Tracing Transactions Across Cryptocurrency Ledgers

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Abstract

One of the defining features of a cryptocurrency is that its ledger, containing all transactions that have ever taken place, is globally visible. As one consequence of this degree of transparency, a long line of recent research has demonstrated that — even in cryptocurrencies that are specifically designed to improve anonymity — it is often possible to track money as it changes hands, and in some cases to de-anonymize users entirely. With the recent proliferation of alternative cryptocurrencies, however, it becomes relevant to ask not only whether or not money can be traced as it moves within the ledger of a single cryptocurrency, but if it can in fact be traced as it moves *across* ledgers. This is especially pertinent given the rise in popularity of automated trading platforms such as ShapeShift, which make it effortless to carry out such cross-currency trades. In this paper, we use data scraped from ShapeShift over a thirteen-month period and the data from eight different blockchains to explore this question. Beyond developing new heuristics and creating new types of links across cryptocurrency ledgers, we also identify various patterns of cross-currency trades and of the general usage of these platforms, with the ultimate goal of understanding whether they serve a criminal or a profit-driven agenda.

1 Introduction

For the past decade, cryptocurrencies such as Bitcoin have been touted for their transformative potential, both as a new form of electronic cash and as a platform to "re-decentralize" aspects of the Internet and computing in general. In terms of their role as cash, however, it has been well established by now that the usage of pseudonyms in Bitcoin does not achieve meaningful levels of anonymity [17, 18, 1, 11, 21], which casts doubt on its role as a payment mechanism. Furthermore, the ability to track flows of coins is not limited to Bitcoin: it extends even to so-called "privacy coins" like Dash [10, 12], Monero [13, 7, 4, 24], and Zcash [16, 6] that incorporate features explicitly designed to improve on Bitcoin's anonymity guarantees.

Traditionally, criminals attempting to cash out illicit funds would have to use exchanges; indeed, most tracking techniques rely on identifying the addresses associated with these exchanges as a way to observe when these deposits happen [11]. Nowadays, however, exchanges typically implement strict Know Your Customer/Anti-Money Laundering (KYC/AML) policies to comply with regulatory requirements, meaning criminals (and indeed all users) risk revealing their real identities when using them. Users also run risks when storing their coins in accounts at custodial exchanges, as exchanges may be hacked or their coins may otherwise become inaccessible [9, 19]. As an alternative, there have emerged in the past few years frictionless trading platforms such as ShapeShift[1] and Changelly,[2] in which users are able to trade between cryptocurrencies without having to store their coins with the platform provider. Furthermore, while ShapeShift now requires users to have verified accounts [22], this was not the case before October 2018.

Part of the reason for these trading platforms to exist is the sheer rise in the number of different cryptocurrencies: according to the popular cryptocurrency data tracker CoinMarketCap there were 36 cryptocurrencies in September 2013, only 7 of which had a stated market capitalization of over 1 million USD,[3] whereas in January 2019 there were 2117 cryptocurrencies, of which the top 10 had a market capitalization of over 100 million USD. Given this proliferation of new cryptocurrencies and platforms that make it easy to transact across them, it becomes important to consider not just whether or not flows of coins can be tracked within the transaction ledger of a given currency, but also if they can be tracked as coins move across their respective ledgers as

[1] `https://shapeshift.io`
[2] `https://changelly.com`
[3] `https://coinmarketcap.com/historical/20130721/`

well. This is especially important given that there are documented cases of criminals attempting to use these cross-currency trades to obscure the flow of their coins: the WannaCry ransomware operators, for example, were observed using ShapeShift to convert their ransomed bitcoins into Monero [3]. More generally, these services have the potential to offer an insight into the broader cryptocurrency ecosystem and the thousands of currencies it now contains.

In this paper, we initiate an exploration of the usage of these cross-currency trading platforms, and the potential they offer in terms of the ability to track flows of coins as they move across different transaction ledgers. Here we rely on three distinct sources of data: the cryptocurrency blockchains, the data collected via our own interactions with these trading platforms, and — as we describe in Section 4 — the information offered by the platforms themselves via their public APIs.

We begin in Section 5 by identifying the specific on-chain transactions associated with an advertised ShapeShift transaction, which we are able to do with a relatively high degree of success (identifying both the deposit and withdrawal transactions 81.91% of the time, on average). We then describe in Section 6 the different transactional patterns that can be traced by identifying the relevant on-chain transactions, focusing specifically on patterns that may be indicative of trading or money laundering, and on the ability to link addresses across different currency ledgers. We then move in Section 7 to consider both old and new heuristics for clustering together addresses associated with ShapeShift, with particular attention paid to our new heuristic concerning the common social relationships revealed by the usage of ShapeShift. Finally, we bring all the analysis together by applying it to several case studies in Section 8. Again, our particular focus in this last section is on the phenomenon of trading and other profit-driven activity, and the extent to which usage of the ShapeShift platform seems to be motivated by criminal activity or a more general desire for anonymity.

2 Related Work

We are not aware of any other research exploring these cross-currency trading platforms, but consider as related all research that explores the level of anonymity achieved by cryptocurrencies. This work is complementary to our own, as the techniques it develops can be combined with ours to track the entire flow of cryptocurrencies as they move both within and across different ledgers.

Much of the earlier research in this vein focused on Bitcoin [17, 18, 1, 11, 21], and operates by adopting the so-called "multi-input" heuristic, which says that all input addresses in a transaction belong to the same entity (be it an individual or a service such as an exchange). While the accuracy of this heuristic has been somewhat eroded by privacy-enhancing techniques like CoinJoin [8], new techniques have been developed to avoid such false positives [12], and as such it has now been accepted as standard and incorporated into many tools for Bitcoin blockchain analytics.[4][5] Once addresses are clustered together in this manner, the entity can then further be identified using hand-collected tags that form a ground-truth dataset. We adopt both of these techniques in order to analyze the clusters formed by ShapeShift and Changelly in a variety of cryptocurrency blockchains, although as described in Section 7 we find them to be relatively unsuccessful in this setting.

In response to the rise of newer "privacy coins", a recent line of research has also worked to demonstrate that the deployed versions of these cryptocurrencies have various properties that diminish the level of anonymity they achieve in practice. This includes work targeting Dash [12, 10], Monero [13, 7, 4, 24], and Zcash [16, 6].

In terms of Dash, its main privacy feature is similar to CoinJoin, in which different senders join forces to create a single transaction representing their transfer to a diverse set of recipients. Despite the intention for this to hide which recipient addresses belong to which senders, research has demonstrated that such links can in fact be created based on the value being transacted [12, 10]. Monero, which allows senders to hide which input belongs to them by using "mix-ins" consisting of the keys of other users, is vulnerable to de-anonymization attacks exploiting the (now-obsolete) case in which some users chose not to use mix-ins, or exploiting inferences about the age of the coins used as mix-ins [13, 7, 4, 24]. Finally, Zcash is similar to Bitcoin, but with the addition of a privacy feature called the shielded pool, which can be used to hide the values and addresses of the senders and recipients involved in a transaction. Recent research has shown that it is possible to significantly reduce the anonymity set provided by the shielded pool, by developing simple heuristics for identifying links between hidden and partly obscured transactions [16, 6].

3 Background

3.1 Cryptocurrencies

The first decentralized cryptocurrency, Bitcoin, was created by Satoshi Nakamoto in 2008 [14] and deployed in January 2009. At the most basic level, bitcoins are digital assets that can be traded between sets of users without the need for any trusted intermediary. Bitcoins can be thought of as being stored in a public key, which is

[4] https://www.chainalysis.com/
[5] https://www.elliptic.co/

controlled by the entity in possession of the associated private key. A single user can store their assets across many public keys, which act as pseudonyms with no inherent link to the user's identity. In order to spend them, a user can form and cryptographically sign a transaction that acts to send the bitcoins to a recipient of their choice. Beyond Bitcoin, other platforms now offer more robust functionality. For example, Ethereum allows users to deploy *smart contracts* onto the blockchain, which act as stateful programs that can be triggered by transactions providing inputs to their functions.

In order to prevent double-spending, many cryptocurrencies are *UTXO-based*, meaning coins are associated not with an address but with a uniquely identifiable UTXO (unspent transaction output) that is created for all outputs in a given transaction. This means that one address could be associated with potentially many UTXOs (corresponding to each time it has received coins), and that inputs to transactions are also UTXOs rather than addresses. Checking for double-spending is then just a matter of checking if an input is in the current UTXO'set, and removing it from the set once it spends it contents.

3.2 Digital asset trading platforms

In contrast to a traditional (custodial) exchange, a digital asset trading platform allows users to move between different cryptocurrencies without storing any money in an account with the service; in other words, users keep their own money in their own accounts and the platform has it only at the time that a trade is being executed. To initiate such a trade, a user approaches the service and selects a supported input currency curIn (i.e., the currency from which they would like to move money) and a supported output currency curOut (the currency that they would like to obtain). A user additionally specifies a destination address $\mathsf{addr_u}$ in the curOut blockchain, which is the address to which the output currency will be sent. The service then presents the user with an exchange rate rate and an address $\mathsf{addr_s}$ in the curIn blockchain to which to send money, as well as a miner fee fee that accounts for the transaction it must form in the curOut blockchain. The user then sends to this address $\mathsf{addr_s}$ the amount amt in curIn they wish to convert, and after some delay the service sends the appropriate amount of the output currency to the specified destination address $\mathsf{addr_u}$. This means that an interaction with these services results in two transactions: one on the curIn blockchain sending amt to $\mathsf{addr_s}$, and one on the curOut blockchain sending (roughly) $\mathsf{rate} \cdot \mathsf{amt} - \mathsf{fee}$ to $\mathsf{addr_u}$.

This describes an interaction with an abstracted platform. Today, the two best-known examples are ShapeShift and Changelly. Whereas Changelly has always required account creation, ShapeShift introduced this requirement only in October 2018. Each platform supports dozens of cryptocurrencies, ranging from better-known ones such as Bitcoin and Ethereum to lesser-known ones such as FirstBlood and Clams. In Section 4, we describe in more depth the operations of these specific platforms and our own interactions with them.

4 Data Collection and Statistics

In this section, we describe our data sources, as well as some preliminary statistics about the collected data. We begin in Section 4.1 by describing our own interactions with Changelly, a trading platform with a limited personal API. We then describe in Section 4.2 both our own interactions with ShapeShift, and the data we were able to scrape from their public API, which provided us with significant insight into their overall set of transactions. Finally, we describe in Section 4.3 our collection of the data backing eight different cryptocurrencies.

4.1 Changelly

Changelly offers a simple API[6] that allows registered users to carry out transactions with the service. Using this API, we engaged in 22 transactions, using the most popular ShapeShift currencies (Table 1) to guide our choices for curIn and curOut.

While doing these transactions, we observed that they would sometimes take up to an hour to complete. This is because Changelly attempts to minimize double-spending risk by requiring users to wait for a set number of confirmations (shown to the user at the time of their transaction) in the curIn blockchain before executing the transfer on the curOut blockchain. We used this observation to guide our choice of parameters in our identification of on-chain transactions in Section 5.

4.2 ShapeShift

ShapeShift's API[7] allows users to execute their own transactions, of which we did 18 in total. As with Changelly, we were able to gain some valuable insights about the operation of the platform via these personal interactions. Whereas ShapeShift did not disclose the number of confirmations they waited for on the curIn blockchain, we again observed long delays, indicating that they were also waiting for a sufficient number.

Beyond these personal interactions, the API provides information on the operation of the service as a whole. Most notably, it provides three separate pieces of information: (1) the current trading rate between any pair of

[6]`https://api-docs.changelly.com/`
[7]`https://info.shapeshift.io/api`

cryptocurrencies, (2) a list of up to 50 of the most recent transactions that have taken place (across all users), and (3) full details of a specific ShapeShift transaction given the address $\mathsf{addr_s}$ in the curIn blockchain (i.e., the address to which the user sent their coins).

For the trading rates, ShapeShift provides the following information for all cryptocurrency pairs $(\mathsf{curIn}, \mathsf{curOut})$: the rate, the limit (i.e., the maximum that can be exchanged), the minimum that can be exchanged, and the miner fee (denominated in curOut). For the 50 most recent transactions, information is provided in the form: $(\mathsf{curIn}, \mathsf{curOut}, \mathsf{amt}, t, \mathsf{id})$, where the first three of these are as discussed in Section 3.2, t is a UNIX timestamp, and id is an internal identifier for this transaction. For the transaction information, when provided with a specific $\mathsf{addr_s}$ ShapeShift provides the tuple $(\mathsf{status}, \mathsf{address}, \mathsf{withdraw}, \mathsf{inCoin}, \mathsf{inType}, \mathsf{outCoin}, \mathsf{outType}, \mathsf{tx}, \mathsf{txURL}, \mathsf{error})$. The status field is a flag that is either `complete`, to mean the transaction was successful; `error`, to mean an issue occurred with the transaction or the queried address was not a ShapeShift address; or `no_deposits`, to mean a user initiated a transaction but did not send any coins. The error field appears when an error is returned and gives a reason for the error. The address field is the same address $\mathsf{addr_s}$ used by ShapeShift, and withdraw is the address $\mathsf{addr_u}$ (i.e., the user's recipient address in the curOut blockchain). inType and outType are the respective curIn and curOut currencies and inCoin is the amt received. outCoin is the amount sent in the curOut blockchain. Finally, tx is the transaction hash in the curOut blockchain and txURL is a link to this transaction in an online explorer.

Using a simple Web scraper, we downloaded the transactions and rates every five seconds for close to thirteen months: from November 27 2017 until December 23 2018. This resulted in a set of 2,843,238 distinct transactions. Interestingly, we noticed that several earlier test transactions we did with the platform did not show up in their list of recent transactions, which suggests that their published transactions may in fact underestimate their overall activity.

4.2.1 ShapeShift currencies

In terms of the different cryptocurrencies used in ShapeShift transactions, their popularity was distributed as seen in Figure 1. As this figure depicts, the overall activity of ShapeShift is (perhaps unsurprisingly) correlated with the price of Bitcoin in the same time period. At the same time, there is a decline in the number of transactions after KYC was introduced that is not clearly correlated with the price of Bitcoin (which is largely steady and declines only several months later).

ShapeShift supports dozens of cryptocurrencies, and in our data we observed the use of 65 different ones. The most commonly used coins are shown in Table 1. It is clear that Bitcoin and Ethereum are the most heavily used currencies, which is perhaps not surprising given the relative ease with which they can be exchanged with fiat currencies on more traditional exchanges, and their rank in terms of market capitalization.

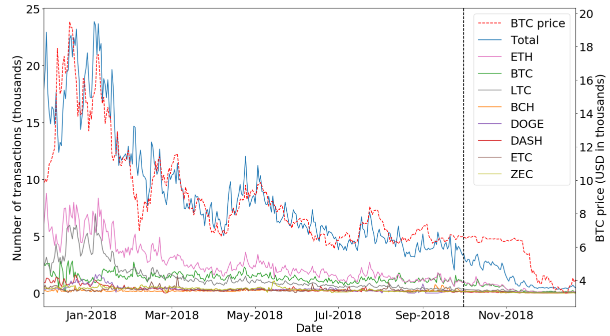


Figure 1: The total number of transactions per day reported via ShapeShift's API, and the numbers broken down by cryptocurrency (where a transaction is attributed to a coin if it is used as either curIn or curOut). The dotted red line indicates the BTC-USD exchange rate, and the horizontal dotted black line indicates when KYC was introduced into ShapeShift.

Currency	Abbr.	Total	curIn	curOut
Ethereum	ETH	1,385,509	892,971	492,538
Bitcoin	BTC	1,286,772	456,703	830,069
Litecoin	LTC	720,047	459,042	261,005
Bitcoin Cash	BCH	284,514	75,774	208,740
Dogecoin	DOGE	245,255	119,532	125,723
Dash	DASH	187,869	113,272	74,597
Ethereum Classic	ETC	179,998	103,177	76,821
Zcash	ZEC	154,142	111,041	43,101

Table 1: The eight most popular coins used on ShapeShift, in terms of the total units traded, and the respective units traded with that coin as curIn and curOut.

4.3 Blockchain data

For the cryptocurrencies we were interested in exploring further, it was also necessary to download and parse the respective blockchains, in order to identify the on-chain transactional behavior of ShapeShift and Changelly. It was not feasible to do this for all 65 currencies used on ShapeShift (not to mention that given the low volume of transactions for many of them, it would likely not yield additional insights anyway), so we chose to focus instead on just the top 8, as seen in Table 1. Together, these account for 95.7% of all ShapeShift transactions if only one of curIn and/or curOut is one of the eight, and 60.5% if both are.

For each of these currencies, we ran a full node in order to download the entire blockchain. For the ones supported by the BlockSci tool [5] (Bitcoin, Dash and Zcash), we used it to parse and analyze their blockchains. BlockSci does not, however, support the remaining five currencies. For these we thus parsed the blockchains using Python scripts, stored the data as Apache Spark parquet files, and analyzed them using custom scripts. In total, we ended up working with 654 GB of raw blockchain data and 434 GB of parsed blockchain data.

5 Identifying Blockchain Transactions

In order to gain deeper insights about the way these trading platforms are used, it is necessary to identify not just their internal transactions but also the transactions that appear on the blockchains of the traded currencies. This section presents heuristics for identifying these on-chain transactions, and the next section explores the additional insights these transactions can offer.

Recall from Section 3.2 that an interaction with ShapeShift results in the deposit of coins from the user to the service on the curIn blockchain (which we refer to as "Phase 1"), and the withdrawal of coins from the service to the user on the curOut blockchain ("Phase 2"). To start with Phase 1, we thus seek to identify the deposit transaction on the input (curIn) blockchain. Similarly to Portnoff et al. [15], we consider two main requirements for identifying the correct on-chain transaction: (1) that it occurred reasonably close in time to the point at which it was advertised via the API, and (2) that the value it carried was identical to the advertised amount.

For this first requirement, we look for candidate transactions as follows. Given a ShapeShift transaction with timestamp t, we first find the block b (at some height h) on the curIn blockchain that was mined at the time closest to t. We then look at the transactions in all blocks with height in the range $[h-\delta_b, h+\delta_a]$, where δ_b and δ_a are parameters specific to curIn. We looked at both earlier and later blocks based on the observation in our own interactions that the timestamp published by ShapeShift would sometimes be earlier and sometimes be later than the on-chain transaction.

For each of our eight currencies, we ran this heuristic for every ShapeShift transaction using curIn as the currency in question, with every possible combination of δ_b and δ_a ranging from 0 to 30. This resulted in a set of candidate transactions with zero hits (meaning no matching transactions were found), a single hit, or multiple hits. To rule out false positives, we initially considered as successful only ShapeShift transactions with a single candidate on-chain transaction, although we describe below an augmented heuristic that is able to tolerate multiple hits. We then used the values of δ_b and δ_a that maximized the number of single-hit transactions for each currency. As seen in Table 2, the optimal choice of these parameters varies significantly across currencies, according to their different block rates; typically we needed to look further before or after for currencies in which blocks were produced more frequently.

In order to validate the results of our heuristic for Phase 1, we use the additional capability of the ShapeShift API described in Section 4.2. In particular, we queried the API on the recipient address of every transaction identified by our heuristic for Phase 1. If the response of the API was affirmative, we flagged the recipient address as belonging to ShapeShift and we identified the transaction in which it received coins as the curIn transaction. This also provided a way to identify the corresponding Phase 2 transaction on the curOut blockchain, as it is just the tx field returned by the API. As we proceed only in the case that the API returns a valid result, we gain ground-truth data in both Phase 1 and Phase 2. In other words, this method serves to not only validate our results in Phase 1 but also provides a way to identify Phase 2 transactions.

The heuristic described above is able to handle only single hits; i.e., the case in which there is only a single candidate transaction. Luckily, it is easy to augment this heuristic by again using the API. For example, assume we examine a BTC-ETH ShapeShift transaction and we find three candidate transactions in the Bitcoin blockchain after applying the basic heuristic described above. To identify which of these transactions is the right one, we simply query the API on all three recipient addresses and check that the status field is affirmative (meaning ShapeShift recognizes this address) and that the outType field is ETH. In the vast majority of cases this uniquely identifies the correct transaction out of the candidate set, meaning we can use the API to both validate our results (i.e., we use it to eliminate potential false positives, as described above) and to augment the heuristic by being able to tolerate multiple candidate transactions. The augmented results for Phase 1 can be found in the last column of Table 2 and clearly demonstrate the benefit of this extra usage of the API. In the most dramatic example, we were able to go from identifying the on-chain transactions for ShapeShift transactions involving Bitcoin 65.75% of the time with the basic heuristic to identifying them 76.86% of the time with the augmented heuristic.

5.1 Accuracy of our heuristics

False negatives can occur for both of our heuristics when there are either too many or too few matching transactions in the searched block interval. These are more common for the basic heuristic, as described above and seen in Table 2, because it is conservative in identifying an on-

Currency	Parameters		Basic %	Augmented %
	δ_b	δ_a		
BTC	0	1	65.76	76.86
BCH	9	4	76.96	80.23
DASH	5	5	84.77	88.65
DOGE	1	4	76.94	81.69
ETH	5	0	72.15	81.63
ETC	5	0	76.61	78.67
LTC	1	2	71.61	76.97
ZEC	1	3	86.94	90.54

Table 2: For the selected (optimal) parameters and for a given currency used as curIn, the percentage of ShapeShift transactions for which we found matching on-chain transactions for both the basic (time- and value-based) and the augmented (API-based) Phase 1 heuristic. The augmented heuristic uses the API and thus also represents our success in identifying Phase 2 transactions.

chain transaction only when there is one candidate. This rate could be improved by increasing the searched block radius, at the expense of adding more computation and potentially increasing the false positive rate.

False positives can occur for both of our heuristics if someone sends the same amount as the ShapeShift transaction at roughly the same time, but this transaction falls within our searched interval whereas the ShapeShift one doesn't. In theory, this should not be an issue for our augmented heuristic, since the API will make it clear that the candidate transaction is not in fact associated with ShapeShift. In a small number of cases (fewer than 1% of all ShapeShift transactions), however, the API returned details of a transaction with different characteristics than the one we were attempting to identify; e.g., it had a different pair of currencies or a different value being sent. This happened because ShapeShift allows users to re-use an existing deposit address, and the API returns only the latest transaction using a given address.

If we blindly took the results of the API, then this would lead to false positives in our augmented heuristic for both Phase 1 and Phase 2. We thus ensured that the transaction returned by the API had three things in common with the ShapeShift transaction: (1) the pair of currencies, (2) the amount being sent, and (3) the timing, within the interval specified in Table 2. If there was any mismatch, we discarded the transaction. For example, given a ShapeShift transaction indicating an ETH-BTC shift carrying 1 ETH and occurring at time t, we looked for all addresses that received 1 ETH at time t or up to 5 blocks earlier. We then queried the API on these addresses and kept only those transactions which reported shifting 1 ETH to BTC. While our augmented heuristic still might produce false positives in the case that a user quickly makes two different transactions using the same currency pair, value, and deposit address, we view this as unlikely, especially given the relatively long wait times we observed ourselves when using the service (as mentioned in Section 4.2).

5.2 Alternative Phase 2 identification

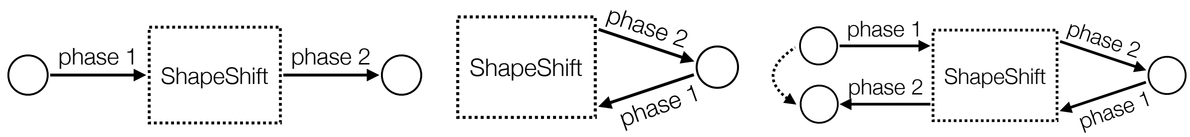
Given that our heuristic for Phase 2 involved just querying the API for the corresponding Phase 1 transaction, it is natural to wonder what would be possible without this feature of the API, or indeed if there are any alternative strategies for identifying Phase 2 transactions. Indeed, it is possible to use a similar heuristic for identifying Phase 1 transactions, by first looking for transactions in blocks that were mined close to the advertised transaction time, and then looking for ones in which the amount was close to the expected amount. Here the amount must be estimated according to the advertised amt, rate, and fee. In theory, the amount sent should be $\mathsf{amt} \cdot \mathsf{rate} - \mathsf{fee}$, although in practice the rate can fluctuate so it is important to look for transactions carrying a total value within a reasonable error rate of this amount.

When we implemented and applied this heuristic, we found that our accuracy in identifying Phase 2 transactions decreased significantly, due to the larger set of transactions that carried an amount within a wider range (as opposed to an exact amount, as in Phase 1) and the inability of this type of heuristic to handle multiple candidate transactions. More importantly, this approach provides no ground-truth information at all: by choosing conservative parameters it is possible to limit the number of false positives, but this is at the expense of the false negative rate (as, again, we observed in our own application of this heuristic) and in general it is not guaranteed that the final set of transactions really are associated with ShapeShift. As this is the exact guarantee we can get by using the API, we continue in the rest of the paper with the results we obtained there, but nevertheless mention this alternative approach in case this feature of the API is discontinued or otherwise made unavailable.

6 Tracking Cross-Currency Activity

In the previous section, we saw that it was possible in many cases to identify the on-chain transactions, in both the curIn and curOut blockchains, associated with the transactions advertised by ShapeShift. In this section, we take this a step further and show how linking these transactions can be used to identify more complex patterns of behavior.

As shown in Figure 2, we consider these for three main types of transactions. In particular, we look at (1) *pass-through* transactions, which represent the full flow



(a) Pass-through (b) U-turn (c) Round-trip

Figure 2: The different transactional patterns, according to how they interact with ShapeShift and which phases are required to identify them.

of money as it moves from one currency to the other via the deposit and withdrawal transactions; (2) *U-turns*, in which a user who has shifted into one currency immediately shifts back; and (3) *round-trip* transactions, which are essentially a combination of the first two and follow a user's flow of money as it moves from one currency to another and then back to the original one. Our interest in these particular patterns of behavior is largely based on the role they play in tracking money as it moves across the ledgers of different cryptocurrencies. In particular, our goal is to test the validity of the implicit assumption made by criminal usage of the platform — such as we examine further in Section 8 — that ShapeShift provides additional anonymity beyond simply transacting in a given currency.

In more detail, identifying pass-through transactions allows us to create a link between the input address(es) in the deposit on the curIn blockchain and the output address(es) in the withdrawal on the curOut blockchain.

Identifying U-turns allows us to see when a user has interacted with ShapeShift not because they are interested in holding units of the curOut cryptocurrency, but because they see other benefits in shifting coins back and forth. There are several possible motivations for this: for example, traders may quickly shift back and forth between two different cryptocurrencies in order to profit from differences in their price. We investigate this possibility in Section 8.3. Similarly, people performing money laundering or otherwise holding "dirty" money may engage in such behavior under the belief that once the coins are moved back into the curIn blockchain, they are "clean" after moving through ShapeShift regardless of what happened with the coins in the curOut blockchain.

Finally, identifying round-trip transactions allows us to create a link between the input address(es) in the deposit on the curIn blockchain with the output address(es) in the later withdrawal on the curIn blockchain. Again, there are many reasons why users might engage in such behavior, including the trading and money laundering examples given above. As another example, if a curIn user wanted to make an anonymous payment to another curIn user, they might attempt to do so via a round-trip transaction (using the address of the other user in the second pass-through transaction), under the same assumption that ShapeShift would sever the link between their two addresses.

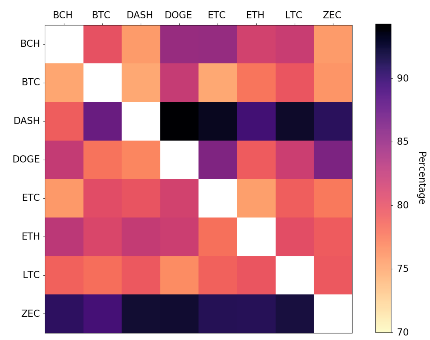


Figure 3: For each pair of currencies, the number of transactions we identified as being a pass-through from one to the other, as a percentage of the total number of transactions between those two currencies.

6.1 Pass-through transactions

Given a ShapeShift transaction from curIn to curOut, the methods from Section 5 already provide a way to identify pass-through transactions, as depicted in Figure 2a. In particular, running the augmented heuristic for Phase 1 transactions identifies not only the deposit transaction in the curIn blockchain but also the Phase 2 transaction (i.e., the withdrawal transaction in the curOut blockchain), as this is exactly what is returned by the API. As discussed above, this has the effect on anonymity of tracing the flow of funds across this ShapeShift transaction and linking its two endpoints; i.e., the input address(es) in the curIn blockchain with the output address(es) in the curOut blockchain. The results, in terms of the percentages of all possible transactions between a pair (curIn, curOut) for which we found the corresponding on-chain transactions, are in Figure 3.

The figure demonstrates that our success in identifying these types of transactions varied somewhat, and depended — not unsurprisingly — on our success in identifying transactions in the curIn blockchain. This means that we were typically least successful with curIn blockchains with higher transaction volumes, such as

Bitcoin, because we frequently ended up with multiple hits (although here we were still able to identify more than 74% of transactions). In contrast, the dark stripes for Dash and Zcash demonstrate our high level of success in identifying pass-through transactions with those currencies as curIn, due to our high level of success in their Phase 1 analysis in general (89% and 91% respectively). In total, across all eight currencies we were able to identify 1,383,666 pass-through transactions.

6.2 U-turns

As depicted in Figure 2b, we consider a U-turn to be a pattern in which a user has just sent money from curIn to curOut, only to turn around and go immediately back to curIn. This means linking two transactions: the Phase 2 transaction used to send money to curOut and the Phase 1 transaction used to send money back to curIn. In terms of timing and amount, we require that the second transaction happens within 30 minutes of the first, and that it carries within 1% of the value that was generated by the first Phase 2 transaction. This value is returned by the ShapeShift API in the outCoin field.

While the close timing and amount already give some indication that these two transactions are linked, it is of course possible that this is a coincidence and they were in fact carried out by different users. In order to gain additional confidence that it was the same user, we have two options. In UTXO-based cryptocurrencies (see Section 3.1), we could see if the input is the same UTXO that was created in the Phase 2 transaction, and thus see if a user is spending the coin immediately. In cryptocurrencies based instead on accounts, such as Ethereum, we have no choice but to look just at the addresses. Here we thus define a U-turn as seeing if the address that was used as the output in the Phase 2 transaction is used as the input in the later Phase 1 transaction.

Once we identified such candidate pairs of transactions $(\mathsf{tx}_1, \mathsf{tx}_2)$, we then ran the augmented heuristic from Section 5 to identify the relevant output address in the curOut blockchain, according to tx_1. We then ran the same heuristic to identify the relevant input address in the curOut blockchain, this time according to tx_2.

In fact though, what we really identified in Phase 2 was not just an address but, as described above, a newly created UTXO. If the input used in tx_2 was this same UTXO, then we found a U-turn according to the first heuristic. If instead it corresponded just to the same address, then we found a U-turn according to the second heuristic. The results of both of these heuristics, in addition to the basic identification of U-turns according to the timing and amount, can be found in Table 3, and plots showing their cumulative number over time can be found in Figures 4 and 5. In total, we identified 107,267 U-turns according to our basic heuristic, 10,566 U-turns according to our address-based heuristic, and 1,120 U-turns according to our UTXO-based heuristic.

Currency	# (basic)	# (addr)	# (utxo)
BTC	36,666	565	314
BCH	2864	196	81
DASH	3234	2091	184
DOGE	546	75	75
ETH	53,518	5248	-
ETC	1397	543	-
LTC	8270	1429	244
ZEC	772	419	222

Table 3: The number of U-turns identified for each cryptocurrency, according to our basic heuristic concerning timing and value, and both the address-based and UTXO-based heuristics concerning identical ownership. Since Ethereum and Ethereum Classic are account-based, the UTXO heuristic cannot be applied to them.

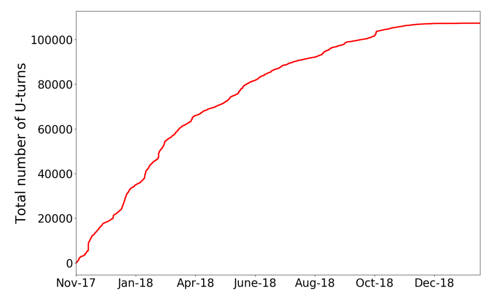


Figure 4: The total number of U-turns over time, as identified by our basic heuristic.

While the dominance of both Bitcoin and Ethereum should be expected given their overall trading dominance, we also observe that both Dash and Zcash have been used extensively as “mixer coins” in U-turns, and are in fact more popular for this purpose than they are overall. Despite this indication that users may prefer to use privacy coins as the mixing intermediary, Zcash has the highest percentage of identified UTXO-based U-turn transactions. Thus, these users not only do not gain extra anonymity by using it, but in fact are easily identifiable given that they did not change the address used in 419 out of 772 (54.24%) cases, or — even worse — immediately shifted back the exact same coin they received in 222 (28.75%) cases. In the case of Dash, the results suggest something a bit different. Once more, the usage of a privacy coin was not very successful since in 2091 out of the 3234 cases the address that received the fresh coins was the same as the one that shifted it back. It was the exact same coin in only 184 cases, however, which suggests that although the user is the same, there is a lo-

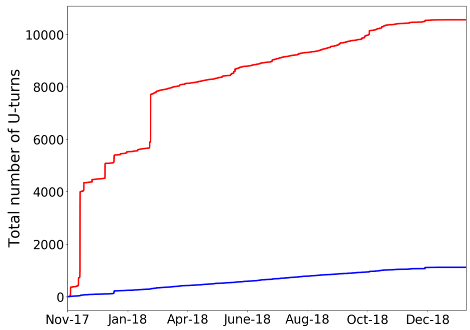


Figure 5: The total number of U-turns over time, as identified by our address-based (in red) and UTXO-based (in blue) heuristics.

Currency	# (regular)	# (same addr)
BTC	35,019	437
BCH	1780	84
DASH	3253	2353
DOGE	378	0
ETH	45,611	4085
ETC	1122	626
LTC	6912	2733
ZEC	472	172

Table 4: The number of regular round-trip transactions identified for each cryptocurrency, and the number that use the same initial and final address.

cal Dash transaction between the two ShapeShift transactions. We defer a further discussion of this asymmetry to Section 8.4, where we also discuss more generally the use of anonymity features in both Zcash and Dash.

Looking at Figure 5, we can see a steep rise in the number of U-turns that used the same address in December 2017, which is not true of the ones that used the same UTXO or in the overall number of U-turns in Figure 4. Looking into this further, we observed that the number of U-turns was particularly elevated during this period for four specific pairs of currencies: DASH-ETH, DASH-LTC, ETH-DASH, and LTC-ETH. This thus affected primarily the address-based heuristic due to the fact that (1) Ethereum is account-based so the UTXO-based heuristic does not apply, and (2) Dash has a high percentage of U-turns using the same address, but a much smaller percentage using the same UTXO. The amount of money shifted in these U-turns varied significantly in terms of the units of the input currency, but all carried between 115K and 138K in USD. Although the ShapeShift transactions that were involved in these U-turns had hundreds of different addresses in the curIn blockchain, they used only a small number of addresses in the curOut blockchain: 4 addresses in Ethereum, 13 in Dash, and 9 in Litecoin. As we discuss further in Section 7.2, the re-use of addresses and the fact that the total amount of money (in USD) carried by the transactions was roughly the same indicates that perhaps a small group of people was responsible for creating this spike in the graph.

6.3 Round-trip transactions

As depicted in Figure 2c, a round-trip transaction requires performing two ShapeShift transactions: one out of the initial currency and one back into it. To identify round-trip transactions, we effectively combine the results of the pass-through and U-turn transactions; i.e., we tagged something as a round-trip transaction if the output of a pass-through transaction from X to Y was identified as being involved in a U-turn transaction, which was itself linked to a later pass-through transaction from Y to X (of roughly the same amount). As described at the beginning of the section, this has the powerful effect of creating a link between the sender and recipient within a single currency, despite the fact that money flowed into a different currency in between.

In more detail, we looked for consecutive ShapeShift transactions where for a given pair of cryptocurrencies X and Y: (1) the first transaction was of the form X-Y; (2) the second transaction was of the form Y-X; (3) the second transaction happened relatively soon after the first one; and (4) the value carried by the two transaction was approximately the same. For the third property, we required that the second transaction happened within 30 minutes of the first. For the fourth property, we required that if the first transaction carried x units of curIn then the second transaction carried within 0.5% of the value in the (on-chain) Phase 2 transaction, according to the outCoin field provided by the API.

As with U-turns, we considered an additional restriction to capture the case in which the user in the curIn blockchain stayed the same, meaning money clearly did not change hands. Unlike with U-turns, however, this restriction is less to provide accuracy for the basic heuristic and more to isolate the behavior of people engaged in day trading or money laundering (as opposed to those meaningfully sending money to other users). For this pattern, we identify the input addresses used in Phase 1 for the first transaction, which represent the user who initiated the round-trip transaction in the curIn blockchain. We then identify the output addresses used in Phase 2 for the second transaction, which represent the user who was the final recipient of the funds. If the address was the same, then it is clear that money has not changed hands. Otherwise, the round-trip transaction acts as a heuristic for linking together the input and output addresses.

The results of running this heuristic (with and without the extra restriction) are in Table 4. In total, we identified 95,547 round-trip transactions according to our regular heuristic, and identified 10,490 transactions where the input and output addresses were the same. Across different currencies, however, there was a high level of variance in the results. While this could be a result of the different levels of accuracy in Phase 1 for different currencies, the more likely explanation is that users indeed engage in different patterns of behavior with different currencies. For Bitcoin, for example, there was a very small percentage (1.2%) of round-trip transactions that used the same address. This suggests that either users are aware of the general lack of anonymity in the basic Bitcoin protocol and use ShapeShift to make anonymous payments, or that if they do use round-trip transactions as a form of money laundering they are at least careful enough to change their addresses. More simply, it may just be the case that generating new addresses is more of a default in Bitcoin than it is in other currencies.

In other currencies, however, such as Dash, Ethereum Classic, Litecoin, and Zcash, there were relatively high percentages of round-trip transactions that used the same input and output address: 72%, 56%, 40%, and 36% respectively. In Ethereum Classic, this may be explained by the account-based nature of the currency, which means that it is common for one entity to use only one address, although the percentage for Ethereum is much lower (9%). In Dash and Zcash, as we have already seen in Section 6.2 and explore further in Section 8.4, it may simply be the case that users assume they achieve anonymity just through the use of a privacy coin, so do not take extra measures to hide their identity.

7 Clustering Analysis

7.1 Shared ownership heuristic

As described in Sections 4.1 and 4.2, we engaged in transactions with both ShapeShift and Changelly, which provided us with some ground-truth evidence of addresses that were owned by them. We also collected three sets of tagging data (i.e., tags associated with addresses that describe their real-world owner): for Bitcoin we used the data available from WalletExplorer,[8] which covers a wide variety of different Bitcoin-based services; for Zcash we used hand-collected data from Kappos et al. [6], which covers only exchanges; and for Ethereum we used the data available from Etherscan,[9] which covers a variety of services and contracts.

In order to understand the behavior of these trading platforms and the interaction they had with other blockchain-based services such as exchanges, our first instinct was to combine these tags with the now-standard "multi-input" clustering heuristic for cryptocurrencies [17, 11], which states that in a transaction with multiple input addresses, all inputs belong to the same entity. When we applied this clustering heuristic to an earlier version of our dataset [23], however, the results were fairly uneven. For Dogecoin, for example, the three ShapeShift transactions we performed revealed only three addresses, which each had done a very small number of transactions. The three Changelly transactions we performed, in contrast, revealed 24,893 addresses, which in total had received over 67 trillion DOGE. These results suggest that the trading platforms operate a number of different clusters in each cryptocurrency, and perhaps even change their behavior depending on the currency, which in turns makes it clear that we did not capture a comprehensive view of the activity of either.

More worrying, in one of our Changelly transactions, we received coins from a Ethereum address that had been tagged as belonging to HitBTC, a prominent exchange. This suggests that Changelly may occasionally operate using exchange accounts, which would completely invalidate the results of the clustering heuristic, as their individually operated addresses would end up in the same cluster as all of the ones operated by HitBTC. We thus decided not to use this type of clustering, and to instead focus on a new clustering heuristic geared at identifying common social relationships.

7.2 Common relationship heuristic

As it was clear that the multi-input heuristic would not yield meaningful information about shared ownership, we chose to switch our focus away from the interactions ShapeShift had on the blockchain and look instead at the relationships between individual ShapeShift users. In particular, we defined the following heuristic:

Heuristic 7.1. *If two or more addresses send coins to the same address in the* curOut *blockchain, or if two or more addresses receive coins from the same address in the* curIn *blockchain, then these addresses have some common social relationship.*

The definition of a common social relationship is (intentionally) vague, and the implications of this heuristic are indeed less clear-cut than those of heuristics around shared ownership. Nevertheless, we consider what it means for two different addresses, in potentially two different blockchains, to have sent coins to the same address; we refer to these addresses as belonging in the *input* cluster of the output address (and analogously refer to the *output* cluster for an address sending to multiple other addresses). In the case in which the addresses are most

[8] https://www.walletexplorer.com/
[9] https://etherscan.io/

closely linked, it could represent the same user consolidating money held across different currencies into a single one. It could also represent different users interacting with a common service, such as an exchange. Finally, it could simply be two users who do not know each other directly but happen to be sending money to the same individual. What cannot be the case, however, is that the addresses are not related in any way.

To implement this heuristic, we parsed transactions into a graph where we defined a node as an address and a directed edge (u,v) as existing when one address u initiated a ShapeShift transaction sending coins to v, which we identified using the results of our pass-through analysis from Section 5. (This means that the inputs in our graph are restricted to those for which we ran Phase 1 to find the address, and thus that our input clusters contain only the top 8 currencies. In the other direction, however, we obtain the address directly from the API, which means output clusters can contain all currencies.) Edges are further weighted by the number of transactions sent from u to v. For each node, the cluster centered on that address was then defined as all nodes adjacent to it (i.e., pointing towards it).

Performing this clustering generated a graph with 2,895,445 nodes (distinct addresses) and 2,244,459 edges. Sorting the clusters by in-degree reveals the entities that received the highest number of ShapeShift transactions (from the top 8 currencies, per our caveat above). The largest cluster had 12,868 addresses — many of them belonging to Ethereum, Litecoin, and Dash — and was centered on a Bitcoin address belonging to CoinPayments.net, a multi-coin payment processing gateway. Of the ten largest clusters, three others (one associated with Ripple and two with Bitcoin addresses) are also connected with CoinPayments, which suggests that ShapeShift is a popular platform amongst its users.

Sorting the individual clusters by out-degree reveals instead the users who initiated the highest number of ShapeShift transactions. Here the largest cluster (consisting of 2314 addresses) was centered on a Litecoin address, and the second largest cluster was centered on an Ethereum address that belonged to Binance (a popular exchange). Of the ten largest clusters, two others were centered on Binance-tagged addresses, and three were centered on other exchanges (Freewallet, Gemini, and Bittrex). While it makes sense that exchanges typically dominate on-chain activity in many cryptocurrencies, it is somewhat surprising to also observe that dominance here, given that these exchanges already allow users to shift between many different cryptocurrencies. Aside from the potential for better rates or the perception of increased anonymity, it is thus unclear why a user wanting to shift from one currency to another would do so using ShapeShift as opposed to using the same service with which they have already stored their coins.

Beyond these basic statistics, we apply this heuristic to several of the case studies we investigate in the next section. We also revisit here the large spike in the number of U-turns that we observed in Section 6.2. Our hypothesis then was that this spike was caused by a small number of parties, due to the similar USD value carried by the transactions and by the re-use of a small number of addresses across Dash, Ethereum, and Litecoin. Here we briefly investigate this further by examining the clusters centered on these addresses.

Of the 13 Dash addresses, all but one of them formed small input and output clusters that were comprised of addresses solely from Litecoin and Ethereum. Of the 9 Litecoin addresses, 6 had input clusters consisting solely of Dash and Ethereum addresses, with two of them consisting solely of Dash addresses. Finally, of the 4 Ethereum addresses, all of them had input clusters consisting solely of Dash and Litecoin addresses. One of them, however, had a diverse set of addresses in its output cluster, belonging to Bitcoin, Bitcoin Cash, and a number of Ethereum-based tokens. These results thus still suggest a small number of parties, due to the tight connection between the three currencies in the clusters, although of course further investigation would be needed to get a more complete picture.

8 Patterns of ShapeShift Usage

In this section, we examine potential applications of the analysis developed in previous sections, in terms of identifying specific usages of ShapeShift. As before, our focus is on anonymity, and the potential that such platforms may offer for money laundering or other illicit purposes, as well as for trading. To this end, we begin by looking at two case studies associated with explicitly criminal activity and examine the interactions these criminals had with the ShapeShift platform. We then switch in Section 8.3 to look at non-criminal activity, by attempting to identify trading bots that use ShapeShift and the patterns they may create. Finally, in Section 8.4 we look at the role that privacy coins (Monero, Zcash, and Dash) play, in order to identify the extent to which the usage of these coins in ShapeShift is motivated by a desire for anonymity.

8.1 Starscape Capital

In January 2018, an investment firm called Starscape Capital raised over 2,000 ETH (worth 2.2M USD at the time) during their Initial Coin Offering, after promising users a 50% return in exchange for investing in their cryptocurrency arbitrage fund. Shortly afterwards, all of their social media accounts disappeared, and it was reported that an amount of ETH worth 517,000 USD was sent from their wallet to ShapeShift, where it was shifted into Monero [20].

We confirmed this for ourselves by observing that the address known to be owned by Starscape Capital participated in 192 Ethereum transactions across a three-day span (January 19-21), during which it received and sent 2,038 ETH; in total it sent money in 133 transactions. We found that 109 of these transactions sent money to ShapeShift, and of these 103 were shifts to Monero conducted on January 21 (the remaining 6 were shifts to Ethereum). The total amount shifted into Monero was 465.61 ETH (1388.39 XMR), and all of the money was shifted into only three different Monero addresses, of which one received 70% of the resulting XMR. Using the clusters defined in Section 7.2, we did not find evidence of any other addresses (in any other currencies) interacting with either the ETH or XMR addresses associated with Starscape Capital.

8.2 Ethereum-based scams

EtherScamDB[10] is a website that, based on user reports that are manually investigated by its operators, collects and lists Ethereum addresses that have been involved in scams. As of January 30 2019, they had a total of 6374 scams listed, with 1973 associated addresses. We found that 194 of these addresses (9% of those listed) had been involved in 853 transactions to ShapeShift, of which 688 had a `status` field of `complete`. Across these successful transactions, 1797 ETH was shifted to other currencies: 74% to Bitcoin, 19% to Monero, 3% to Bitcoin Cash, and 1% to Zcash.

The scams which successfully shifted the highest volumes belonged to so-called trust-trading and MyEtherWallet scams. Trust-trading is a scam based on the premise that users who send coins prove the legitimacy of their addresses, after which the traders "trust" their address and send back higher amounts (whereas in fact most users send money and simply receive nothing in return). This type of scam shifted over 918 ETH, the majority of which was converted to Bitcoin (691 ETH, or 75%). A MyEtherWallet scam is a phishing/typosquatting scam where scammers operate a service with a similar name to the popular online wallet MyEtherWallet,[11] in order to trick users into giving them their account details. These scammers shifted the majority of the stolen ETH to Bitcoin (207 ETH) and to Monero (151 ETH).

Given that the majority of the overall stolen coins was shifted to Bitcoin, we next investigated whether or not these stolen coins could be tracked further using our analysis. In particular, we looked to see if they performed a U-turn or a round-trip transaction, as discussed in Section 6. We identified one address, associated with a trust-trading scam, that participated in 34 distinct round-trip transactions, all coming back to a different address from the original one. All these transactions used Bitcoin as curOut and used the same address in Bitcoin to both receive and send coins; i.e., we identified the U-turns in Bitcoin according to our address-based heuristic. In total, more than 70 ETH were circulated across these round-trip transactions.

8.3 Trading bots

ShapeShift, like any other cryptocurrency exchange, can be used by traders who wish to take advantage of the volatility in cryptocurrency prices. The potential advantages of doing this via ShapeShift, as compared with other platforms that focus more on the exchange between cryptocurrencies and fiat currencies, are that (1) ShapeShift transactions can be easily automated via their API, and (2) a single ShapeShift transaction acts to both purchase desired coins and dump unwanted ones. Such trading usually requires large volumes of transactions and high precision on their the timing, due to the constant fluctuation in cryptocurrency prices. We thus looked for activity that involved large numbers of similar transactions in a small time period, on the theory that it would be associated primarily with trading bots.

We started by searching for sets of consecutive ShapeShift transactions that carried approximately the same value in curIn (with an error rate of 1%) and involved the same currencies. When we did this, however, we found thousands of such sets. We thus added the extra conditions that there must be at least 15 transactions in the set that took place in a span of five minutes; i.e., that within a five-minute block of ShapeShift transactions there were at least 15 involving the same currencies and carrying the same approximate USD value. This resulted in 107 such sets.

After obtaining our 107 trading clusters, we removed transactions that we believed were false positives in that they happened to have a similar value but were clearly the odd one out. For example, in a cluster of 20 transactions with 19 ETH-BTC transactions and one LTC-ZEC transaction, we removed the latter. We were thus left with clusters of either a particular pair (e.g., ETH-BTC) or two pairs where the curOut or the curIn was the same (e.g., ETH-BTC and ZEC-BTC), which suggests either the purchase of a rising coin or the dump of a declining one. We sought to further validate these clusters by using our heuristic from Section 7.2 to see if the clusters shared common addresses. While we typically did not

[10] https://etherscamdb.info/
[11] https://www.myetherwallet.com/

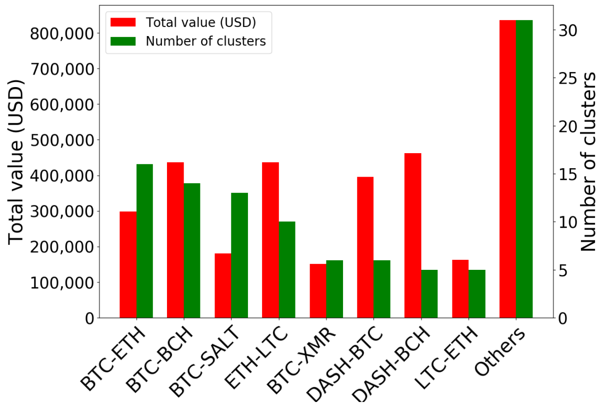


Figure 6: Our 107 clusters of likely trading bots, categorized by the pair of currencies they trade between and the total amount transacted by those clusters (in USD).

find this in UTXO-based currencies (as most entities operate using many addresses), in account-based currencies we found that in almost every case there was one particular address that was involved in the trading cluster.

We summarize our results in Figure 6, in terms of the most common pairs of currencies and the total money exchanged by trading clusters using those currencies. It is clear that the most common interactions are performed between the most popular currencies overall, with the exception of Monero (XMR) and SALT. In particular, we found six clusters consisting of 17-20 transactions that exchanged BTC for XMR, and 13 clusters that exchanged BTC for SALT, an Ethereum-based token. The sizes of each trading cluster varied between 16 and 33 transactions and in total comprise 258 transactions, each of which shifted exactly 0.1 BTC. In total they originated from 514 different Bitcoin addresses, which may make it appear as though different people carried out these transactions. After applying our pass-through heuristic, however, we found that across all the transactions there were only two distinct SALT addresses used to receive the output. It is thus instead likely that this represents trading activity involving one or two entities.

8.4 Usage of anonymity tools

Given the potential usage of ShapeShift for money laundering or other criminal activities, we sought to understand the extent to which its users seemed motivated to hide the source of their funds. While using ShapeShift is already one attempt at doing this, we focus here on the combination of using ShapeShift and so-called "privacy coins" (Dash, Monero, and Zcash) that are designed to offer improved anonymity guarantees.

In terms of the effect of the introduction of KYC into ShapeShift, the number of transactions using Zcash as

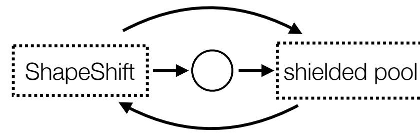


Figure 7: The three types of interactions we investigated between ShapeShift and the shielded pool in Zcash.

curIn averaged 164 per day the month before, and averaged 116 per day the month after. We also saw a small decline with Zcash as curOut: 69 per day before and 43 per day after. Monero and Dash, however, saw much higher declines, and in fact saw the largest declines across all eight cryptocurrencies. The daily average the month before was 136 using Monero as curIn, whereas it was 47 after. Similarly, the daily average using it as curOut was 316 before and 62 after. For Dash, the daily average as curIn was 128 before and 81 after, and the daily average as curOut was 103 before and 42 after.

In terms of the blockchain data we had (according to the most popular currencies), our analysis in what follows is restricted to Dash and Zcash, although we leave an exploration of Monero as interesting future work.

8.4.1 Zcash

The main anonymity feature in Zcash is known as the *shielded pool*. Briefly, transparent Zcash transactions behave just like Bitcoin transactions in that they reveal in the clear the sender and recipient (according to so-called *t-addresses*), as well as the value being sent. This information is hidden to various degrees, however, when interacting with the pool. In particular, when putting money into the pool the recipient is specified using a so-called *z-address*, which hides the recipient but still reveals the sender, and taking money out of the pool hides the sender (through the use of zero-knowledge proofs [2]) but reveals the recipient. Finally, Zcash is designed to provide privacy mainly in the case in which users transact *within* the shielded pool, which hides the sender, recipient, and the value being sent.

We considered three possible interactions between ShapeShift and the shielded pool, as depicted in Figure 7: (1) a user shifts coins directly from ShapeShift into the shielded pool, (2) a user shifts to a t-address but then uses that t-address to put money into the pool, and (3) a user sends money directly from the pool to ShapeShift.

For the first type of interaction, we found 29,003 transactions that used ZEC as curOut. Of these, 758 had a z-address as the output address, meaning coins were sent directly to the shielded pool. The total value put into the pool in these transactions was 6,707.86 ZEC, which is 4.3% of all the ZEC received in pass-through transactions. When attempting to use z-addresses in our own interactions with ShapeShift, however, we encountered errors or were told to contact customer service. It is thus not clear if usage of this feature is supported at the time of writing.

For the second type of interaction, there were 1309 where the next transaction (i.e., the transaction in which this UTXO spent its contents) involved putting money into the pool. The total value put into the pool in these transactions was 12,534 ZEC, which is 8.2% of all the ZEC received in pass-through transactions.

For the third type of interaction, we found 111,041 pass-through transactions that used ZEC as curIn. Of these, 3808 came directly from the pool, with a total value of 22,490 ZEC (14% of all the ZEC sent in pass-through transactions).

Thus, while the usage of the anonymity features in Zcash was not necessarily a large fraction of the overall usage of Zcash in ShapeShift, there is clear potential to move large amounts of Zcash (representing over 10 million USD at the time it was transacted) by combining ShapeShift with the shielded pool.

8.4.2 Dash

As in Zcash, the "standard" transaction in Dash is similar to a Bitcoin transaction in terms of the information it reveals. Its main anonymity feature — *PrivateSend* transactions — are a type of CoinJoin [8]. A CoinJoin is specifically designed to invalidate the multi-input clustering heuristic described in Section 7, as it allows multiple users to come together and send coins to different sets of recipients in a single transaction. If each sender sends the same number of coins to their recipient, then it is difficult to determine which input address corresponds to which output address, thus severing the link between an individual sender and recipient.

In a traditional CoinJoin, users must find each other in some offline manner (e.g., an IRC channel) and form the transaction together over several rounds of communication. This can be a cumbersome process, so Dash aims to simplify it for users by automatically finding other users for them and chaining multiple mixes together. In order to ensure that users cannot accidentally de-anonymize themselves by sending uniquely identifiable values, these PrivateSend transactions are restricted to specific denominations: 0.01, 0.1, 1, and 10 DASH. As observed by Kalodner et al. [5], however, the CoinJoin denominations often contain a fee of 0.0000001 DASH, which must be factored in when searching for these transactions. Our parameters for identifying a CoinJoin were thus that (1) the transaction must have at least three inputs, (2) the outputs must consist solely of values from the list of possible denominations (modulo the fees), and (3) and all output values must be the same. In fact, given how Dash operates there is always one output with a non-standard value, so it was further necessary to relax the second and third requirements to allow there to be at most one address that does not carry the specified value.

We first looked to see how often the DASH sent to ShapeShift had originated from a CoinJoin, which meant identifying if the inputs of a Phase 1 transaction were outputs from a CoinJoin. Out of 100,410 candidate transactions, we found 2,068 that came from a CoinJoin, carrying a total of 11,929 DASH in value (6.5% of the total value across transactions with Dash as curIn). Next, we looked at whether or not users performed a CoinJoin after receiving coins from ShapeShift, which meant identifying if the outputs of a Phase 2 transaction had been spent in a CoinJoin. Out of 50,545 candidate transactions, we found only 33 CoinJoin transactions, carrying a total of 187 DASH in value (0.1% of the total value across transactions using Dash as curOut).

If we revisit our results concerning the use of U-turns in Dash from Section 6.2, we recall that there was a large asymmetry in terms of the results of our two heuristics: only 5.6% of the U-turns used the same UTXO, but 64.6% of U-turns used the same address. This suggests that some additional on-chain transaction took place between the two ShapeShift transactions, and indeed upon further inspection we identified many cases where this transaction was a CoinJoin. There thus appears to have been a genuine attempt to take advantage of the privacy that Dash offers, but this was completely ineffective due to the use of the same address that both sent and received the mixed coins.

9 Conclusions

In this study, we presented a characterization of the usage of the ShapeShift trading platform over a thirteen-month period, focusing on the ability to link together the ledgers of multiple different cryptocurrencies. To accomplish this task, we looked at these trading platforms from several different perspectives, ranging from the correlations between the transactions they produce in the cryptocurrency ledgers to the relationships they reveal between seemingly distinct users. The techniques we develop demonstrate that it is possible to capture complex transactional behaviors and trace their activity even as it moves across ledgers, which has implications for any criminals attempting to use these platforms to obscure their flow of money.

Acknowledgments

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