is important to validate the matches by verifying the checksum embedded in valid addresses, e.g., using online blockchain explorers or by using tools that perform such validation during the extraction [12].

Takeaway 1

To be replicable, works should release their payment addresses (as seeds may change with the block height), the clustering results (if any), and the block height used for the estimation.

2.2 Expansions

Given a set of seeds, the simplest estimation consists of adding all direct deposits the seeds have received, i.e., for each transaction where a seed address appears in an output slot, accumulate the value of the seed's output slot. This simple estimation is used in three surveyed works [42, 52, 71]. However, if the campaign uses a large number of payment addresses, the seeds may only receive a small portion of the revenue received from victims, i.e., there may exist many unknown payment addresses that also received victim payments. To discover previously unknown payment addresses, it is common to apply expansions to the seeds that identify additional addresses that also belong to the seed owners. Then, the same estimation as above is performed on the expanded set of addresses (i.e., seeds plus additional addresses the expansions

identified). Two main expansions are used in the surveyed works: *multi-input clustering* used by 8 works and *change address* heuristics used by 4 works. They can be combined, e.g., all works using change address also use multi-input clustering. We also discuss an *exploration* expansion, which generalizes the approach used in one work for one group.

Multi-input clustering. The most popular expansion is multiinput (MI) clustering [15, 45, 48, 59]. It assumes that input addresses to the same transaction have the same owner because their private keys are used together to sign the transaction. Clusters can be created transitively. If a transaction has addresses *A* and *B* as inputs, and another transaction has *B* and *C* as inputs, then *A*, *B* and *C* are all clustered together and have the same owner. One exception is CoinJoin [44] transactions where a group of users creates a single transaction that simultaneously spends all their inputs into a shuffled list of outputs. For this reason, before computing MI clustering, it is common to apply proposed heuristics to identify CoinJoin transactions [29, 38]. Kappos et al. [40] recently proposed a machine learning (ML) classifier to reduce the false negatives of the CoinJoin heuristics. However, their classifier has not yet been used in estimations.

Once the MI clusters are computed, the seeds and all addresses in the MI cluster of a seed are added to the expanded set. If the seeds belong to different MI clusters, the expanded set contains the union of all addresses in those MI clusters (including the seeds). Of the 9 works using MI clustering, 5 use open-source platforms to compute it: one uses BitIodine [19], two use BlockSci [38], and two use GraphSense [34]. The rest use their own implementation. As far as we know, no work has compared that different implementations of MI clustering indeed produce the same results.

While MI clustering is an extremely popular and reliable expansion [33, 49], there are two caveats that could affect the estimation. First, MI clustering captures *same ownership*. If the same cybercriminals run multiple campaigns, MI clustering may add to the expanded set addresses from campaigns different from the one the seeds belong to. If the goal is to estimate the revenue of a specific campaign, rather than the revenue of a cybercriminal group, or of a type of cybercrime, this may introduce overestimation.

Takeaway 2

MI clustering may add to the estimation other campaigns from the same owner.

Second, *double ownership* is common in services (e.g., exchanges) offering online wallets for their users. In that scenario, the service owns the address (i.e., has the private key), but the address is handled (and thus indirectly owned) by the user for which it is created. Performing MI clustering on an online wallet address can bring into the expanded set thousands (and even millions) of addresses that also belong to the service, but are unrelated to the estimation as they belong to other customers of the service. For seeds that are online wallets, only their direct deposits should be considered, i.e., other addresses in their MI cluster should not be added to the expanded set. Failure to filter seeds that are online wallets, can make the estimation hugely overestimate the financial impact. We discuss the filtering of online wallets in Section 2.3.

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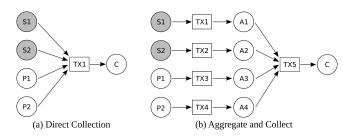


Figure 1: Two approaches to collect payments from two seeds S_1, S_2 (in gray) and two unknown payment address P_1, P_2 into a collector address C. On the left, MI clustering discovers the unknown addresses P_1, P_2 , while on the right it does not.

Takeaway 3

It is possible for MI clustering to largely overshoot the actual revenue if some seeds are online wallets in services like exchanges, and the estimation includes all the cluster deposits. For seeds that are online wallets in services, the expanded set should contain only the seeds, i.e., it should not contain other addresses in the MI clusters of those seeds.

Change address. Bitcoin's UTXO-based model does not allow the partial spending of transaction outputs. Since the sum of input values to a transaction may be larger than the amount that needs to be paid, a change address can be used by the owner of the input addresses to collect back the change. Several heuristics have been proposed for identifying which output slot in a transaction is the change address [15, 27, 29, 40, 45]. Once identified, the change address (and other addresses in its MI cluster) are added to the expanded set. Three works ([24, 43, 64]) use the change address heuristic by Androulaki et al., which checks transactions with two output addresses. If one output address is fresh (i.e., never used before) and the other is not, the fresh address is considered the change address. Instead, Lee et al. use one of the variants implemented by BlockSci [38], but do not detail which one. Recently, Kappos et al. [40] compare different change address heuristics, showing that most have high false positives (FPs). They propose a new heuristic to reduce FPs, which has not yet been used by any estimation.

Takeaway 4

4

The change address heuristics currently used by estimation works can generate a large number of false positives, and thus overestimate the financial impact.

Exploration. Cybercriminals may accumulate the received payments prior to cashing them out or sending them to a mixer to obfuscate their origin. MI clustering may capture such aggregation if multiple payment addresses are used as input to the same transaction. However, the effectiveness of applying MI clustering on the seeds depends on how the cybercriminals withdraw their funds. Consider the example in Figure 1(a), where the cybercriminals use two seeds (S_1, S_2) and two unknown payment addresses (P_1, P_2) as input to a withdrawal transaction (withdrawal for short) that accumulates the payments into a *collector* address *C*. In this case, MI clustering would identify the previously unknown payment

addresses (P_1 , P_2). Instead, in Figure 1(b) the funds are first moved from the 4 payment addresses into 4 aggregation addresses ($A_1 - A_4$) in separate transactions, and then collected using a MI transaction into collector *C*. In this case, MI clustering on the two seeds would not identify the unknown payment addresses or the aggregators.

Withdrawals from the seeds evade MI clustering if they use a single input address. We can classify withdrawals based on their number of distinct input and output addresses. We focus on distinct addresses rather than on transactions slots because a transaction can use multiple input slots for the same address. For example, a payment address may be reused for multiple victims; each victim payment generates a different UTXO and all UTXOs are consumed by the same withdrawal. We say a transaction is *1-to-n* ($n \ge 1$) if it has a single input address, regardless of its number of input slots. In Section 3.5 we measure that 40% of groups only use MI-defeating 1-to-n withdrawals from their seeds, indicating that this evasion is widely used.

Figure 1(b) captures how the Cerber ransomware operated. To handle this family, Huang et al. proposed to manually add the aggregators (A_1, A_2) into the set of seeds. That allows MI to discover the other two aggregators (A_3, A_4) and thus perform a more accurate estimation. In Section 6 we discuss how we believe their approach could be generalized to address MI clustering evasion.

Takeaway 5

Cybercriminals can use 1-to-n withdrawals from payment addresses to defeat MI clustering.

2.3 Filtering

Not all deposits to the expanded set are necessarily victim payments. The seeds and the additional addresses the expansions identify could be used for other purposes, e.g., for aggregating funds. For these reasons, 8 of the 12 works apply filters to exclude deposits that do not look like victim payments. We describe them next.

Value filtering. If the amounts the victims should pay are known, deposits for other amounts can be excluded. One consideration is that some victims may ignore that, in addition to the requested amount, they also need to pay a transaction fee. This results in some victim payments not reaching the requested amount since the transaction fee is discounted prior to depositing the funds. Some payments can also be slightly higher than the requested amount because the victim conservatively increases the amount to make sure any fees are covered. To account for these small deviations in amounts, some works apply an epsilon around the known payment values [24, 43]. A limitation of value filtering is that, due to limited coverage, it may not be possible to know all valid amounts (e.g., each victim could be given a different amount). Thus, some victim payments could be incorrectly excluded. For example, 13 of the 20 ransomware families considered in [24] have no seeds matching the expected ranges, and thus cannot be estimated. Another limitation is that value filtering does not apply to cases where the victim decides how much to pay, e.g., giveaway scams [42].

Time filtering. If the time periods when a campaign was active are known, deposits to the expanded set outside of those periods can be excluded. This helps exclude other uses of the payment addresses

before or after a campaign happened. Similar to value filtering, due to limited coverage, it may not be possible to know all periods when a campaign was active, which may exclude valid victim payments.

Some works combine value and time filtering by taking as input a list of time ranges, each associated with a list of values victims could pay on the period. This handles campaigns where the amounts change over time, e.g., they are lowered when the BTC conversion rate spikes to avoid exorbitant fees that discourage victims to pay.

Takeaway 6

If payment addresses are not reused, value and time filtering are needless. The problem of coverage affects not only the discovery of seeds, but also value and time filtering ranges, possibly introducing underestimation.

Online wallet filtering. If a seed is an online wallet in a service, only direct deposits to that seed should be considered. Other addresses in its cluster should not be included in the expanded set. Two works [41, 54] filter exchange clusters by looking for clusters that are outliers, in terms of large number of addresses, large total amount received, and cluster age. Unfortunately, these filters are not detailed. In addition, two works identify exchange clusters using tag databases that associate addresses with additional information like their owner. Lee et al. [41] use the public WalletExplorer [13] tag database and Huang et al. [36] a proprietary database from Chainalysis [9]. However, Huang et al. [36] do not use the tags to identify seeds that are online wallets. Instead, they filter deposits to the expanded set that do not originate from exchanges, since most victims likely do not own BTCs and need to purchase them from exchanges. However, they discarded this filter due to concerns about the coverage of the tag database. To address this intrinsic limitation of tag databases, Gomez et al. [31] recently proposed to complement tag databases with an ML classifier to identify (untagged) exchanges. However, their exchange classifier has not been used in any estimation.

Takeaway 7

The identification of exchange clusters is better performed using a combination of tag databases and a machine learning classifier.

Double-counting. Simply adding all deposits to addresses in the expanded set, without considering their procedence, may lead to double-counting, i.e., counting the same payment multiple times, thus overestimating the revenue. The simplest such double-counting can occur when, in a transaction, one input address also appears in the outputs, e.g., an input address is used as a change address. While this is not recommended for privacy reasons, it often happens in practice. Imagine Alice has two BTCs in one UTXO from a previous payment and wants to send one BTC to Bob. Instead of creating a fresh change address, Alice uses the sender address as the change address. After the payment, the balance of Alice's address will be one BTC, but the total amount deposited to her address will be three BTCs, two BTCs from the original payment that created the UTXO plus one BTC she received as change from this transaction.

More generally, double-counting can occur when a transaction that deposits into an address in the expanded set has an input address that also belongs to the expanded set. Imagine two deposits. In the first one, address A which is not in the expanded set deposits some funds into address B which is part of the expanded set. In the second one, address B moves the received funds to address C which is also in the expanded set. The funds B received from A are first counted. Then, if we add the second deposit that only moves funds between addresses inside the expanded set, we are double counting the funds that B received from A as also being received by C.

Only the two works by Paquet-Clouston et al. [53, 54] try to avoid such double-counting by filtering transactions. In [53], they define collectors as addresses receiving deposits from at least two addresses in the expanded set. Collectors belonging to the expanded set were filtered to avoid double-counting. However, it is possible to double count with a single deposit if the change address is one of the inputs. In [54] they exclude transactions with at least one input address and one output address in the expanded set.

One issue to keep in mind is that any filter that tries to minimize double-counting will be affected by the coverage issue, i.e., it will not be able to filter deposits between two MI clusters that belong to the group if one of the two MI clusters has not been included in the expanded set, i.e., no seed is available from that MI cluster.

Takeaway 8

To avoid overestimating the revenue, deposits into the expanded set that have an input address also belonging to the expanded set should be filtered. Double-counting filtering is also affected by the lack of seed coverage.

2.4 Conversion Rates

Adding the amounts of the filtered deposits to the expanded set produces an estimation of BTC revenue. Due to Bitcoin's highly volatile conversion rate, the estimated BTCs can have very different values over time. Converting the BTC amount into US Dollars makes it easier to understand the revenue and to compare it with other cybercrime, e.g., those not abusing Bitcoin. To perform this conversion, 9 of the 12 works use the conversion rate from BTC to USD on the day the deposit was received. This conversion rate captures the financial impact on victims, i.e., how much it cost the victims to pay assuming they bought the BTCs from an exchange just prior to paying. Two works [64, 71] use instead the conversion rate on a specific day, e.g., the day of the analysis. Since cybercriminals may not cash out victim payments immediately, this approach includes the rise or depreciation in value of the payments from the day the payment was received until the day of the conversion rate. Finally, one work uses the highest and lowest conversion rates in their analysis period [42], providing a USD range.

Takeaway 9

To estimate the financial impact on victims using fiat currency, it is recommended to apply the conversion rate on the day each payment was received.

3 METHODOLOGY IMPACT

This section quantifies how the different methodology options presented in Section 2 impact the estimation. We first introduce the analyzed methodologies and datasets in Section 3.1, then quantify their impact on the CryptoLocker ransomware in Section 3.2, and on our whole dataset in Section 3.3.

3.1 Methodologies and Datasets

Given the 2 main expansions (excluding the exploration as it is only used for one ransomware family in one work) and 4 filters detailed in Table 1, 64 different methodologies can be used for the estimation. We have created a naming scheme to refer to those methodologies. The name always starts with *DD* which is an abbreviation for direct deposits. Then, it can have at most 6 parts for multi-input clustering (*MI*), change address expansion (*CA*), online wallet filtering (*OW*), value filtering (*VF*), time filtering (*TF*), and double-counting filtering (*DC*). We prefix expansions with a plus sign and filters with a minus sign. The last column in Table 1 captures the methodology used by each work using our naming scheme.

We have implemented an extension to the WYB platform [7], itself built on top of BlockSci [38], which can produce any of the estimations. Given as input a set of seeds, a block height, a set of value and time filtering ranges, and a methodology string using our naming scheme; it produces the estimation using that methodology. While our extension implements all previously used methodologies, the results it produces are not guaranteed to be the same as those obtained in the works in Table 1, even when using the same methodology on the same seeds. Differences may happen because the implementation of the expansions and filters may not exactly match the ones in those works. For example, we use BlockSci to obtain clusters using multi-input and change address expansions, while other works use other open-source platforms or their own implementations.

Selected methodologies. We analyze 15 selected methodologies, which cover those used in the surveyed works and additional ones illustrating interesting cases. The first 5 estimations test the filters without applying expansions. We exclude the filter of online wallets as it only applies to expansions. *DD* is the simplest estimation that sums all deposits to the seeds. *DD-VF, DD-TF,* and *DD-VF-TF* apply value filtering, time filtering, and both, respectively, on the direct deposits to the seeds using the 7 ranges proposed by Conti et al. [24]. *DD-DC* removes overlaps in the direct deposits caused by transactions where seeds appear as both input and output.

The next 6 estimations correspond to expanding using only MI clustering and then applying the different filters. The final 4 estimations correspond to expanding with both MI clustering and change address expansions and then applying the different filters. MI clustering and change address expansions both use the clusters that BlockSci precomputes for the given block height. MI clustering excludes CoinJoin transactions using the heuristics in BlockSci. DD+MI and DD+MI+CA first query BlockSci for the clusters of the seeds (precomputed using only MI clustering or both expansions, respectively) and add the seeds and other addresses in the clusters of the seeds to the expanded set. Then, they obtain all deposits to the expanded set and sum their value without any filtering. DD-OW+MI and DD-OW+MI+CA first query BlockSci for the clusters of

Work	Blk Height	Methodology	Seeds	Clust.	Addrs.	Payments	BTC	USD
Spagnuolo et al. [64]	2013-12-15	DD+MI+CA-VF	≥12	≥ 12	2,118	771	1,226.0000	1,100,000
Liao et al. [43]	2014-01-31	DD+MI+CA-VF-TF	2	1	968	795	1,128.4000	310,472
Conti et al. [24]	2017-12-07	DD+MI+CA-VF-TF	4	1	956	804	1,403.7548	449,275
Huang et al. [36]	2017-08-31	DD-OW+MI-VF	2	2	4,457	-	-	667,000
Paquet-Clouston et al. [53]	489,181	DD+MI-TF-DC	2	1	944	-	1,511.7100	519,991

Table 2: Previous estimations on CryptoLocker.

the seeds. Then, they check whether the seed clusters appear in the WYB tag database marked as service clusters. For any seed cluster identified as a service, only the seed is added to the expansion set. For other seed clusters, the seed and other addresses in the cluster are added to the expanded set. Then, they obtain all deposits to the expanded set and sum their value without applying any filtering. *DD-OW+MI-DC* applies *DD-OW+MI* but avoids double-counting by filtering deposits to the expanded set that have an input address belonging to any of the clusters in the expanded set. All other estimations correspond to the ones above with value filtering, time filtering, or both, applied on the deposits to the expanded set.

Datasets. We collect all publicly available labeled datasets of cybercrime Bitcoin seeds that we are aware of. These include all datasets mentioned in Table 1, as well as an additional dataset of 9,478 addresses used by clippers [31]. Since the ransomware datasets overlap, we use the Ransomwhere dataset [20], which contains the seeds used in prior works. For scam datasets containing addresses for different blockchains [5, 11] we focus exclusively on the Bitcoin addresses. Other sources of Bitcoin cybercrime seeds exist such as abuse databases (e.g., [6]), but they do not provide a reliable categorization of cybercrime type. The six datasets used, summarized in Table 5, in total comprise 30,424 cybercrime Bitcoin addresses, of which 8,816 have deposits at block height 785,100 (April 12, 2023). Some works clustered the seeds, but their datasets do not include the cluster identifier for each seed. To estimate individual groups, we use a subset of 8,021 labeled seeds belonging to 141 groups: 88 ransomware families, 22 clipper families, and 31 Ponzi schemes.

3.2 Impact on CryptoLocker

We first analyze the CryptoLocker ransomware because its revenue has been estimated in five prior works with varying results, as illustrated in Table 2. For each prior estimation, the table shows the maximum block height (or date) considered in the estimation, the methodology used, the number of seeds, the number of MI clusters for the seeds, the total addresses in the expanded set, the number of victim payments identified after filtering, and the estimation in BTC and USD. The table illustrates that the estimations can widely vary, e.g., the highest estimation of \$1.1M is 3.5 times larger than the lowest estimation of \$310K. Due to the estimations use different seeds, methodologies, and block heights, it is complicated to isolate the impact of each methodology decision on the estimation. To address this issue, we perform estimations using different methodologies, but on a fixed set of seeds and on the same block height. This allows us to analyze the impact of each methodology decision.

Of the 5 prior estimations, two do not specify the seed addresses used [36, 64]. Two use the same pair of seeds [43, 53], and one [24] uses 4 seeds (the two in [43, 53] and two additional ones). We fix the block height at 498,150 (December 7, 2017) and perform two estimations: one starting with the two seeds in [43, 53] and another

Methodology	Addr.	Deposits	BTC	USD
DD	2	54	100.8608	\$12,532
DD-VF	2	48	94.8625	\$11,786
DD-TF	2	53	100.8607	\$12,531
DD-VF-TF	2	47	93.8625	\$11,667
DD-DC	2	54	100.8608	\$12,532
DD+MI	968	1,101	1,544.9144	\$528,046
DD+MI-VF-TF	968	803	1,130.1121	\$309,935
DD-OW+MI	968	1,101	1,544.9144	\$528,046
DD-OW+MI-VF-TF	968	803	1,130.1121	\$309,935
DD-OW+MI-DC	968	1,077	1,511.7579	\$520,238
DD-OW+MI-VF-TF-DC	968	801	1,110.3121	\$304,791
DD+MI+CA	-	-	-	-
DD-OW+MI+CA	2	54	100.8608	\$12,532
DD+MI+CA-VF-TF	-	-	-	-
DD-OW+MI+CA-VF-TF	2	47	93.8625	\$11,667

Table 3: CryptoLocker estimations using different methodologies starting from the two seeds used in [43, 53]. A dash indicates the estimation did not finish in 5 days.

Methodology	Addr.	Deposits	BTC	USD
DD	4	321	70,426.0298	\$11,442,063
DD-VF	4	59	123.6568	\$18,006
DD-TF	4	288	57,987.8966	\$10,094,385
DD-VF-TF	4	50	106.8525	\$15,062
DD-DC	4	227	41,614.1073	\$6,339,388
DD+MI	12,770,529	27,617,860	134,110,936.7365	\$26,405,734,619
DD+MI-VF-TF	12,770,529	39,015	54,091.2840	\$32,786,920
DD-OW+MI	970	1,368	71,870.0835	\$11,957,577
DD-OW+MI-VF-TF	970	806	1,143.1021	\$313,330
DD-OW+MI-DC	970	1,208	34,771.1654	\$5,453,205
DD-OW+MI-VF-TF-DC	970	797	1,112.8791	\$305,080
DD+MI+CA	-	-	-	-
DD-OW+MI+CA	4	321	70,426.0298	\$11,442,063
DD+MI+CA-VF-TF	-	-	-	-
DD-OW+MI+CA-VF-TF	4	50	106.8525	\$15,062

Table 4: CryptoLocker estimations using different methodologies starting from the four seeds used in [24]. A dash indicates the estimation did not finish in 5 days.

from the four seeds in [24]. We convert from BTC to USD using the rate at the time of each payment, obtained from CoinDesk [10].

Two seeds. Table 3 presents the estimations on the two seeds from [43, 53]. The estimations without expansions are pretty consistent in the range of \$11.6K-\$12.5K. MI clustering is quite successful at discovering additional CryptoLocker addresses increasing the estimations 26-42 times to \$304.7K-\$528.0K. Among filters, value filtering has the largest impact, especially after MI clustering, indicating that some deposits may not correspond to victim payments. Online wallet filtering has no effect as none of the seeds are online wallets. The double-counting filter reduces the estimations by 1.5%-1.7%.

Surprisingly, we are unable to compute some estimations with change address expansion. The cluster with the seeds returned by BlockSci has 160M addresses. Due to the huge number of deposits to that cluster (261M), the estimation does not finish in 5 days and we stop it. Three works in Table 2 claim to use change address expansion. However, their estimates are very close to ours using

Cybercrime	Dataset	Seeds	Labels	ow	BTC	USD
Ransomware	[52]	7,352	88	12	31,434.4069	\$115,513,569
Giveaway scams	[42]	494	-	17	386.0907	\$12,207,462
Ponzi schemes	[17]	32	31	7	7,956.3913	\$5,029,029
Clippers	[31]	637	22	23	891.5331	\$2,814,443
Sextortion	[54]	248	-	5	305.9584	\$1,504,437
Exchange scams	[71]	53	-	2	117.2569	\$1,021,764
Total		8,816	141	66	41,091.6373	\$138,090,704

Table 5: Cybercrime type estimates on April 12, 2023 using the seeds in public datasets and a *DD-OW+MI-DC* estimation.

only MI clustering. One possibility is that the change address expansion they implemented was not transitive, and thus avoided the explosion affecting BlockSci's implementation. Similar to what has been observed in prior work [40], our results indicate that change address heuristics can have high false positives. We further examine this issue for all groups in Section 3.3. Once online wallets are filtered, the estimations with change address expansion finish. This happens because the huge cluster that contains the seeds also contains multiple addresses tagged as exchanges. Thus, the cluster is considered to belong to an exchange, and both seeds are (incorrectly) considered online wallets. Thus, *DD-OW+MI+CA* matches the results for *DD* and *DD-OW+MI+CA-VF-TF* matches the results for *DD-VF-TF*.

Four seeds. Table 4 presents the estimations on the four seeds from [24]. In this case, the estimations without expansions widely vary from \$15K up to \$11.4M, due to the additional seeds receiving deposits of millions of USD. Value and time filtering removes most of those deposits as likely not being victim payments, resulting in a \$15K estimate, only 30% higher than with two seeds. After applying MI clustering, the expanded set grows to 12.7M addresses, and the estimation is an astronomical 26 Billion USD. The online wallet filter uncovers the reason for this by identifying one of the additional seeds as an online wallet in the btc-e exchange and the other as belonging to an incorrect huge cluster due to an address whose private key is the empty string [31]. Considering both additional seeds as online wallets reduces the estimation to \$11.9M, and value and time filtering brings it down to \$313K. A key question is whether the two additional seeds are indeed related to CryptoLocker. We are inclined to think they are not, but we have no definite proof. Still, this experiment illustrates how failing to consider seeds that are online wallets or belong to other problematic MI clusters can hugely overestimate the financial impact. Value filtering significantly reduces the impact of incorrectly applying MI clustering on online wallets, but it cannot entirely correct the problem as some fraction of the massive amount of deposits will match the expected value ranges.

3.3 Impact on the Whole Dataset

This section quantifies the impact of expansions and filters on the whole dataset. We exclude the value and time filters since we only have ranges for a few ransomware families. All experiments are performed on block height 785,100 (April 12, 2023).

Online wallet filter impact. We use BlockSci to precompute the MI clusters and query the 8,816 seeds to obtain their cluster identifier. Then, we use the WYB tag dataset to identify tagged clusters. This step flags 58 seeds. Of those, 57 are online wallets in exchanges. The other is the only seed for the Razy family in the

Ransomwhere dataset, which really is an FBI address used to seize the Silk Road funds after its takedown. We remove Razy from our datasets.

An intrinsic issue in tag databases is the limited coverage, i.e., only a fraction of all MI clusters belonging to services will be tagged. Indeed, when we perform an initial DD-OW+MI-DC estimation for each cybercrime type, the estimation for giveaway scams returns an astronomical 6.1 Billion USD. This indicates that the WYB tag database likely missed some service clusters. To identify untagged service clusters, we run MI seed clusters with at least 1K addresses through the exchange classifier provided by WYB. The classifier identifies 8 of those 11 MI clusters as exchanges: 5 in the giveaway scams dataset, 2 in the Ransomwhere dataset, and 1 in the exchange scams dataset. We consider the 9 seeds in these 8 clusters to be online wallets for all other estimations. Had we not identified these 9 online wallets, we would have grossly overestimated the financial impact of three cybercrime types: \$6.1B for giveaway scams (503 times higher than our final estimation), \$543M for ransomware (5 times higher), and \$231M for exchange scams (226 times higher).

While only 0.7% of seeds are online wallets, they can introduce huge overestimation. To avoid missing online wallets, we recommend complementing tag databases with ML classifiers.

MI clustering impact. We use BlockSci to precompute the MI clusters and query each of the labeled seeds that are not online wallets to obtain their cluster. The seeds belong to 968 clusters, with an average cluster size of 19.5 addresses, and a median size of 1 address. Four clusters contain seeds from more than one group. One cluster holds the seeds for *mekotio* and *mekotion40*, which are known to be run by the same operators [31]. Another holds Towerweb and Cryptohitman seeds and was already reported in [53]. The other two clusters hold Jigsaw and Cryptowall, and TripleM and APT, respectively. We have not found reports linking the groups in these two clusters. However, the small size of those two clusters (3 and 4 addresses, respectively) makes us think they may be true relations or incorrect labels on the seeds. Clustering FPs typically create a snowball effect that quickly grows the clusters, as we show next for the change address expansion.

Change address impact. We use BlockSci to precompute the MI+CA clusters and query each of the 8,021 labeled seeds from the 141 groups to obtain their cluster. The 8,021 seeds belong to 251 clusters with an average cluster size of 2.2M addresses, and a median size of 2 addresses. The higher average is due to a huge cluster with 543M addresses. This cluster contains seeds from 91 of the 141 groups (64.5%). For 70 groups, all their seeds are in this cluster. It also contains addresses tagged by WYB as belonging to a variety of different services such as exchanges, gambling sites, and mixers. All other clusters with seeds contain one group at most, except for one cluster that contains two malware families known to belong to the same operators (*mekotio* and *mekotion40*) [31].

The fact that one cluster contains 91 unrelated groups and many unrelated services indicates the change address heuristic is introducing FPs. Because of this, we suggest that estimations do not use change address expansion. We further discuss this in Section 6.

Double-counting filter impact. To quantify the impact of the DC filter, we perform two estimations on all 8,816 seeds using the DD-OW+MI and DD-OW+MI-DC methodologies, respectively.

Name	Seeds	OW	Clust	Addr.	BTC	USD	
R:Netwalker	66	0	65	329	3,131.7562	\$28,262,120	
R:Conti	26	0	26	35	410.8025	\$18,869,852	
R:REvil	7	0	6	77	369.5363	\$12,540,689	
R:DarkSide	3	0	3	3	158.7086	\$9,124,091	
R:Locky	7,036	0	2	7,094	15,396.6934	\$7,833,613	
R:Ryuk	26	0	26	39	866.8069	\$4,844,149	
R:RagnarLocker	1	0	1	1	414.0007	\$4,547,241	
R:MountLocker	1	0	1	1	298.5000	\$4,226,277	
R:BlackMatter	1	0	1	1	96.3863	\$4,068,295	
R:Makop	1	0	1	996	316.0883	\$3,853,713	
R:Egregor	9	0	9	9	197.9554	\$3,129,599	
R:Tejodes	1	0	1	178	345.5527	\$2,798,239	
P:Leancy	1	0	1	1	3,092.8482	\$1,896,583	
R:CryptXXX	1	0	1	1,742	3,338.5464	\$1,877,833	
R:DMALockerv3	9	0	3	177	1,833.9286	\$1,757,464	
R:MedusaLocker	3	0	3	26	56.1546	\$1,454,776	
R:HelloKitty	1	0	1	1	32.3529	\$1,070,653	
R:Bitpaymer	1	0	1	1	90.0004	\$1,058,347	
C:cliptomaner	1	1	1	1	38.7643	\$1,004,397	
P:Cryptory	1	1	1	1	1,677.5167	\$886,689	
Total	8,021	42	383	17,040	40,282.3312	\$123,357,041	

Table 6: Top-20 groups by USD financial impact on April 12, 2023 using a *DD-OW+MI-DC* estimation. Ransomware families are prefixed by R:, clipper families by C:, and Ponzi schemes by P:. The last row captures total revenue of all 141 labeled groups.

DD-OW+MI estimates a total revenue of 171,994.9777 BTC, while DD-OW+MI-DC estimates 41,091.6373 BTC. Thus, the DC filter reduces the BTC estimate by 76.1%. This is much higher than the reduction observed in CryptoLocker, as the impact of the DC filter quickly grows as the volume and fund movement increases. In detail, the DC filter drops 43.7% of deposits to the expanded set and only 80.8% of the addresses in the expanded set receive funds from outside the expanded set.

3.4 Cybercrime Estimations

All works in Table 1 have estimated one or multiple groups of the same type of cybercrime. In this section, we instead compare revenue across cybercrimes. We perform all estimations at the same block height of 785,100 (April 12, 2023), using the same DD-OW+MI-DC methodology, and the conversion rate on the day of each payment. We select this methodology because we have shown that change address expansion introduces many false positives and we only have value and time filtering ranges for some ransomware families.

Cybercrime comparison. The right side of Table 5 summarizes the BTC and USD estimations for the 6 cybercrimes. The largest estimated revenue is \$115.5M for ransomware, followed by giveaway scams (\$12.2M), Ponzi schemes (\$5.0M), clippers (\$2.8M), sextortion scams (\$1.5M), and exchange scams (\$1.0M). Giveaway scams collect lower BTCs (386.0907) than Ponzi schemes (7,956.3913) and clippers (891.5331). However, their USD financial impact on victims is larger due to their seeds being collected in 2022, when the conversion rate BTC-USD was higher than for older seeds.

Group comparison. We also estimate the 141 groups. Table 6 shows the top-20 groups by USD revenue and the 141 groups are detailed in the Appendix of our extended version [32]. We prefix each name with R: for ransomware families, C: for clipper families, and P: for Ponzi schemes. Of the top-20 groups, 17 are ransomware families, two are Ponzi schemes and one is a clipper family. The highest revenue is for the *Netwalker* ransomware which collects

\$28.2M. The highest revenue among Ponzi schemes is *Leancy* with \$1.8M and the highest revenue among clippers is *Cliptomaner* with \$1.0M. The average revenue per operation is \$874K, and the median is \$17.5K. There are 19 groups with revenues higher than one million USD and 14 groups (13 ransomware families and one Ponzi scheme) with revenue below \$20, likely due to limited seed coverage for those groups.

Similar to what we observe in the cybercrime comparison, higher BTC revenue does not necessarily imply a higher financial impact on victims, measured using fiat currency, due to the wide oscillations of the Bitcoin conversion rate. For example, Locky collected the most BTCs (15,396.6934). However, its financial impact measured in USD is below that of DarkSide, which received nearly two orders of magnitude fewer BTCs (158.7086). The reason is that Locky was active from the beginning of 2016 to mid-2017 when the value of 1 BTC was \$780 on average. In contrast, DarkSide was active during the first half of 2021, when the conversion rate ranged from \$29k to \$61k (\$55.2k on average). This example highlights the importance of using the conversion rate at the time of the payment for more accurate estimations of the financial impact on the victims.

The top-4 earners in Table 6 (Netwalker [25], Conti [66], REvil [30], DarkSide [50]) leverage the ransomware-as-a-service (RaaS) model, where the ransomware operators recruit affiliates to take care of the infections [46]. Affiliates are paid a fraction of the victim's ransom payment or a fixed fee. Outsourcing infections to affiliates helps ransomware gangs target more victims. These families focus on high-value targets such as large companies and hospitals, e.g., DarkSide was behind the Colonial Pipeline attack [57]. They often use different ransom values for each victim, threaten victims to release their data publicly, and may even perform double extortion, i.e., demand a second payment for not leaking the data. Targeted victims may not want to disclose the attacks, making it difficult to obtain seeds. For example, there are reports of DarkSide having at least 90 victims in the US [57], but we only have 3 seeds for that group and MI clustering does not reveal additional payment addresses. We examine the impact of the lack of coverage in Section 4.

3.5 Multi-Input Evasion

This section examines how useful MI clustering on the seeds is, and whether cybercriminals may be using evasive techniques to defeat it. For this, we examine the withdrawal transactions from the seeds of the 141 groups, and their MI clusters. For each group, we first remove seeds identified as online wallets. Then, we compute the total number of withdrawals from the remaining seeds and the fraction of *1-to-n* withdrawals. Next, we compute the expanded set of each group by doing the union of the addresses in the MI clusters of the seeds that are not online wallets and recompute the above numbers for all withdrawals from the expanded set of each group.

Figure 2 shows the cumulative distribution of 1-to-n withdrawals across the 141 groups. 40% of the groups exclusively move funds from their payment addresses using MI-defeating 1-to-n withdrawals. Three-quarters of the groups use at least 50% of 1-to-n withdrawals, indicating their preference for such MI-defeating withdrawals. Only 9% of the groups do not use 1-to-n withdrawals at all, but most of these have not withdrawn any funds yet. The fact that 40% of

Gibran Gomez, Kevin van Liebergen, and Juan Caballero

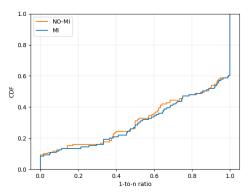


Figure 2: Cumulative distribution of the proportion of withdrawals with one input address (1-to-n) over all the withdrawals across the 141 groups for both withdrawals of seeds (orange line) and withdrawals of their MI clusters (blue line).

the groups exclusively use MI-defeating withdrawals and 75% use them more than half of the time, likely indicates that cybercriminals are aware of the limitations of MI clustering and are actively taking steps to defeat it. We discuss how to address this evasion in Section 6.

4 COVERAGE IMPACT

A recurring issue in cybercrime estimations is that they start from a small number of seeds (a median of one seed per group) and it is not clear how many other payment addresses with victim deposits may exist. Expansions are used to try to discover missing payment addresses, but as shown in Section 3 their effectiveness is limited. As far as we know, no prior work has tried to quantify the impact of the lack of coverage in the estimations, due to the complexity of obtaining the needed vantage point. In this section, we quantify this issue for the first time using two novel techniques that allow us to obtain very high coverage, possibly nearly complete, on the DeadBolt server ransomware [14]. We introduce DeadBolt in Section 4.1, describe our DeadBolt datasets in Section 4.2, present our techniques to expand DeadBolt's coverage in Section 4.3, and compare the estimations obtained from different vantage points in Section 4.4.

4.1 DeadBolt

On January 25th, 2022, BleepingComputer first reported a new server ransomware strain that called itself *DeadBolt* and was spreading by exploiting vulnerabilities in network-attached storage (NAS) devices [14]. DeadBolt encrypted specific data directories and file extensions and hijacked the login page of the NAS to display a ransom note titled "WARNING: Your files have been locked by DeadBolt". The ransom note requested a Bitcoin payment of 0.03 BTC (1,100 USD at the time) to be sent to a Bitcoin payment address to obtain the decryption key. In mid-June 2022, DeadBolt introduced a new ransom value of 0.05 BTC, possibly due to a drop in the BTC-USD conversion rate at that time, and both amounts are used therefore.

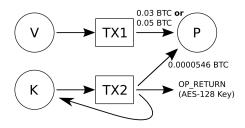


Figure 3: DeadBolt key release transactions. First, the victim deposits the ransom of 0.03 BTC or 0.05 BTC to the payment address. Then, the cybercriminals release the decryption key to the blockchain through a deposit to the payment address.

Engine	Events	IP	Port	ASN	CC	Notes	Addr.	Seeds
Shodan	23,413	9,999	171	769	89	4,938	4,940	64
Censys	15,886	6,147	66	671	87	-	4,014	49
All	39,299	11,282	199	780	98	4,938	4,997	64
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Table 7: DeadBolt datasets summary.

One novel feature in DeadBolt is that after the victim pays the ransom, the decryption key is automatically posted to the Bitcoin blockchain by the DeadBolt operators. Figure 3 illustrates the two transactions involved. First, the victim (address V) pays the ransom of 0.03 BTC or 0.05 BTC to the payment address P. Then, the DeadBolt operators perform a deposit of value 0.0000546 BTC (\$1.2) from a *key release address K* to the payment address P. This second transaction has an OP_RETURN output that stores the AES-128 decryption key on the blockchain.

On October 2022, the Dutch National Police tricked the DeadBolt operators into handing over 155 decryption keys by performing ransom payments with a very small fee when the blockchain was heavily congested, and canceling the payment transactions before they appeared in a block [28]. Since the decryption key was automatically posted to the blockchain, without waiting for the payment transaction to appear in a block, the police recovered 155 keys before the attackers realized. A webpage was set up that given one of the 155 addresses, outputs its decryption key [58]. After that event, the DeadBolt operators maintained the key release procedure in Figure 3 but adjusted their processing to wait for the payment transaction to appear in a block before releasing the decryption key. From this moment on, the time difference between victim payments and key release transactions starts varying significantly, reaching even 3 days in some cases, indicating the key release transactions are now manually triggered.

4.2 DeadBolt Datasets

DeadBolt exploited network-facing vulnerabilities in the NAS and hijacked the NAS login page to display the ransom note. A NAS had to be connected to the Internet to get infected. Thus, the ransom note was (potentially) visible to Internet scanners. However, Internet scanners may not observe all victims since an infected NAS may have been disconnected or cleaned before being scanned. We obtain data about DeadBolt infections from two Internet scanners: Censys [21], and Shodan [63]. The datasets are summarized in Table 7.

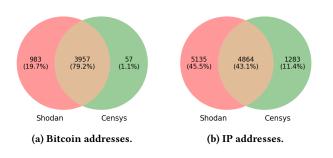


Figure 4: Overlap in DeadBolt datasets.

Censys. Censys publishes servers infected with DeadBolt in a Google Datastudio [22]. Each entry in the dataset represents an infection and contains the IP address, the port number, the country code (CC) and ASN of the IP address, the payment address, the ransom amount, and the DeadBolt variant. The raw content of the ransom notes is not available. We collect Censys data for four months, from December 13, 2022, until March 13, 2023. We obtain 4,014 DeadBolt payment addresses from 6,147 IP addresses. The large number of payment addresses likely indicates each infected server is given a different one. The number of IP addresses is larger than the number of payment addresses likely due to infected servers that change IP addresses.

Shodan. We identify DeadBolt events in Shodan by querying its API with the dork http.title: "Your files have been locked by DEADBOLT.". Each query returns events from the last 30 days, so we query once a month, from December 13, 2022, until March 13, 2023. From each event, we extract the timestamp, IP address, port number, country code and ASN of the IP address, and the ransomware note in HTML format. We obtain 4,938 distinct ransom notes from 9,999 IP addresses. We extract 4,940 payment addresses from the ransom notes using the *iocsearcher* tool [12].

Both scanners observe different sets of infected servers, largely due to their scanning happening at different times. Figure 4a shows that 79.2% of the payment addresses appear in both datasets, 19.7% only in Shodan, and 1.1% only in Censys. Figure 4b shows that 43.1% of the IP addresses appear in both datasets, 45.5% only in Shodan, and 11.4% only in Censys. Thus, our Shodan dataset has slightly better coverage on DeadBolt, but the set of payment addresses and infected IPs observed from both vantage points significantly overlaps. The larger overlap in payment addresses is likely due to servers that appear multiple times on different IP addresses.

4.3 Increasing the Coverage

Of the 4,997 DeadBolt payment addresses collected from Shodan and Censys, only 64 addresses had received deposits as of April 12, 2023. For 30 of those 64 seeds, the Bitcoin ledger does not show the victim's payment, but only the key release transaction, all of them on October 13, 2022. These 30 addresses are part of the 155 addresses for which the Dutch police recovered their decryption key. Since the ransom payment was withdrawn after the key was released, the payment transactions do not appear on the ledger. The fact that our datasets only have 30 of the 155 addresses for which the Dutch police recovered the keys indicates that we only have partial coverage. None of the seeds have withdrawals. Thus, the received payments have still not been moved and expansions can not reveal new addresses. In the remainder of this section, we present two novel techniques that leverage unique characteristics of DeadBolt, which allow us to obtain very high coverage, possibly nearly complete, on the payments performed by DeadBolt victims.

Key release analysis. All key release transactions to the 64 seeds have the same format, illustrated in Figure 3, with one input key release address and three output slots that correspond to (a) the payment address that receives 0.0000546 BTC, (b) the input key release address which is used as change address and (c) the OP RETURN script that stores the decryption key on the blockchain.

Critically, all key release transactions for the 64 seeds originate from one of two key release addresses: $bc1qh6^1$ or $bc1q62^2$. The reuse of key release addresses to post the decryption keys of many victims allows us to identify ransom payments to previously unknown payment addresses (i.e., not in our datasets) that correspond to infected servers the Internet scanners did not observe (e.g., NAS devices disconnected from the Internet right after infection). For this, we retrieve all withdrawals from the two key release addresses. All these transactions match the expected pattern, so their output addresses receiving 0.0000546 BTC are (potentially unknown) payment addresses. This technique identifies 2,481 payment addresses, of which 2,418 (97.5%) are previously unknown.

The payment addresses with deposits we know at this point contain 154 addresses with only the key release transaction, but no victim payment. This almost matches the 155 keys the Dutch Police were able to extract in October 2022. Still, there is one missing address indicating we may still be missing some victim payments. One possible reason for this is that there could exist other key release addresses that we have not observed in our datasets.

Key release signature. We propose a novel technique to identify additional DeadBolt key release addresses. We leverage that Dead-Bolt key release transactions are quite distinct, build a signature for them, and scan all transactions in the Bitcoin ledger for over 15 months to search for unknown key release addresses. Given a transaction, our signature checks that it has one input and three outputs slots, where the output slots correspond (in any order) to (1) an OP RETURN address, (2) an address receiving exactly 5460 satoshis (0.0000546 BTC), and (3) an address that is the same as the sending address. We apply the signature to all Bitcoin transactions from block 716,591 (2022-01-01) up to block 785,100 (2023-04-12). The search takes 16 minutes to complete. We decode the OP RE-TURN payload data from the matched transactions and observe that several decoded values start with the string omni, indicating that they are part of the OMNI protocol [51]. After filtering the OMNI transactions, all remaining transactions originate from 3 addresses, two of them are the known key release addresses, and the third one $(bc1q3g^3)$ is a previously unknown key release address. The newly discovered key release address has delivered the decryption key to 18 (previously unknown) payment addresses. Of those, 17 receive the expected payments of 0.03 BTC or 0.05 BTC. The other address only received the key release transaction, but no victim payment.

 $^{3}bc1q3guvg2yp5mzmf7hnfr7zlg2unah9t6mjwyky72$

 $^{^1}bc1qh6pku7gg2d6pw87z3t4f6d4rk6c48ajvsmfjjl\\$

²bc1q62rjm9a82s3qmjzffc6uyytw25p3fppftl5zpd

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Collection	Coverage	Seeds	Addr.	Dep.	BTC	USD
Censys	2.0%	50	50	86	2.45686936	53,151.89
Shodan	2.6%	66	66	114	2.82608808	63,077.10
Censys+Shodan	2.6%	66	66	114	2.82608808	63,077.10
Key rel. analysis	99.2%	2,484	2,485	2,596	97.83718238	2,453,532.39
Key rel. signature	100.0%	2,503	2,504	2,615	98.35008368	2,472,845.02
T.1.1. 0. D 1	D - 14 4!		. C	1:0		

Table 8: DeadBolt estimations from different vantage points.

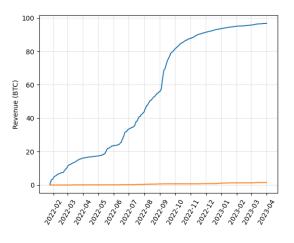


Figure 5: Cumulative revenue for DeadBolt over time using full coverage (blue line) and only scan engines (orange line).

This address receives the missing key of those recovered by the Dutch police, as confirmed by using the public Web service.

The fact that we have scanned all Bitcoin transactions since DeadBolt started to operate and have not identified further key release addresses, along with the fact that we observe all 155 keys recovered by the Dutch Police, give us strong confidence that we have achieved nearly perfect coverage on DeadBolt's victim payments. Of course, our key release signature assumes a unique key release transaction pattern, so we could miss victim payments if multiple patterns exist.

4.4 Coverage Comparison

Table 8 summarizes the coverage and revenue estimation on Dead-Bolt from different vantage points: using only Censys, only Shodan, both Censys and Shodan, and extending our coverage using the key release analysis and the key release signature cumulatively. The table shows the fraction of DeadBolt addresses, i.e., payment addresses plus key release addresses, found at each step (Coverage), the number of addresses with deposits (Seeds), the number of addresses found after applying MI clustering (Addr.), the number of deposits to the addresses (Dep.), the BTC estimation on block height 785,100 using a *DD-OW+MI-DC* methodology, and the USD estimation using the conversion rate at the time of each payment.

Had we focused only on the payment addresses observed in the union of the Censys and Shodan datasets, we would have only identified 66 addresses (64 payment addresses and 2 key release addresses), 2.6% of all DeadBolt addresses finally identified. Of those addresses, only 34 had victim payments and the MI expansion fails to identify additional addresses since the funds have not yet been

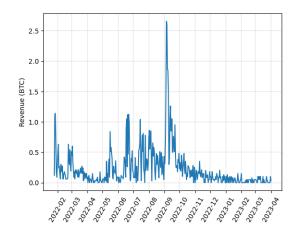


Figure 6: DeadBolt revenue per day.

moved from those 34. Thus, we would have estimated a very modest revenue of 2.826 BTCs or \$63,077.

Instead, by applying our two coverage-expanding techniques, we identify 38 times more seeds. The estimation jumps to 98.350 BTC, 35 times higher than the 2.826 BTC. The estimated USD revenue is \$2.47M, 39 times higher than the \$63,077 using the Internet scanners datasets. Figure 5 shows the difference in cumulative DeadBolt revenue using both vantage points and Figure 6 the daily BTC amounts received by DeadBolt using our most complete coverage.

In summary, the estimation using only the Shodan and Censys datasets would have been 2.5% of the total USD estimation, highlighting the huge impact of the (lack of) coverage in the estimation. This in turn means our estimations in Section 3.4 may significantly underestimate the financial impact of Bitcoin-related cybercrimes.

5 HOW TO ESTIMATE

It is widely accepted that estimated cybercrime Bitcoin revenue is a lower bound on the actual revenue due to the impact of the lack of coverage on the seeds. Indeed, we have quantified the coverage impact to be very significant on the DeadBolt ransomware. However, our results show that some methodology steps, e.g., handling online wallets in services and using change address heuristics, may introduce huge overestimation. In some cases, such methodological errors can outweigh the underestimation caused by the lack of coverage, thus overshooting the actual revenue.

This section presents our recommendations on how to perform estimations. At a high level, we recommend performing two BTC revenue estimations: DD-DC and DD-OW+MI-DC. First, as a conservative estimation, we recommend authors provide the sum of direct deposit on seeds excluding deposits where seeds appear both in the input and output slots (DD-DC). This estimation does not use expansions. Thus, it is easy to compute without specialized platforms, e.g., deposit transactions to seeds are available from blockchain explorer webpages and APIs, and the double counting filter only requires examining if the seeds appear in the input slots of the deposits. On the other hand, DD-DC may significantly underestimate revenue if seed coverage is low. Overestimation only happens if seeds are incorrectly labeled or reused for other purposes. We discuss the latter below in the discussion of value and time filtering.

As a tighter estimation, we recommend using DD-OW+MI-DC, which we used for the comparison in Section 3.4. This estimation uses the MI clustering expansion (with special handling for seeds that are online wallets in services), avoids change address expansion, and removes duplicate deposits. We have shown that identifying online wallets in services like exchanges is critical to prevent huge overestimation when using MI clustering. For such identification, it is possible to use publicly available tag databases like those in WYB [31] and GraphSense [34]. However, tag datasets have limited coverage. For example, our initial giveaway scams estimation was an astronomical 6.1 Billion USD (503 times higher than the final estimation) due to seeds in five exchanges not identified by the WYB tags. Because of that, an ML classifier such as the one in WYB should complement tag databases. An alternative is using heuristics to exclude outlier clusters. However, it is hard to select reliable thresholds on cluster size (e.g., Locky's MI cluster has 7,094 addresses) or BTC volume (given the highly volatile BTC conversion rate). The best option may be to exclude clusters with multi-million USD revenue, but this may prevent the analysis of large operations. To prevent overestimation, MI clustering should use detection heuristics for CoinJoin mixing transactions [29, 38], available in open-source platforms [34, 38]. This estimate avoids the change address expansion due to its potentially high false positives, which prevented us from obtaining some results in Section 3.2. Recently, Kappos et al. [40] proposed a new change address heuristic with lower false positives than prior heuristics. This heuristic has not been used for estimations yet, but we would like to evaluate it in future work. This estimate also avoids double counting deposits, which we have shown can introduce overestimation. In particular, we have measured that applying the double-counting filter on all 8,816 seeds removes 76% of the estimated revenue.

Value and time filtering. The proposed estimations do not use value and time filtering for several reasons. First, these filters are helpful only if payment addresses are reused for multiple purposes (e.g., different campaigns or cybercrimes) and the estimation targets just one (e.g., a specific campaign). Second, they are group-specific, and the selection of a proper filtering range is affected by the group's coverage. In addition, value filtering does not apply to cases where the payment amount is not pre-determined (e.g., clippers and giveaway scams) and when each victim is assigned a different amount (e.g., some ransomware families). If authors believe value and time filtering (or any other group-specific filtering) should be applied, we recommend providing estimations with and without those filters.

Other blockchains. Three surveyed works also collect seeds for other blockchains such as Cardano, Ethereum, Monero, and Ripple [41, 42, 71]. We have focused on estimating Bitcoin revenue for two reasons. First, prior works exclusively apply a DD estimation on other blockchains. Thus, there are no methodologies to compare. Besides, our tool currently only supports Bitcoin. To estimate the revenue of a cybercriminal activity that solicits victim payments on multiple blockchains, we recommend performing a separate DD-DC estimation on each blockchain. For each blockchain, deposits to the seeds can be obtained using the webpage or API of

blockchain explorers and the double counting filter only requires checking if seeds appear among the inputs of each deposit. We expect future research to investigate more sophisticated estimation methodologies for other blockchains (e.g., novel expansions).

Conversion rate. The above recommendations focus on estimating BTC revenue. To estimate the financial impact on victims using flat currency (e.g., USD) we recommend applying the BTC to flat conversion rate on the day each payment was received. This conversion accounts for a victim's loss at the time it happened. Conversions using a later fixed date are difficult to interpret due to the high variability of the BTC conversion rate over time. In particular, we have shown how older cybercriminal campaigns that collected high amounts of BTC (e.g., Locky) had a lower USD financial impact on victims than more recent campaigns that collected fewer BTCs (e.g., DarkSide).

Enabling replicability. Bitcoin transactions are immutable and public, so in theory, estimation results should be easy to replicate. In practice, it is often not so due to missing information. To make results replicable, we recommend that estimation works estate their estimation target (e.g., a cybercrime type, a cybercriminal group, or a specific campaign) and release their seeds and the block height used for the estimation. If applicable, they should also release filtering ranges and clustering results. We also recommend releasing other payment addresses that have not received deposits yet, as that could change at higher block heights. If using expansions, authors should mention which platform they are using to implement them and release their code if custom. If using change address expansion, authors should specify the specific variant employed.

6 FURTHER DISCUSSION

This section discusses other insights and future improvements.

Evasion. MI clustering fails to find new addresses for 40% of the 141 groups, arguably indicating cybercriminals are actively evading this expansion. Huang et al. [36] addressed this issue for the Cerber ransomware by observing that the seeds sent the funds to aggregators, on which MI clustering could be successfully applied. We believe their approach can be generalized using recent platforms for tracing cybercriminal flows [31]. In particular, it may be possible to perform a 1-step forward exploration from the seeds and apply heuristics to determine if the discovered addresses belong to the cybercriminals. For example, if the attackers use 1-to-1 withdrawals then the no change heuristic [8] would determine the destination address belongs to the seed owners. Cybercriminals can also evade the estimation by hiding their payment addresses. For example, some ransomware families do not provide the payment address and value in their ransom notes, but only a contact email or IM address [26]. That extra level of indirection complicates the collection of seeds.

Another common evasion is the use of mixers. While their goal is to obfuscate the destination of funds, mixing transactions can also introduce estimation errors. First, undetected mixing transactions may lead to overestimation with MI clustering by bringing into the expanded set unrelated addresses from other entities. Second, undetected mixing transactions that deposit to the expanded set may originate from the same entity that owns the expanded set addresses, but will not be removed by the DC filter, thus introducing overestimation. We use mixer tags available in WYB [31] and CoinJoin detection heuristics implemented by BlockSci [29, 38] to address both issues. However, we acknowledge that both approaches are incomplete. Heuristics in BlockSci target CoinJoin, but there exists a variety of other mixing protocols (e.g., CoinShuffle [61]) and mixing techniques [70]. Tags can only identify known mixers and may miss mixing transactions in those, e.g., if mixing commission fees are not aggregated. Future work should develop new mixing detection techniques that can be added to blockchain analysis platforms.

Generality of DeadBolt results. Our two coverage-increasing techniques are specific to DeadBolt. Thus, the coverage impact may differ for other groups. We believe the coverage impact will likely be larger in other cases because Internet scanners should have better coverage on server ransomware than most security vendors would on a malware family. Furthermore, our two techniques generalize beyond the DeadBolt coverage measurement. The key release analysis technique is an instance of doing one backward exploration step from a payment address to identify a key release address, followed by one forward exploration step from the key release address to discover other payment addresses. It is related to the exploration Huang et al. [36] performed for Cerber, although that case was one forward step from the seeds followed by one backward step. We believe such forward+backward or backward+forward exploration will be critical to improving estimation methodologies (e.g., to address MI clustering evasion). The key release signature technique builds a signature for a distinctive malicious transaction and scans all blockchain transactions in a time range to identify more transactions matching the signature. We believe it should be possible to build signatures for other types of malicious Bitcoin transactions, such as those used in C&C signaling [31].

DeadBolt conversion rate. Measuring the conversion rate of a cybercrime, i.e., the fraction of targets that pay, is challenging and may require developing novel methodologies [39]. The fact that DeadBolt's ransom notes are publicly available on the Internet allows us to identify infected servers (i.e., victims), obtain their payment addresses, and check what fraction received a deposit in the expected ranges ([0.029,0.031] or [0.049,0.051]). Since we collect 4,997 payment addresses from Censys and Shodan, and only 34 of those have received valid payments, this indicates that 0.7% of the victims paid the ransom. This estimate relies on each server being assigned a unique payment address. Among the 2,500 payment addresses with victim payments, only 13 (0.52%) receive more than one deposit in the expected ranges. Thus, while not every server may have been assigned a unique address (it is unlikely that the same victim payed multiple times), most seem to have their own, and the 0.7% ratio is likely a good estimate of DeadBolt's conversion rate. Given the nature of DeadBolt targets, i.e., NAS devices possibly storing much data (including data backups), this conversion rate may be very specific to DeadBolt and may not represent other (e.g., desktop) ransomware, which may have lower conversion rates.

7 CONCLUSION

We have presented the first systematic analysis on the estimation of cybercrime bitcoin revenue. Our analysis has quantified the impact in the estimation of the methodology used and the limited seed coverage. We have built a tool able to replicate the different methodologies and have collected a dataset of 30,424 cybercrime payment addresses. We have used them to quantify the impact of different methodology steps and to compare the revenue obtained by 6 cybercrimes and 141 cybercriminal groups. We show that some methodologies may produce large overestimation by introducing addresses unrelated to the campaign, through undetected online wallets in services like exchanges, or by double-counting deposits. We have measured that for 40% of the groups MI clustering fails to discover additional addresses, and that ransomware dominates the Bitcoin-payment cybercrime scene with a revenue almost 10 times larger than other cybercrimes. For the first time, we have quantified the impact of the lack of coverage in the estimation. We propose two techniques to achieve possibly complete coverage of victim payments to the DeadBolt server ransomware. From our privileged vantage point, we estimate a revenue of \$2.47M, 39 times higher than estimated from the vantage point provided by two popular Internet scan engines.

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